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THE CHALLENGE OF INFLATION FORECASTING DURING THE COVID-19 PANDEMIC

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Abstract

This study analyses the impact of domestic and international factors on inflation in Montenegro, with a particular focus on methods for its management. The central hypothesis for inflation management is based on the adoption of fiscal and monetary policy. Previous studies have relied on the relationship between fiscal and monetary policy and have not been able to separate the effects of unconventional policies on inflation from the effects of other conventional policies. Using data from January 2006 to December 2023 and applying a new statistical approach, this study quantifies the correlation between shocks to inflation driven by: a) fiscal and monetary shocks, b) shocks in foreign markets, c) demand and supply, d) economic inequality and e) internal and external shocks. Contrary to assumptions, inflation is not maintained by conventional fiscal and monetary policy alone. Unsustainable supply and the effects of an overheated labour market are persistent, discouraging the expectations of citizens and investors, disrupting commodity and financial markets and destabilizing the key macroeconomic factor: inflation. Our new findings indicate that the maintenance of stable inflation should not be based only on conventional assumptions and reveal the mechanism of key gaps on the part of the prudential authority.

Keywords: Inflation, Connectedness, Forecast, Policy objectives, Macroeconometrics.

JEL classification: E31, C54, E17, E61, B23.

1. Introduction

Predicting a rise in inflation during the COVID-19 pandemic has been a major challenge faced by both advanced and developing economies. The creators of macroprudential policies were slow in their reaction and due to the attitude that the surge of inflation will be but temporary, the action was further delayed. Inflation during the pandemic forced countries to face long periods of instability, a long but urgent problem of global politics, with implications for a range of phenomena from economic growth and political stability, public health, family well-being and social trust. Large swings in inflation can have different effects on a country's macroeconomic variables. Policies that promote social and gender equality, such as including the bottom 50% national income share and reducing the wage gap or improving access to health care and education, can affect income distribution, the poverty rate and citizens' consumption. However, these policies affect macroeconomic indicators such as GDP, income inequality and inflation.

Countries with solid inflation stability can attract sophisticated and long-term investors, positively influence capital flows, foreign direct investments, employment and exchange rates (Bojaj and Aharon, 2024). Since a lack of commitment to inflation stability may discourage investment, corporate macroprudential policymakers must therefore find strong social, demographic, economic, and political reasons to examine and identify factors that lead to higher inflation. Determining dynamic volatility spillovers and spatio-temporal linkages between inflationary factors is a significant challenge in policy makers' efforts to address these issues and design appropriate policies, which is the main objective of this study.

Global inflationary consequences harm personal and social cohesion, thus affecting billions of people worldwide (Giovanni et al., 2023). Blanchard and Bernanke (2023) emphasize that the imbalance in labour supply and demand was a key driver of the world's inability to absorb price shocks, such as the debt and inflation crisis in 2022, which represents a huge risk for socio-economic systems and democracy in the European Union (EU) (especially for small countries like Montenegro; Bojaj et al., 2022; Ivanović 2023). Fabris (2023) emphasizes that the COVID-19 pandemic has radically changed the world. Inflation stabilization policies can contribute to a country's long-term economic resilience by addressing systemic and systematic risks within and across countries, thereby improving resilience to future economic shocks.

The reasons for focusing research on Montenegro are manifold. As a small, euroised and open economy, Montenegro relies heavily on foreign capital inflows to stimulate economic growth. For economies such as Montenegrin, which need structural reforms and are in the process of joining

the EU, the analysis of sensitivity to crisis, the connection between the market and the measurement and policy of systemic risk volatility is a suitable example for the analysis in terms of the interconnectedness of inflation, management and political decisions. The specific characteristics of Montenegro allow us to detect inflationary policy shocks. Furthermore, the connectedness between these shocks and their volatility spillovers is very important because it helps us identify which variables are causing the shocks and which are receiving the shocks.

One line of research literature predicts that inflation will be insensitive to fiscal spending, so the Phillips curve will remain flat (Reifschneider and Wilcox, 2022). Ball et al., (2022) point out that the tightening of the labour market caused inflationary pressure. Cecchetti et al. (2023) explain that non-linearities in the Phillips curve can explain recent changes in inflation. Gagliardone and Gertler (2023) emphasize that the Fed's monetary policy caused inflation. Koch and Noureldin (2023) fail to give adequate weight to commodity prices and their dynamics with output growth. Misestimations of the economic effects of fiscal programs from the period of the COVID-19 pandemic, both in advanced economies and in developing economies, are one of the potential explanations for inflation forecasting challenges.

The literature on the linkage of inflation policy shocks that exists to date is very scarce. Baqaee and Farhi (2022), Rubbo (2023), Guerrieri et al. (2021), and Lorenzoni and Verning (2023), emphasize a multi-sector approach to modelling inflation, using input-output linkages and wage rigidity. In contrast to these works, we allow for the full range of both domestic and global input–output structures, ensuring that shocks spanning across country sectors affect all sectoral and aggregate price changes endogenously. However, these works often limit their analysis to a limited number of variables and, therefore, miss the true contagion spillovers of dynamic linkages between sectors. Unlike these models, our nonlinear multilevel approach can account for different shocks that explain inflation dynamics at different times with the coexistence of indicators of tight governance.

The overarching goal of this study is to create an "interdependence profiling" model of inflation policy that could provide policy makers with a decision-making direction to visualize, size, and assess risk, even before the onset of an inflation shock, optimizing forecasting and policy-making efficiency. The discovery of internal and external inflationary determinants is helpful as a basis for decision-making in organizing operations and planning. This paper uses a wide range of econometric models, each carrying robust time series, and assesses their forecasting performance across time and models. Various studies have compared predictions on one particular model. However, this paper focuses on combining key internal and external inflation factors and performing a combination of forecasts for the same event: since there is no single "one-fits-all" model. The importance of discovering internal and external inflationary determinants lies primarily in the (inevitably approximate) evaluation of anti-inflationary policies, but also in the basic story of how it came about and what it portends for the future of the Montenegrin economy. Discovering the determinants of inflation is important for individuals, businesses, and institutions because it helps clarify the relationship between indicators (e.g., the relationship between oil and inflation,

the aggregate macroeconomic relationship, or the full relationship of other indicators with inflation). The correlation analysis of the variance matrix can help various participants to clearly understand the micro and macro aspects of market risks.

Stabilization of inflation has become one of the main priorities for global authorities, especially after the introduction of the 2030 Agenda for Sustainable Development by the United Nations in 2015. As Montenegro has since shown its commitment to achieving the associated Sustainable Development Goals (SDGs), while also negotiating full membership in the EU since June 2012 (Dimitrijević et al., 2016; Fabris and Luburić, 2017; Jakšić et al., 2018; Bojaj et al., 2023), we try to answer the following questions: (a) Are there spillover effects through variables associated with inflation factors? (b) Which variables are the main transmitters/receivers to/from other variables? (c) Which economic sectors seem to exert the most pressure on prices and drag on demand in relation to inflationary policy? (d) What is the best combined inflation model? In order to respond to all of the above, our inflation policy model mainly focuses on SDG goal 9 (Ministry of Finance of Montenegro, 2017). SDG 9 (build resilient infrastructure, promote sustainable industrialization and foster innovation) supports employment and income generation by developing new technologies, promoting international trade and encouraging resource efficiency (Bojaj et al., 2023).

The key novelty of this study has four aspects. First, we extend the work of Diebold and Yilmaz (2014) by applying a structural Bayesian vector autoregression (BVAR) model and spillover connectedness effects to predict and estimate the impact of exogenous policy shocks on the real economy, especially on inflation. Second, we add breadth by combining, for the first time to our knowledge, specific sets of variables in six models. Unlike previous literature, we specifically analyze the effect of a wide range of internal and external shocks on inflation. Our findings show that different shocks have different effects. Third, we identify specific risk factors that could potentially act as mechanisms that transmit destabilization. Fourth, we combine the six models and assign appropriate weight to each model to obtain the best prediction model. Finally, our evaluation offers new perspectives by illustrating dynamic effects in several hypothetical situations. This study fills a gap in existing research by offering empirical measurements of the interconnectedness of inflation and spillover effects. By providing clear economic insights and measuring potential political inflation shocks in normal and extreme situations across different time intervals, we contribute to the prediction of normal conditions and extreme inflationary shocks and the measurement of volatility of their macroeconomic connectedness using the BVAR model that combines inherent-systemic and systemic market vulnerability.

2. Methodology

Montenegro nationalized the 2030 Sustainable Development Agenda by adopting the National Sustainable Development Strategy (NSDS) in 2016, and responded to the implementation with an Action Plan (Bojaj et al., 2022). NSDS is an umbrella, horizontal and long-term development strategy of Montenegro, which considers the environment, economy and human resources, key social capital and proposals for the development of a funding and management system for long-term development. NSDS is a strategic mechanism for transposing the goals of sustainable development - SDG goals and their indicators into the national context. Following the Agenda above, our macroeconometric model of the production function and inflation is remodelled as we include additional variables.

We use a combined approach, Bayesian VAR and connectedness. We begin by identifying six models. Using a combined approach, we combine these with equal, trimmed, AIC, and inverse MSE weighting approaches. The new models allow for a wide range of time-varying shocks, including aggregate demand shocks, demand changes, supply and productivity shocks, monetary and fiscal policy shocks, and inflationary expectations. We include a number of variables within the model because adding more regressors to a prediction model exacerbates size problems (Clark and West, 2006). The identified models are as follows:

$$\pi_t = \beta_0 + \beta_1 \log(FAO)_t + \beta_2 \log(OIL)_t + \beta_3 Gov\_exp_t + \beta_4 \log(Household)_t + \beta_5 Un_t + \beta_6 GDP\_GAP_t + \beta_7 infeu_t + \beta_8 dum_3 + \beta_9 dum_4 + u_t \quad (1)$$

$$\pi_t = \beta_0 + \beta_1 logwages_t + \beta_2 exchange\ rate_t + \beta_3 GDP_{GAP\,t} + u_t \quad (2)$$

$$\pi_t = \beta_0 + \beta_1 SRinf_t + \beta_2 BHinf_t + \beta_3 ALinf_t + EMUinf_t + u_t \quad (3)$$

$$\pi_t = \beta_0 + \beta_1 BDP_t + \beta_2 \log(extreme\ weather)_t + \beta_3 \log(innovations)_t + \beta_4 global\ temperature_t + \beta_5 logocean_t + u_t \quad (4)$$

$$\pi_t = \beta_0 + \beta_1 liquidity_t + \beta_2 \log(credit)_t + \beta_3 npl_t + \beta_4 npl\_C_t + \beta_5 npl\ prov_t + \beta_6 reg\_C_t + \beta_7 t1\_cap_t + \beta_8 t1\_l_1 + \beta_9 roa_1 + \beta_9 roe_1 + u_t \quad (5)$$

$$\pi_t = \beta_0 + \beta_1 curr\ acc_t + \beta_2 interest_t + \beta_3 GDP_t + u_t \quad (6)$$

Historically, time-series forecasting of economic variables has focused on low-dimensional models such as autoregressions, single-equation regressions using leading indicators as predictors, or vector autoregressions with perhaps half or fewer variables. These low-dimensional models poten-

tially leave out the information contained in the many variables available to real-time economic forecasters. In order to forecast using many predictors, it is necessary to impose enough constraints to keep the number of estimated parameters small. One way to impose such constraints on high-dimensional systems is to assume that the variables have a dynamic factor structure, and research (Stock and Watson, 2002; Forney et al., 2001) suggests that there are potential predictive gains from using high-dimensional dynamic factor models. There are, however, other ways to impose structure on high-dimensional forecasting models, and one such way is to apply model-combining forecasting methods.

Forecasts based on individual predictors are calculated using h-step projections. Equations 1–6 represent the parameter estimates and main features of the model. The first identified recursive SVAR model is model 1 (equation 1), where π_t - denotes the inflation rate, log - denotes the natural logarithm so that the inflation function has a constant price elasticity, $\log(FAO)_t$ - the natural logarithm of food prices, $\log(OIL)_t$ – natural logarithm of oil prices, Gov_exp_t – state expenditures (% of GDP), $\log(Household)_t$ – natural logarithm of household consumption percentage, Un_t - unemployment percentage, GDP_GAP_t - gross domestic product, $infeu_t$ – inflation in the European Economic and Monetary Union (EMU). Oil and food prices are critical variables in model 1 and we are interested in following their dynamics, as they are determined exogenously. Montenegro has set its national development strategy, therefore it is worth analyzing how this set of factors that determines the dynamics of economic growth affects inflation (ERP, 2024-2026).

Model 2 examines how changes in $logwages_t$ - natural logarithm of earnings, $exchange\ rate_t$ - natural logarithm of exchange rates (EUR/USD), and GDP affect inflation in Montenegro, using recursive structural VAR approach. As the euro is used in Montenegro, model 2 will help us identify the dynamics of the exchange rate, together with wages and GDP.

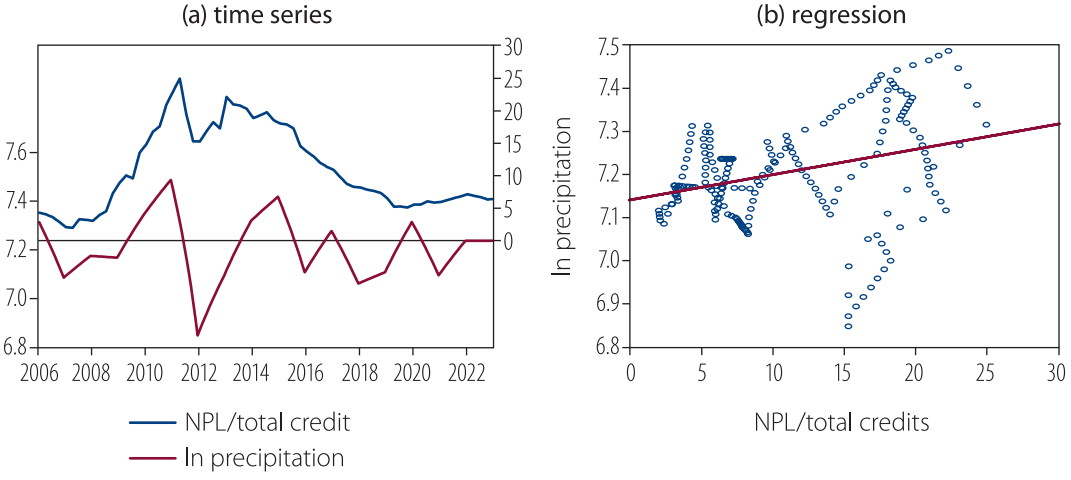
The monitoring of inflationary pressure and its dynamics from the EMU and the neighbouring countries of the Western Balkans (WB) is presented through model 3, where $SRinf_t$ denotes inflation in Serbia, $BHinf_t$ denotes inflation in Bosnia and Herzegovina, $ALinf_t$ denotes inflation in Albania, and $EMUinf_t$ is inflation in the EMU. Montenegro trades with all the listed countries and model 3 identifies the weight and spillover effect of each country on the Montenegrin economy.

Model 4 identifies the main indicators of climate change and their impact on inflation, where $\log(extreme\ weather)_t$ denotes the natural logarithm of extreme weather, $\log(innovations)_t$ denotes the natural logarithm of innovation, and $global\ temperature_t$ - indicates global temperature, and $logocean_t$ denotes the natural logarithm of ocean. The extreme weather variable consists of seven components that provide information on the main hazards: cold and heat stress, droughts, heavy precipitation, intense winds, hail and wildfire conditions. The innovation index includes elements of the national economy that enable innovative activities: (1) institutions, (2) human capital and research, (3) infrastructure, (4) market sophistication, and (5) business sophistication. Two output pillars include real evidence of innovation results: (6) knowledge and technology results and (7) creative results.

Compared to the average temperature in the period 1961–1990, the global average temperature has changed. If there were no carbon dioxide (CO_2) and other greenhouse gases in the atmosphere, too little sunlight would be absorbed and too much radiated, so it is estimated that the global temperature would be around -18°C. However, if there is excess CO_2, the earth's temperature would increase, leading to global warming. Significant global warming would be catastrophic, leading to rising sea levels, extreme weather events and parts of the world becoming uninhabitable. Since the industrial revolution, the use of fossil fuels (primarily coal) has led to a large increase in CO_2 emissions. At the same time, there has been a steady increase in the average global temperature, which has increased by about 1.2°C since 1850, with most of the increase occurring since the late 1970s. Global warming is a major global concern, and limiting CO_2 can alleviate the problem. Turning from the past to the future, the main question is how fast global warming will occur. This indicator in model 4 is of great importance because it allows us to estimate the relationship between inflation and global temperature.

Model 5 examines how changes in financial stability indicators affect inflation, where $liquidity_t$ - denotes liquidity, $\log(credit)_t$ denotes the natural logarithm of total loans, npl_t denotes non-performing loans, npl_C_t denotes non-performing loans net of provisions to capital, $npl\ prov_t$ denotes provisions to non-performing loans, reg_C_t denotes regulatory capital, $t1\_cap_t$ denotes tier 1 capital to risk-weighted assets, $t1\_l_1$ denotes tier 1 capital to assets, roa_1 – denotes return on assets, and roe_1 – denotes return on equity. Climate change poses urgent and serious systematic and systemic risks to the financial sector with serious consequences for a range of outcomes, including political stability, economic growth, increased borrowing, public debt, unemployment and inflation.

Graph 1 – NPL/total credits and precipitation in Montenegro (2006–2022)



Source: Author's calculations

Note: Graph 1a shows the relationship between the natural logarithm of precipitation (ln precipitation) and NPL/TC in Montenegro for 2006–2022. Graph 1b shows NPL/TC versus ln precipitation

Graph 1(a) shows the relationship between non-performing loans/total credits (NPLS/TC) and the natural logarithm of precipitation (ln precipitation) in Montenegro from January 2006 to 2022. Graph 1a indicates that there is a significant positive relationship between NPL/TC and ln precipitation. To be sure, Graph 1 is hardly a proof of causality. Both variables show a positive trend until April 2011, and from May to January 2012, both variables show a negative trend. From February 2012 to January 2015, non-performing loans/total loans and ln precipitation show a positive trend. Graph 1(b) examines the correlation between the increase in ln precipitation in Montenegro between January 2006 and December 2022 and the increase in NPL/TC. Graph 1b shows a significant positive correlation between NPL/TC and ln precipitation.

Model 6 examines how changes in $curr\ acc_t$ – current account, $interest_t$ – interest rates, and GDP affect inflation. It is of great importance to assess the dynamics of volatility and spillover between the current account, interest rates, and inflation. Model 6 will identify interdependencies and reveal risk severity.

The models in equations 1–6 monitor the dynamics of internal and external demand factors and cost increases, which will indicate the shocks coming from the global market to the Montenegrin economy. Bogetić et al. (2013) point out that Montenegro does not use the main engine of growth - export. Exports have transformed many small countries, especially those with significant location advantages. Given the uncertainty associated with identifying the true data-generating process (DGP), combining individual predictor forecasts offers a simple way to build a sophisticated, more flexible prediction model to explain the data.

A pooled-combined forecast is a weighted average of Z forecasts (Zhang, 2019):

$$\hat{y}^{c}_{T+h} = \sum_{i=1}^{Z} w_{T,h,i} x_{T,h,i} \tag{7}$$

and choosing weights $w_{T,h,i}$, minimizes the risk associated with the loss from making a forecast error. The optimal weight for $x_{T,h,1}$ is:

$$w^{*} = \frac{\sigma^2_{T+h,3} - \sigma_{T+h,1,2,3}}{\sigma^2_{T+h,1} + \sigma^2_{T+h,2} + \sigma^2_{T+h,3} - 3\sigma_{T+h,1,2,3}} \tag{8}$$

and more significant weight is assigned to the more precise model. The vector of optimal weights w' with Z forecasts is:

$$w^{'} = \frac{u^{'} \sum^{-1}_{T,h}}{u^{'} \sum^{-1}_{T,h} u} \tag{9}$$

The squared bias and the forecast variance of the MSE loss function of a forecast is:

$$E\left[\left(y_{T+h}-x_{T,h,i}\right)^2\right]=\sum_{i}^{Z} w_{T,h,i}^2\, bias_{T,h,i}^2+\sigma_y^2+\sum_{i}^{Z} w_{T,h,i}^2\, Var_{T,h,i}^2 \tag{10}$$

The recursive MSE of individual forecasts is:

$$MSE_{T,h,i}=\frac{1}{T-h-1}\sum_{t=1}^{T-h}\left(y_{t+h}-x_{t,h,i}\right)^2 \tag{11}$$

Moreover, MSE weights, as the relative performance weights, are:

$$\omega_{T,h,i}=\frac{\frac{1}{MSE_{T,h,i}}}{\sum_{i=1}^{Z}\frac{1}{MSE_{T,h,i}}} \tag{12}$$

Computing relative performance weights (inverse MSE) using either rolling windows or discounting allows more attention to be paid to recent performance. Combined forecasts imply diversification of risk.

We are mainly interested in the dynamic response of output to an exogenous shock to the economy. In our case, we need to identify seven structural VAR models (equations 1-7) and structural shocks using recursive ordering. The goal is to follow the footprints of internal and especially external shocks (e.g. food and oil prices) to the economy. Based on this model, we are interested in generating forecasts and, for policy analysis, using economic intuition to set restrictions. Since Montenegro's specific characteristics as a small euroised economy are crucial, we aim to obtain empirical results from this structural vector autoregression (SVAR) model as follows:

$$A_0 z_t = A_1 z_{t-1} + A_2 z_{t-2} + \ldots + A_p z_{t-k} + \varepsilon_t \tag{13}$$

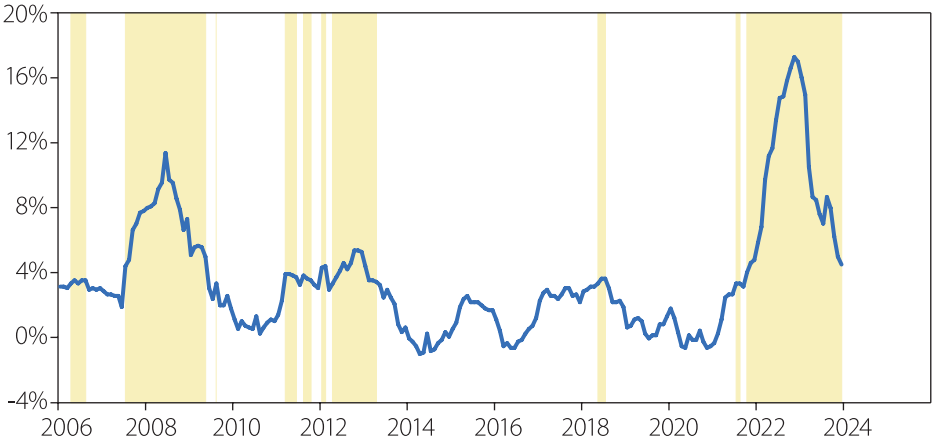
Matrix A_0 will be defined as

$$A_0=\begin{bmatrix} a_{11}^0 & -a_{12}^0 & . & . \\ -a_{21}^0 & a_{22}^0 & -a_{23}^0 & . \\ . & . & . & . \\ . & . & . & . \end{bmatrix}.$$

z_t is ($nx1$) vector of endogenous variables. Matrix A is invertible and has (nxn) coefficients of contemporaneous relations on the endogenous variables. $A_i^{'}s$ are matrices (nxn) capturing the dynamics of variables, and ε_t is a ($nx1$) structural shock vector. The signs on a_{ij}^0 are chosen to enable each equation to be written in regression form.

Graph 2 shows the inflation rate volatility from January 2006 to December 2022. Light yellow shades denote swings greater than 3%. The Central Bank of Montenegro (CBCG) aims to trace shocks to the Montenegrin economy, especially inflation.

Graph 2 – Inflation rate evolution



Source: authors' calculations

Note: The sample is the inflation rate, from January 2012 to December 2019. Yellow shading denotes swings greater than 3% per month. We notice three big episodes of swings: (a) June 2007 to June 2009, (b) March 2012 to May 2013, and (c) January 2022 to December 2022. There appear six other nonnegligible swings of inflation rate above 3%.

Consider an event in which Montenegro anticipates an overheating economy. Hypothetically, the CBCG imports the increase of the interest rate, but the overheating is not stopped as anticipated. One could infer that an interest rate increase leads to overheating. It is an *endogenous* reaction to economic activity that is *expected*. We must identify policy shocks that are entirely *exogenous* to trace the dynamic effects of shocks (Terzioglu et al., 2021). Thus, SVAR is used. Impulse responses (IRs) explore the effects of structural shocks in the VAR model. For each structural innovation of Bitcoin and stablecoin, an IR shows the change in endogenous variables (Inoue & Kilian, 2016).

We use the classic relationships among assessments of estimated errors and structural shocks. Bojaj et al., (2023) emphasize that in the case of VAR, the stability condition requires that coefficient $| g_i |< 1$. The condition that guarantees stability is that G has eigenvalues smaller than 1 in modulus and is a prevalent and valid result for any VAR(p).[1]

[1] *This becomes clear when the standard VAR is iterated backward. For a simple VAR(1), after successive iterations, we get:* $Z_t = G_0 + G_1(G_0 + G_1(G_0 + G_1 Z_{t-3} + e_{t-2}) + e_{t-1}) + e_t;; Z_t = (I + G_1 + G_1^2 + \ldots + G_1^{\infty})G_0 + e_t + \sum_{i=1}^{\infty} G_1^i e_{t-i} + G_1^i X_{t-n-i}$. $i \to \infty$ *Z reduces to a sum of errors or into a sum of shocks, which is called the Wold representation of Z:* $Z_t = \mu + \sum_{i=1}^{+\infty} G_1^i e_{t-i} + e_t$ *where* G_1^i *denotes the matrix of coefficients. Assume* $\psi_i = G_1^i$; *then* $Z_t = \mu + \sum_{i=1}^{+\infty} \psi_i e_{t-i} + e_t$. *If Z has Wold representation, then Z is stable. Since VAR is stationary, the estimated reduced-form VAR has a moving average:* $X_t = \mu + \sum_{i=1}^{\infty} \psi_i e_{t-i}$.

Using the same relation between the forecast errors and structural shocks, we find

$$X_t = \mu + A^{-1}u_t + \sum_{i=1}^{\infty} \psi_i A^{-1}u_{t-i}, \tag{14}$$

where X_t denotes the matrix of endogenous variables, μ denotes constants, A^{-1} denotes the inverse of A (Cholesky factor of Σ_e; the variance–covariance matrix), u_t denotes the structural shocks, and ψ_i denotes the matrix of coefficients. We can write Equation (15) more concisely:

$$X_t = \mu + \sum_{i=1}^{\infty} C_i\, u_{t-i}. \tag{15}$$

$c_{11,i}$, $c_{12,i}$, and $c_{12,n}$ are y to x IRs to a change in u_{yt} and u_{xt}, respectively. Note that $c_{11,0}$ is the effect at impact, $c_{11,1}$ is the effect of u_{yt} on y in $t+1$, and so on in succession:

$$\frac{\partial y_{t+k}}{\partial \epsilon_{yt}} = C_{11,k}. \tag{16}$$

The total effect is $\sum_{i=0}^{\infty} C_{11,i}$. The IRs of inflation rate to one-unit standard deviation shocks are traced out. The ordering of the variables is important. Recursive ordering means there is a sequential chain. If correlations between the errors are low, the order is irrelevant. Correlations are usually strong, however, so the order matters. It is crucial to determine the ordering (restrictions), and to this end, we use economic intuition. An example is a three-variable recursive ordering with y, π, and r; if the movements of r are monetary policy decisions, the policy reacts to output and inflation within the period. All shocks affect r within the period. The interest rate policy only affects other variables (y, π) with a lag, and with A^{-1}, we get the IRs.

We move to the BVAR model for inflation likelihood. VARs often involve estimating many coefficients relative to the available number of observations, which results in imprecise coefficient estimation. We may quantify this likelihood using Bayes's theorem. Bayes's theorem is used to derive the posterior likelihood distribution of coefficients β in regression with coefficients β, the variance–covariance Σ_e, i $e_t \sim$ *nid* $N(0, \Sigma_e)$. This is based on prior distribution related to the dataset likelihood function (Ouliaris & Pagan, 2016; Chin & Li, 2018):

$$\overbrace{p(\beta \mid \textstyle\sum_e, Y)}^{posterior} = \frac{\overbrace{L(Y|\beta, \textstyle\sum_e)}^{likelihood}\ \overbrace{p(\beta|\textstyle\sum_e)}^{prior}}{p(Y)}, \tag{17}$$

where $p(Y) = \int p(Y \mid \beta)\, p(\beta) d(\beta)$ is a normalizing constant. Consequently, we get that the likelihood function multiplied by the prior distribution yields the posterior distribution:

$$p(\beta \mid \textstyle\sum_e, Y) \ \propto\ L(Y \mid \beta, \textstyle\sum_e)\, p(\beta \mid \textstyle\sum_e). \tag{18}$$

The estimate of β, considering the posterior mean as a point estimator, is a weighted average of the OLS estimate and the prior mean, and the priors would be

$$\bar{b} = [\underline{V^{-1}} + \sum_e^{-1} \otimes (X'X)]^{-1}[\underline{V^{-1}}\,\underline{b} + (\sum_e^{-1} \otimes X')y], \tag{19}$$

where $\bar{b}$ and V represent our prior for the true beta and its variance–covariance matrix, respectively. X represents the right-hand-side variables in the linear regression, and Sigma(e) is the covariance matrix of the regression error term. This is the formula for the Bayesian estimates of the OLS estimator, given a prior, b, and a covariance matrix, V. Note that the Bayesian estimator is simply a weighted average of the OLS estimates and the Bayesian priors. The weights depend on the covariance matrix of the OLS estimates and the covariance matrix of the priors. Notice that if we set $b = 0$, the estimator is simply OLS. Further, as $V \to 0$, the weight on the Bayesian prior (relative to the OLS estimator) approaches infinity.

The Bayesian approach relies on a specific choice of a prior distribution and loss function; this produces a posterior distribution and a specific point estimate when combined with the likelihood. The latter might be "close" or not close to the OLS estimate, according to the previous choices and the information content of the data.

Overfitting is a common concern with VARs, leading to inaccurate forecasts. VARs evaluate a large number of variables, *n(np+1)*, many of which are incorrect because of inadequate data. Therefore, response functions and forecasts are not well defined. The number of projected coefficients easily proliferates. This leads the bands of standard errors to neglect considering parametric uncertainties, creating the impression that the forecast findings are more accurate than they actually are. The Bayesian method introduces prior distributions, such as parameter uncertainty. A prior distribution must be specified any time a Bayesian approach is chosen. Then, the class of the chosen prior might induce sparsity or shrinkage of the model parameters, which helps solve VAR models' overfitting issue. However, this is not a given: some prior distributions allow for this behaviour while others do not (Gujarati & Porter, 2009; Tsionas & Mallick, 2019). Solutions that do not include some lag values p in the relevant equations have appeared in the literature; this is also known as "best subset VARs" (Ouliaris & Pagan, 2016). In this part, we use Bayesian approaches to obtain a parsimonious onset by applying relevant prior distributions. We need an estimate of β to get a forecast; we do this by maximizing the following:

$$C(\beta) = ln\{L(Y \mid \beta, \sum_e)\} + ln(p(\beta \mid \sum_e)). \tag{20}$$

We assess BVAR prior types of Minnesota, Normal-Wishart, and normal-flat (Doan et al., 1984). In the case of Minnesota prior-type $b_{11}^1, b_{12}^1, \ldots, b_{18}^1$, the prior means are unity while the other coefficients have a zero mean. The coefficients of the prior of the variance–covariance matrix are represented as follows:

$$\left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2 \quad for\ (i = j), \tag{21}$$

$$\left(\frac{\lambda_1\lambda_2\sigma_i}{l^{\lambda_3}\sigma_j}\right)^2 \quad for\ (i \neq j), \tag{22}$$

and the σ_i^2 is the ith diagonal element of the covariance matrix Σ_e.

We continue a step further and apply variance decomposition to measure connectedness as central risk measurement and management (Adrian and Brunnermeier, 2016; Acharya et al. 2017). Our method for determining connectedness is based on Diebold and Yilmaz's (2014) unified framework concept of connectedness. The econometric concept of variance decomposition is used.

Box 1 – Measuring the 2007–2008 Global Financial Crisis

Diebold and Yilmaz (2014) study the volatility of stock returns for thirteen large US financial institutions that survived the 2007–2008 crisis. Their sample includes seven commercial banks, two investment banks, one credit card company, two mortgage finance companies, and one insurance company. The sample covers the period May 1999 - April 2010. It also includes several important financial episodes in addition to the 2007–2008 crisis. These include dot-com in 2000, Enron in October 2001, and WorldCom/MCI in July 2002. Therefore, they were not only able to assess the connectedness of companies during the crisis of 2007-2008, but they compared and contrasted the connectedness during other episodes.

They have successfully proposed measures of connectedness at all levels, from the whole system to pairs, that are rigorous in theory and easily implemented in practice and which capture different strengths of different ties and temporal variation in connectedness. Their methodology could accurately predict the crisis. Their approach effectively combines VAR theory and connectedness topology theory, the recognition that variance decompositions of VARs form weighted directed network connectedness, characterizing connectedness in those networks, and a twist that characterizes connectivity in VARs.

We use BVAR, thereby identifying a recursive structural model and examining the effects of different stress test scenarios on the corresponding variable. Finally, we continue with measures of connectedness, as a central measure of risk.

The method described above has not been used, at least not in Montenegro`s data analysis. We use multiple hypothetical scenarios (e.g. increase in internal and external factors such as food prices, household consumption, global temperature, credit, etc.) because policymakers may be interested in understanding how inflation and GDP react under different circumstances.

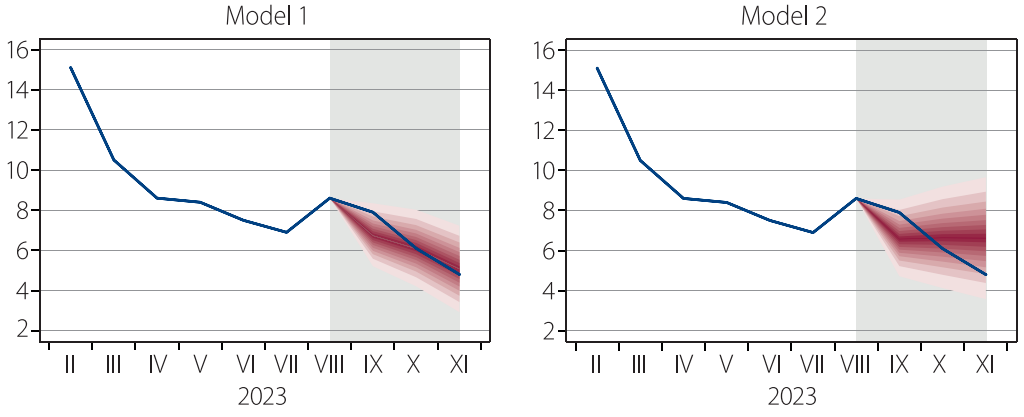
3. Results

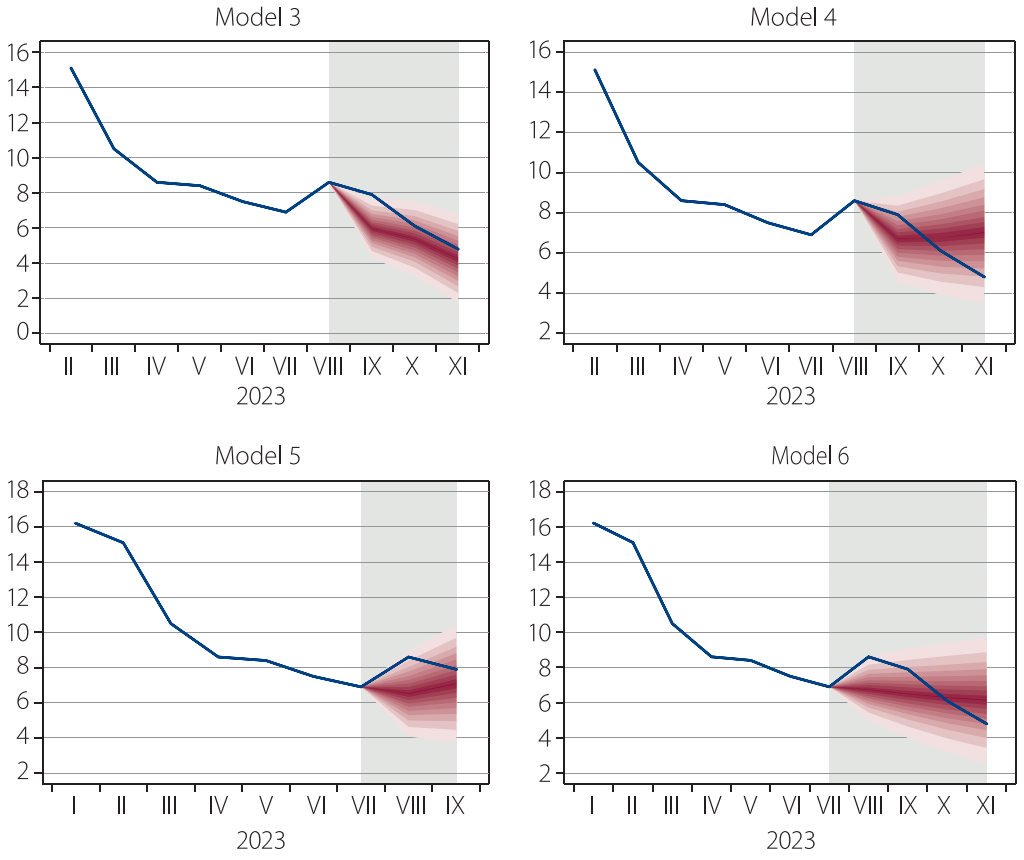
We use the fan chart technique introduced in the Bank of England's monthly reports. We create a visual illustration of the confidence interval process of continuous change across the forecast timeline. Graph 3 employs the fan chart forecasting of inflation for seven models. The sample for estimation is 2006m01–2020m12, while the sample for forecasting is 2021m01–2021m12. We portray results, showing ten confidence intervals: from 90% to the mode.

The lightest red band corresponds to the 90% confidence interval. The next corresponds to the 80% confidence interval, and the one in the middle corresponds to 10%. The blue line in the middle corresponds to the mode, and the grey area corresponds to the 10% bounds. Our actual inflation forecasting performances fit completely into the 90% band, even though coefficient uncertainty generally adds an approximate 10% increase in the bands. The confidence bands widen over time until 2023m11.

Since introducing additional explanatory variables into the models, we obtain different model fits into fan charts but all models are useful since each one has different valuable information and explanatory shocks to inflation. The forecasting performances of inflation in Graph 3 confirm that models 1-7 are well suited for prediction.

Graph 3 – Fan Charts - Stochastic simulator





Source: authors' estimates.

Note: The models 1-6 for inflation VAR are estimated for the period 2006m1 to 2023m6 and are forecast for the period 2023m7 to 2023m11. Errors for the confidence bounds are bootstrapped, and normality is assumed. Confidence bounds include coefficient uncertainty. The fan charts include nine different equally spaced confidence bounds—90%, 80%, 70%, 60%, 50%, 40%, 30%, 20%, and 10%—and the mode.

3.1. Combination forecasts

We evaluated six different models and then compared their forecasting performance, based on the evaluation statistics, as seen in Table 1. In addition, we calculated three combined forecasts with these models. The first model has the smallest root mean square error (0.93) and has the best covariance proportion (0.965). The true forecast has a small bias and proportion of variance, with most of the error concentrated in the proportion of covariance, all adding up to 1. All forecast evaluation statistics have very valuable information, but we use root mean square error (RMSE) as the benchmarking evaluation statistic. Combining the above seven forecasts, with equal weights, truncated and relative performance weights (inverse MSE weights), reveals three more columns of forecast evaluation statistics, specifically RMSE.

Table 1 reveals that model 1 and the inverse MSE combination have the lowest RMSEs, 0.92 and 1.00. The forecast based on ARIMA has RMSE=2.381 and a bias ratio of 90.10%. The relative weight numbers, based on the inverse MSE, are as follows: r_1 = 1.37, r_2 = 0.55, r_3 = 0.32, r_4 = 0.39, r_5 = 0.54, r_6 = 0.69, and r_7 =0.18. While the value of the denominator is r_t = 4.05. By construction, the weights should sum up to 1, and the relative weights are as follows: w_1 = 0.34, w_2 = 0.14, w_3 = 0.08, w_4 = 0.10, w_5 = 0.13, and w_6 = 0.17, and w_7=0.04.

Table 1 – Forecast evaluation statistics

		Forecast models 1-6							Combined forecasts		
Forecast evaluation statistics		Forec 1	Forec 2	Forec 3	Forec 4	Forec 5	Forec 6	Forec ARIMA	F comb	F trim	F MSE
Bias		-0.019	0.359	-0.313	0.55	-0.297	0.287	-2.260	-0.39	-0.119	-0.351
Mean square error (MSE)		0.866	1.691	1.248	1.632	1.573	1.776	5.670	1.203	1.457	1.017
Root mean square error (RMSE)		**0.93**	1.3	1.117	1.278	1.254	1.333	2.381	1.097	1.207	1.008
Standard forecast error (SE)		0.87	1.56	1.15	1.33	1.48	1.69	0.56	1.05	1.44	0.89
Mean absolute error (MAE)		0.701	1.143	0.731	1.191	1.104	1.128	2.260	0.859	1.018	0.803
Mean percentage error (MPE)		0.919	7.512	-2.676	10.783	-3.351	6.653	-33.668	-2.828	1.969	-2.546
Mean absolute percentage error (MAPE)		9.298	16.636	9.804	18.237	13.564	16.437	33.668	12.206	15.62	11.338
Theil U1		0.069	0.095	0.085	0.092	0.081	0.097	0.202	0.081	0.088	0.075
	Bias proportion	0.000	0.076	0.079	0.185	0.056	0.046	0.901	0.126	0.01	0.121
	Variance proportion	0.035	0.021	0.113	0.112	0.174	0.03	0.001	0.718	0.924	0.693
	Covariance proportion	**0.965**	**0.903**	0.809	0.703	0.77	**0.924**	0.099	0.156	0.066	0.186

Source: Author's estimation.

Note: Forecast evaluation statistics such as bias, MSE, RMSE, SE, MAE, MPE, MAPE, Theil U1 and Theil U2, bias proportion, variance proportion and covariance proportion are used, confirming the prediction performance results.

Although the relative weights of models 3 and 7 are relatively low, when combined into relative weights, the combination models reveal vital and robust information for macroprudential policymakers: lower RMSE. It is important to note that the ARIMA model has the lowest weight of only 4% of all models, while model 1 has more than 34%.

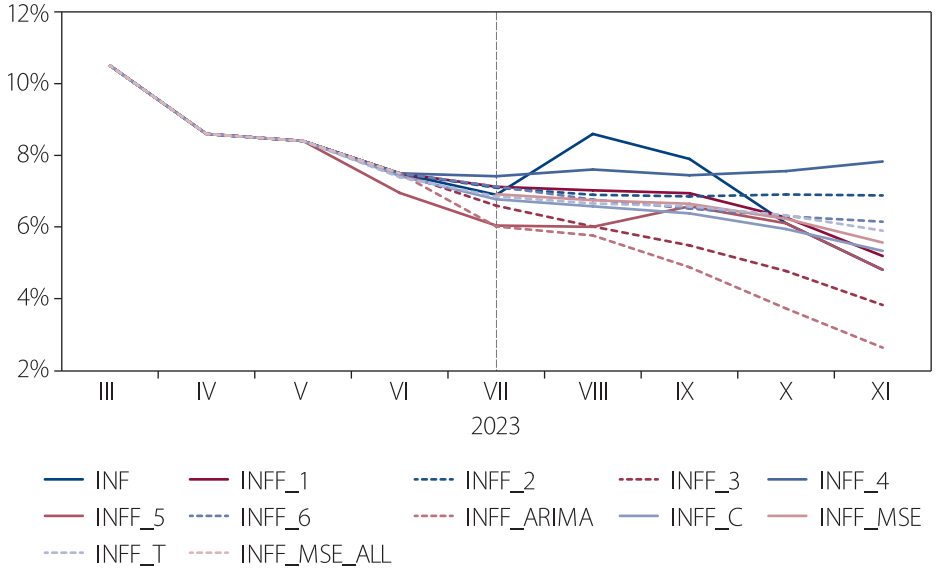
We conclude that the inclusion of adequate forecasts in the combination of forecasts reduces the RMSE of the combined forecasts. Therefore, combined forecasts, which combine individual-predictor forecasts, represent the optimal solution for inflation forecasts.

Graph 4 shows a comparison of actual inflation forecasts (inf), combined inflation forecast using relative weights based on inverse MSE (inff_mse), combined forecast using equal weights (inff_c), combined forecast using trimmed weights (inf_t), forecast using model 1 (inff_1) , forecast using model 2 (inff_2), forecast using model 3 (inff_3), forecast using model 4 (inff_4), forecast using model 5 (inff_5), forecast using model 6 (inff_6) and forecast using model 7-ARIMA (inff_arima).

The results are remarkable because, initially, in the first three months of the forecast (July-September), model 4 (dark line) is the closest forecast to real inflation. Also, model 2 (inff_2-green line) tracks real inflation very closely. In essence, model 1 (inff_1) has the best performance of all the individual models, which include food prices, energy, budget expenditures, consumption, unemployment, and GDP.

Model 1 would be much better in forecasting if they had the ratio of job vacancies to unemployment because this indicator would give a much better picture of the labour market that uses information from both workers and employers. Also, model 3 and model 4 perform well, implying that inff_3 and inff_4 have valuable information. Model 3, including neighbouring countries with which Montenegro has significant trade, has the inflation of Serbia, Albania, Bosnia and Herzegovina, and the European Union. Model 4, as explained in Equation 4, has extreme weather, global temperature, and innovation.

Graph 4 – Forecast comparison



Source: Author's estimates.

Note: Graph 4 shows the forecasting performance of all models 1--6, including the ARIMA model, and the three combinations.

The autoregressive (AR) part of ARIMA indicates that the evolving variable of interest, in our case inflation, regresses on its own prior values. The moving average (MA) part indicates that the regression error is actually a linear combination of error terms whose values occurred simultaneously and at different times in the past. Moreover, the I (for "integrated") indicates that the data values are replaced by the difference between their values and previous values (and this differentiation process may have been performed more than once). The purpose of each of these features is to make the model as close as possible to the data.

Inff_c and inff_mse track actual inflation very well. At the end of the forecast period, November 2023, actual inflation is 4.8%, while inff_1 predicts 5.1%, inff_c=5.3%, inff_mse=5.6%. Although models 2, 3 and 4 are not close compared to actual inflation, the inclusion of these variables is significant because they have valuable information. In fact, they show that the importance of the information in these models is not a central focus at the moment, while on the other hand, they still show that these models could be a potential for consideration in the upcoming circumstances. The above results allow forecasters to analyze, address, evaluate, compare and exploit the power of using high-dimensional dynamic composite forecast models.

3.2. Bayesian VAR

Inflation is the primary variable we are interested in. Table 2 shows a comparison of the predictions of six VAR and BVAR models. There is an improvement in the RMSE-based forecasts for all models, implying that we imposed a good prior on the models.

Table 2 – Forecast comparison performance of VAR and BVAR

Method			Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Standard VAR		RMSE	0.8821	1.2561	1.7384	1.623	1.6638	1.1896
Priors	Minnesota		0.8688	1.267	**1.2954**	1.3905	**1.3817**	**1.0678**
	Normal-flat		**0.8514**	1.274	1.7545	1.4354	1.4182	1.1849
	Normal-Wishart		0.8543	1.2724	1.7516	1.4394	1.4191	1.183
	Giannone L&P		0.8718	**1.2545**	20.85	**1.2357**	2191.8	2.1E

Source: Author's calculations

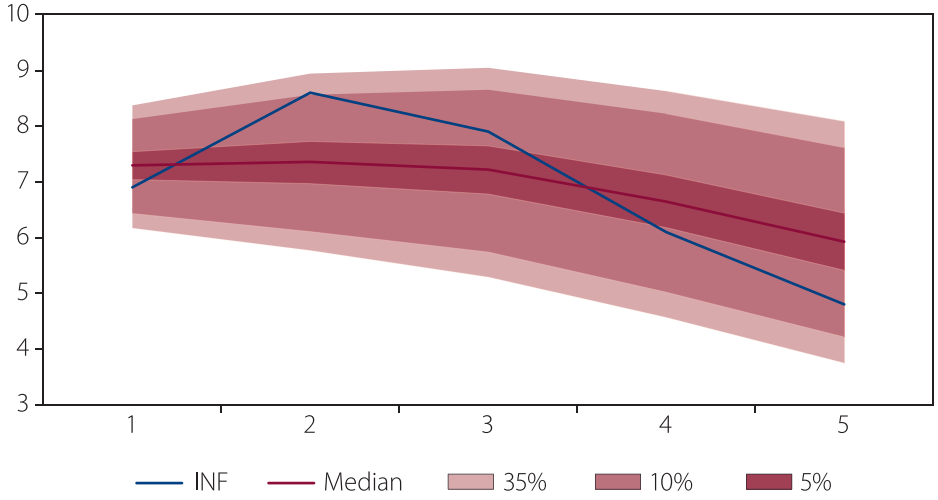
Note: We use six VAR and BVAR models estimated to perform an out-of-sample forecasting experiment for the period July to November 2023, focusing on inflation. The results indicate an advantage over Bayesian methods for all models.

The settings, $\mu_1 = 0$ and $\lambda_1 = 0.5$, implying a relatively uncertain prior for β. Lambda1 (λ_1) adjusts the β prior's overall tightness. Since the volatility of the inflation rate is uncertain about the prior, we set lambda1 to 0.5. Lambda2 λ_2 is used to regulate the relevance of lagged coefficients in the ith equation ($\lambda_2 = 0.99$). The lag decay rate $l^{\lambda 3}$ is determined by lambda3 ($\lambda_3 = 1$), where l denotes the lag index. We assigned $\lambda_3 = 1$ for no decay.

Graph 5 shows the central inflation forecast of Model 1, showing Bayesian confidence intervals. Fan charts include one view, which represents the center of gravity of the outlook for the Montenegrin economy. The red-shaded fan areas in Graph 5 show our view of the likelihood of inflation lying within that range. In Graph 5, the blue line represents the actual values, while the central red line represents the mean value. Specifically, the darkest red bar in Graph 5 represents a 10% probability. So, there is a 10% probability that inflation will be within this range. Moving away

from the darkest red bar, the area covered by the lighter red bars (each side of the regime has one bar) represents a 20% probability. Consequently, the probability of inflation between these ranges is 30%, whereas the third bar represents a probability of 60%. The effect of the inflation forecast ranges from 4.2% to 7.6%, and the actual inflation is 4.3% in November 2023.

Graph 5 – Performance of inflation forecasting using BVAR, normal-flat prior type for the period from July to November 2023



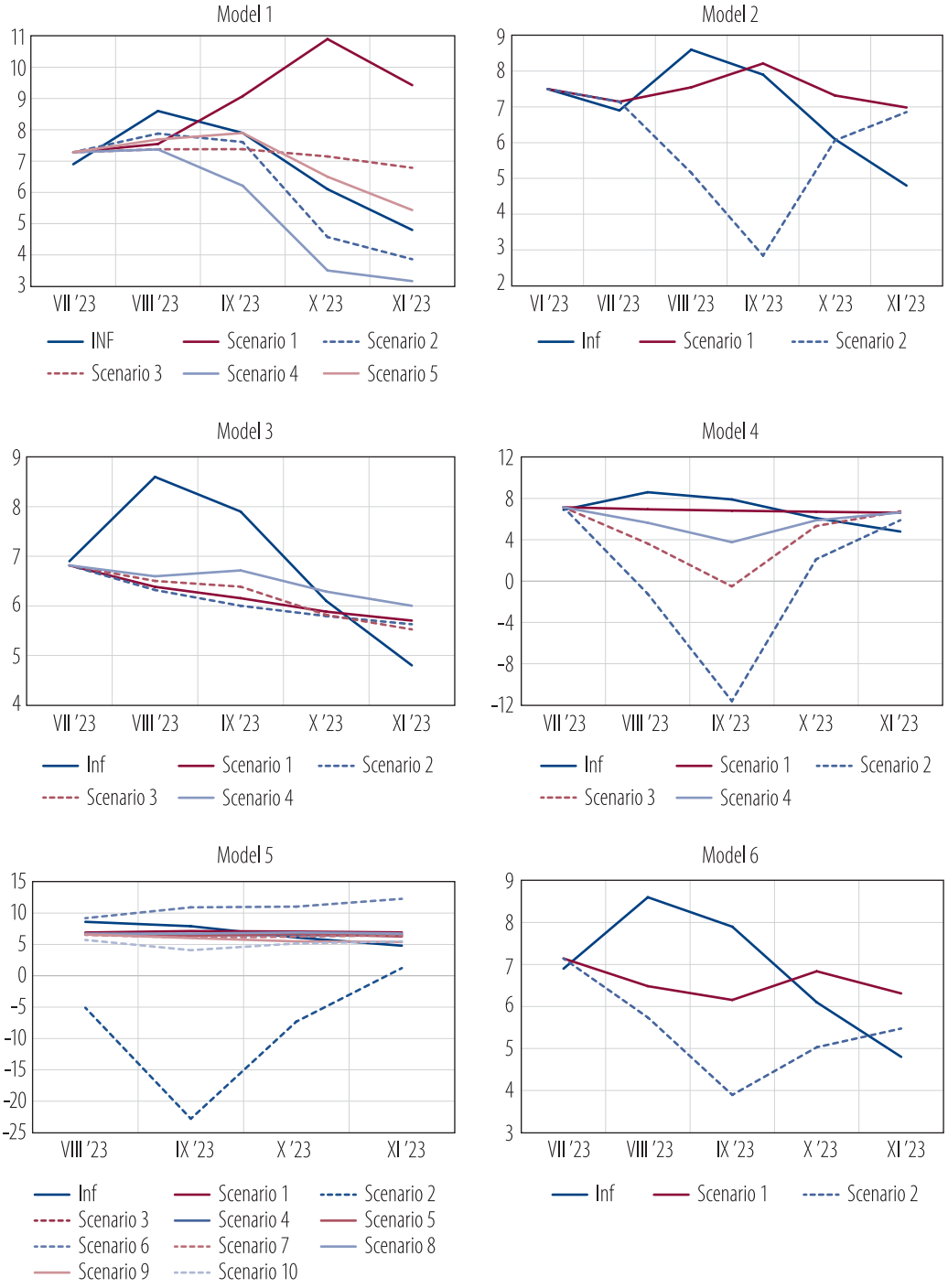
Source: Author's calculations.

3.3. Sensitivity analysis and macro-stress testing

Montenegro`s macroprudential authorities are interested in evaluating inflation in relation to various shocks (stress tests). To achieve this, we increase all variables in six VAR and BVAR models in alternative scenarios and change the simulation data during the period from July to August 2023. We alternatively increase the shocks to all variables by +15% and +30% during the period July to August 2023. The hypothetical direct effect starts in July and continues until the end of August as the potential shocks have persistent significant volatility.

Instead of using real data, the dynamic solution - a deterministic simulation solution uses predicted values with lags over the forecast period, cumulating the forecast error from one month to the next. A visual inspection of model 1 in Graph 6 reveals that scenario 1 (increase in international food prices) rapidly increases inflation from 6.9% to 10.9% in just two months: September and October. Scenario 3 (government expenditures) and scenario 5 (unemployment) predict that the inflation rate will rise, while scenario 2 (oil prices) and scenario 5 (household expenses) predict that the inflation rate will decrease in the first three months. The implication is this: food prices drastically increase the rate of inflation, even up to 37% in just three months.

Graph 6 – Macro-stress testing of inflation



Source: author's estimation.

Note: Graph 6 shows the macro-stress testing, forecasting performance of all models 1–6, scenarios of hypothetical increase of variables with 15% and 30% in July and August 2023

In model 2, we notice that scenario 1 (exchange rate) and scenario 2 (earnings) increase the inflation rate in the short term quite quickly. This indicates that inflation is very sensitive to the labour market and the exchange rate. An increase in general wages, without an increase in productivity, will increase the price margin in order to keep the profit margin for producers. As a result, inflation has higher pressure and general prices increase. The old qualified generation is ready to work at least for the same salary, even accepting a lower salary, but the new qualified generation has higher expectations regarding the introduction of a new technological process. This process would shift the wage-setting relationship to the right if the new skilled generation outnumbered the old skilled ones. This wage inequality also comes from the educational level. Scenario 2 shows the case where productivity expectations A^e do not rise faster than price expectations P^e, and the unemployment rate increases. The unemployment rate will remain higher until the expectations of producers and workers adjust to the new reality. In other words: after an increase in wages, firms will offer less wages than workers demand. This will increase unemployment. Eventually, businesses and workers adjust their expectations, returning to the natural level of employment.

Model 5, scenario 4 (EMU inflation) and scenario 3 (inflation in Serbia) create a lot of oscillations in the Montenegrin economy, predicting the growth of the inflation rate. The biggest impact is the transfer of inflation from the EMU.

Scenario 2 (innovation), model 4, shows inflation falling to -12% within just two months, then increasing until November 2023. This happens until the mechanism of determining prices and wages is adjusted in the labour market. Scenario 1 (extreme weather), scenario 3 (ocean level), and scenario 4 (global temperature), predict a decrease in the inflation rate for the first two months, but then inflation picks up pace. The implication is clear: firms increase unemployment if they estimate that there will be an increase in extreme weather conditions, which creates a large gap in the labour market, but very quickly producers adapt to the situation of normality and increase employment and, consequently, spur inflation. A very important conclusion from model 4: innovation and extreme weather places a great strain on the labour market.

Scenario 2, model 6, shows that the increase in loans predicts a decrease in the inflation rate in the first two months, while after that inflation rises approximately to the real inflation rate. What does this mean? The expectations of the citizens of Montenegro are oriented towards the future and they expect that a higher level of credit will bring a higher level of competitiveness. As a result, overall price margins fall, and so does the inflation forecast on the chart. After two months, citizens notice that the increase in loans did not make prices more competitive and adjust their expectations to reality: in this way, the labour market reaches equilibrium. On the other hand, it was noted that the increase in regulatory capital increases inflation by up to 12.3% in just three months. As commercial banks are left with less assets, they increase interest rates and commissions in order to maintain their profitability margin.

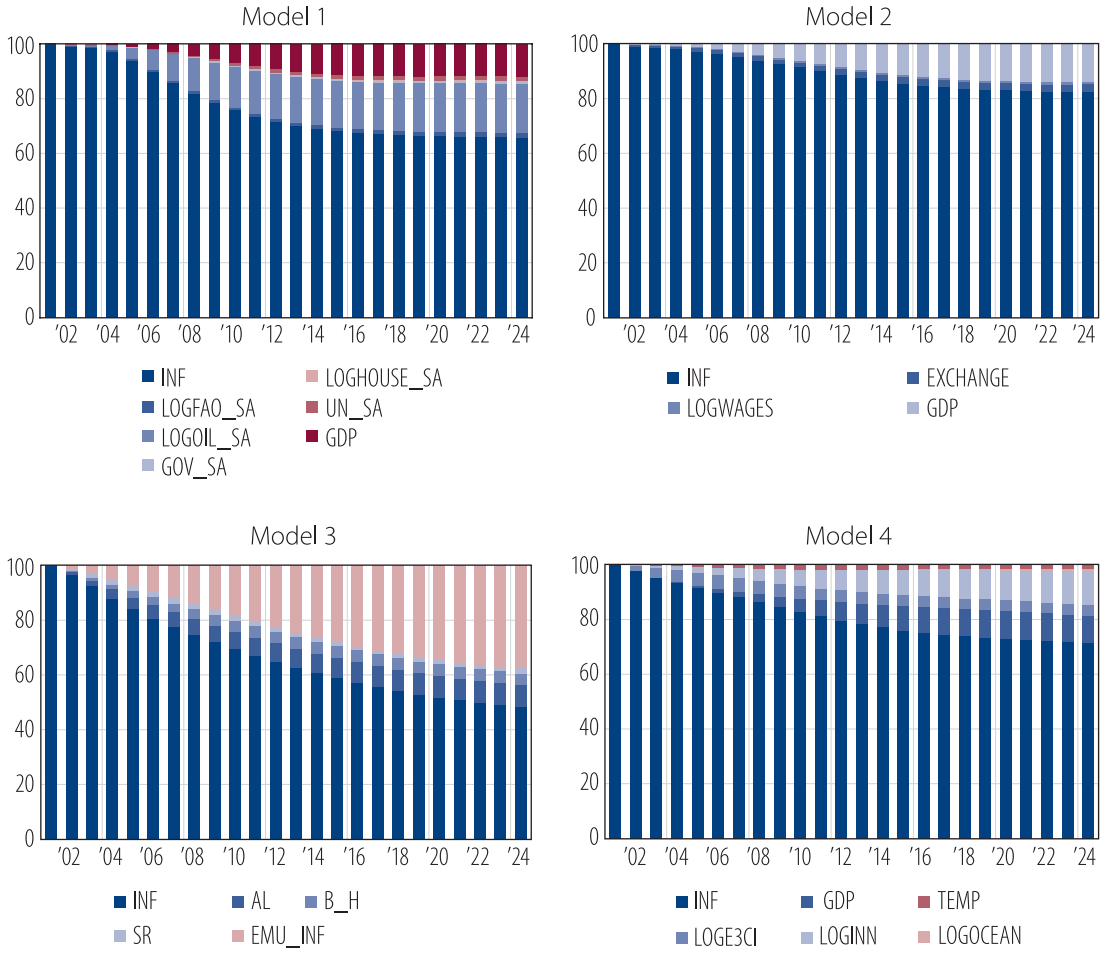
Scenario 1 (current account balance) and scenario 2 (interest rates) will reduce the rate of inflation in the first two months, but after that, inflation in both scenarios has the same upward trend.

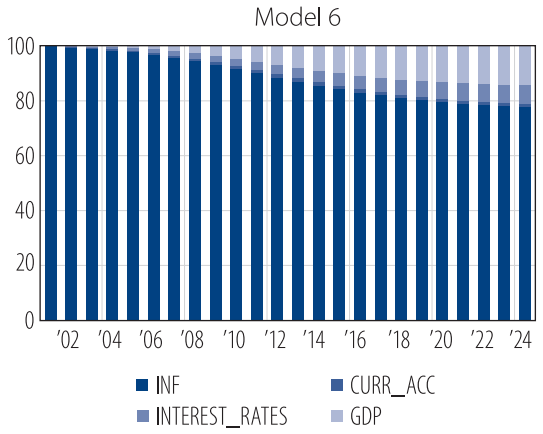
In November, scenario 1 predicts an increase in inflation from 4.8% to 6.3%, while scenario 2 predicts an increase in the inflation rate to 5.5%. The implications are direct: production growth is a mechanism for sustainable development, otherwise imports increase prices and inflation.

3.4. Decomposition of inflation

We track the responses of inflation to shocks of one standard deviation. It is important to note that shocks cannot be caused by what happens to other variables. The shock must be exogenous, i.e. come from outside. In our model, exogenous shocks are clearly identified. The mechanism we use allows us to identify a structural model, which isolates purely exogenous shocks and reveals the responses of endogenous variables after these shocks hit the economy. Once we identify structural errors, we can calculate the responses of the dependent variables and make predictions (e.g. what will happen to inflation if exogenous shocks hit the economy).

Graph 7 – Decomposition of inflation





Source: author's calculations

Note: Graph 7 shows the decompositions of inflation sources, based on the solutions of six models and the implied impulse response functions. The solid lines show actual inflation, and the total net column heights are the model's forecast inflation in each period. The coloured part of each bar-column shows the contribution of the data. The coloured segments of each bar show the general equilibrium, fully dynamic contribution of each exogenous variable to inflation over that period, as implied by the estimated model.

We are interested in analyzing how exogenous shocks contribute to inflation fluctuations. Understanding prediction errors is useful for analyzing relationships between variables. The variance decomposition gives us the proportion of the variance of the forecast errors for y_{jt+h} in percentage, explained by each of the shocks. Thus, finding shocks to u_t raises the question of the importance of one innovation over another in explaining y_t. The variance decomposition of the forecast error has been used as an argument in the debate about the origin of business cycles. For example, Montenegrin policymakers want to know whether oil and food price shocks are the primary external sources of errors in long-term inflation forecasts?

In Graph 7, already in the first month, the contribution of: a) oil and GDP (model 1), b) exchange rate (model 2), c) inflation of EMU and Albania (model 3), d) innovations and extreme weather conditions (model 4), e) liquidity, allowances/NPLs, return on assets, and loans (model 5 in Annex), and f) interest rates (model 6) in the inflation decomposition are significant. After 12-month horizons, the effects of oil shocks on inflation increase to 16.22%. The exchange rate affects the decomposition of inflation with 2.02% after 12 months. Earnings have a small contribution to the inflation decomposition: 0.82% after 24 months. Meanwhile, EMU and Albania's inflation contributions and their associated shocks to Montenegro's inflation rise to 22.25% and 6.8%, respectively, over a 12-month horizon. In the 24-month horizon, the proportions of inflation movements resulting from EMU inflation shocks rise to 37.26%. Innovation and extreme weather are also sources of inflation over a 12-month horizon, with shocks of 4.3% and 7.34%, respectively. Over a 24-month horizon, the impact of extreme weather increases to 12.03%. Over a 24-month horizon, the proportions of inflation movements resulting from liquidity shocks, impairment/NPLs, and total capital reach 18.88%, 10.06%, and 6.14%, respectively. In a horizon of 24 months, the impact

of loan interest rates on inflation rises to 7.05%. This implies that policymakers should create appropriate policies to attract hub investors while anticipating such volatility shocks.

The contributions of food and (especially) energy price shocks to inflation were large. Energy price shocks in particular contribute to an increase in overall inflation. Inflation shocks in the EMU, Albania and Serbia and their associated shocks are also large. Extreme weather is of great importance to macroprudential policymakers. As for the internal factors, liquidity, bad loans (NPL), total capital, interest rates and innovation are significant.

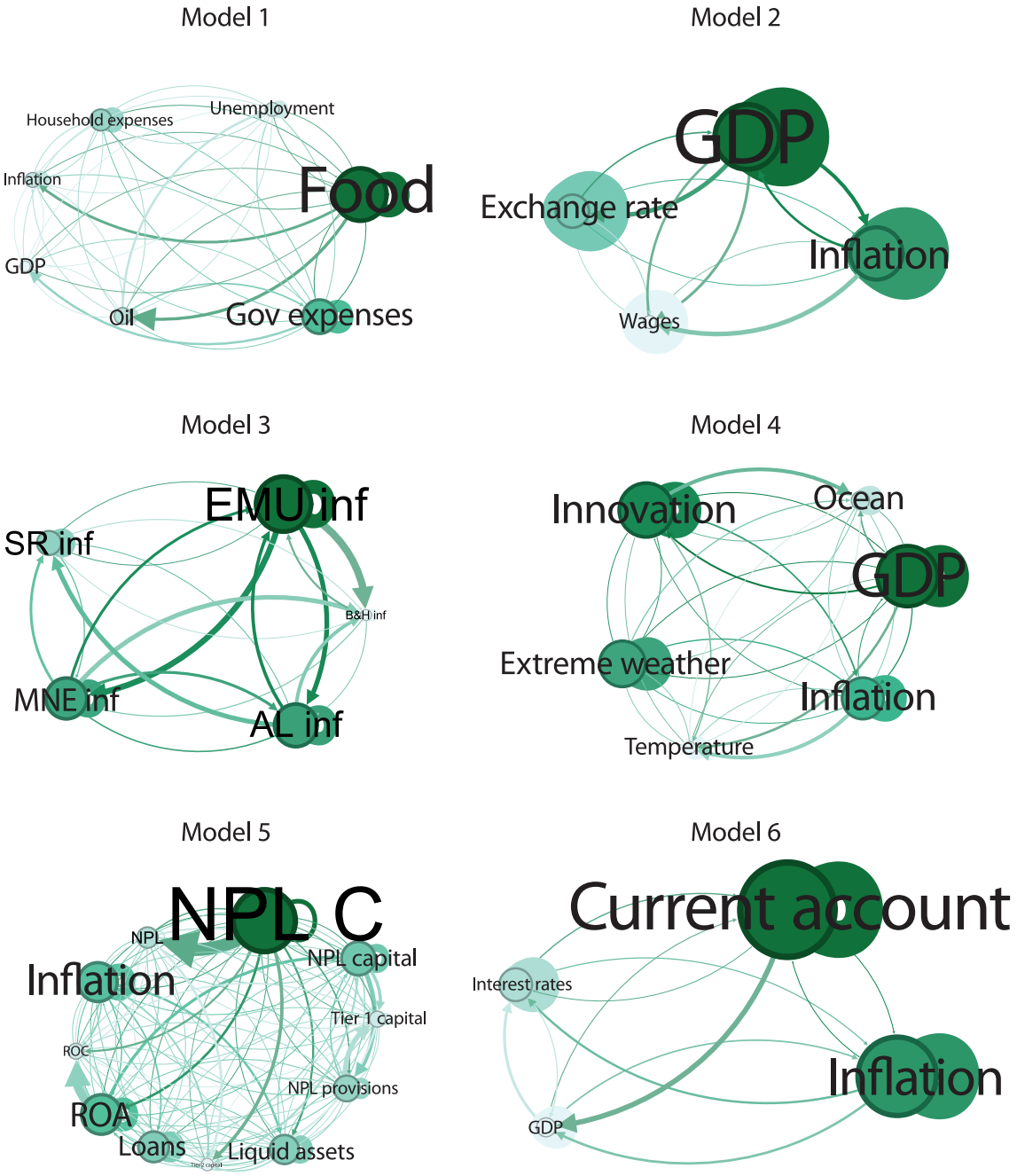
3.5. Network visualization

In high-dimensional system modelling, it is very important how to display findings as best as possible. In our research, in order to obtain better knowledge, we estimate networks of core fundamental macroeconomic concerns, including internal and external shocks. Therefore, for network visualization, we use the following elements to visually represent the forecast network: node identification, node size, node colour shade, and link arrow dimensions. The node size indicates the spillover connectedness effect of a variable on the network. The shade of the node colour indicates the strength of a variable in the macroeconomic network. The size and the colour of the link arrows indicate the degree of pairwise connectivity to and from, respectively. It is worth noting that the whole set of link arrow sizes discloses the entire collection of reciprocal directional connectedness from which everything else can be inferred.

Figure 1 shows the spillover connectedness of the variables, models 1-6. There are several distinguishing characteristics in the figure. Some arrows have strong reciprocal directional connectivity. The "received–from" arrows show the share of volatility obtained from other variables in the total variance. Similarly, the launched "transmitted–to" arrows show the share of volatility distributed to other variables in the total variance of the forecast error. As Figure 1 shows, the variables are highly differentiated in terms of receiving shocks from others and launching and transmitting shocks to others.

Figure 1, Model 1, shows the relationship of spillover variables. The pairwise relationship between food and oil prices is the strongest ($\hat{C}^{H}_{oil \leftarrow food} = 55.70\%$). This is shown by the largest and darkest gradient of the green circle and the thickness of the arrow. The second largest correlation in the pair, in model 1, is from government expenditures to GDP. Then, the pairing is from oil to unemployment ($\hat{C}^{H}_{unemployment \leftarrow \text{oil}} = 22.50\%$). This is an important finding that is consistent with our sensitivity and impulse response analysis results. Food and energy prices are the main sources of volatility spillovers.

Figure 1 – Inflation macroeconomic spillover connectedness



Source: Author's calculations.

Note: Figure 1 shows the spillover (connectedness) network. The size of the nodes and the colour gradient correspond to the degree. A node with a higher degree is shown as a larger circle and a darker gradient. The thickness of the arrows connecting the variables indicates the strength of the transmission between the variables. The thicker the arrow, the greater the connectedness/spillover.

As Montenegro imports most of its products and as a large percentage of energy/oil is imported (along with shocks), the price of food and energy are central factors for the systematic and systemic spillover of macroeconomic and financial risk linkages. Although some other variables are not directly related to energy, it is an influential platform that directly affects the most important factors of financial stability: inflation and growth. Especially in non-peaceful times, changes in food and energy prices have a greater degree of connectedness with the financial and banking sectors, resulting in greater interconnectedness. The net total spillover of food prices is the largest, with 176.60% ($\hat{C}_i^H = \hat{C}_{\cdot \leftarrow i}^H - \hat{C}_{i \leftarrow \cdot}^H$).

In Model 2, the pairwise link between inflation and earnings is the largest (7.1%). The implication is clear: inflation transmits volatility to earnings, which is reflected in the labour market. An increase in wages will increase unemployment until expectations return to equilibrium.

Model 3 shows that the pairwise connectedness between EMU inflation and Bosnia and Herzegovina inflation is the strongest ($\hat{C}^H_{B\&H\ inflation \leftarrow EMU\ inflation} = 32.90\%$). The second largest correlation in the pair, in model 3, is between EMU inflation and Montenegro inflation ($\hat{C}^H_{Montenegro\ inflation \leftarrow EMU\ inflation} = 26.60\%$). This is an important finding: inflation in the EMU transmits high volatility to the Montenegrin economy. Implication: cooperation with the ECB is of great importance. Recommendation of findings: co-integrated analysis of macroprudential factors is of great importance for making the right decisions.

Model 4 shows that innovation is of great importance. Innovations transfer volatility directly to inflation at 6.4%. Based on the results, it can be recommended that investments in endogenous innovation are very important. The creation of various programs that stimulate new endogenous innovations are a guarantee for sustainable development and stability of inflation. The implication: imported innovations are not healthy for maintaining price stability.

In model 6, the pairwise association between NLP/capital and NPL is the strongest ($\hat{C}^H_{oil \leftarrow food} = 76.10\%$). This is shown by the largest and darkest gradient of the green circle and the thickness of the arrow. The second largest correlation in the pair, in model 6, is from government expenditures to GDP. Then, the pairwise connectedness is from return on assets to return on equity ($\hat{C}^H_{ROE \leftarrow ROA} = 52.30\%$). This is an important finding that is consistent with our sensitivity and impulse response analysis results. The stability of financial indicators is of great importance. The implication is clear: preserving the stability of non-performing loans is a major financial and macroprudential factor. The expectation mechanism is very important in this process.

Information about a shock reduces the expectations of citizens and companies, and increases cost pressure. These management shocks increase inflation. The above implies a price adjustment mechanism of expectations P^e in relation to the current price level P. We need to carefully observe how expectations are formed in the labour market in Figure 1.

If society expects the price level to increase, then the price-setting (PS) ratio should decrease, shifting the PS ratio downward. The wage-setting ratio (WS) will also change based on expectations of shocks, unemployment, and institutional factors.

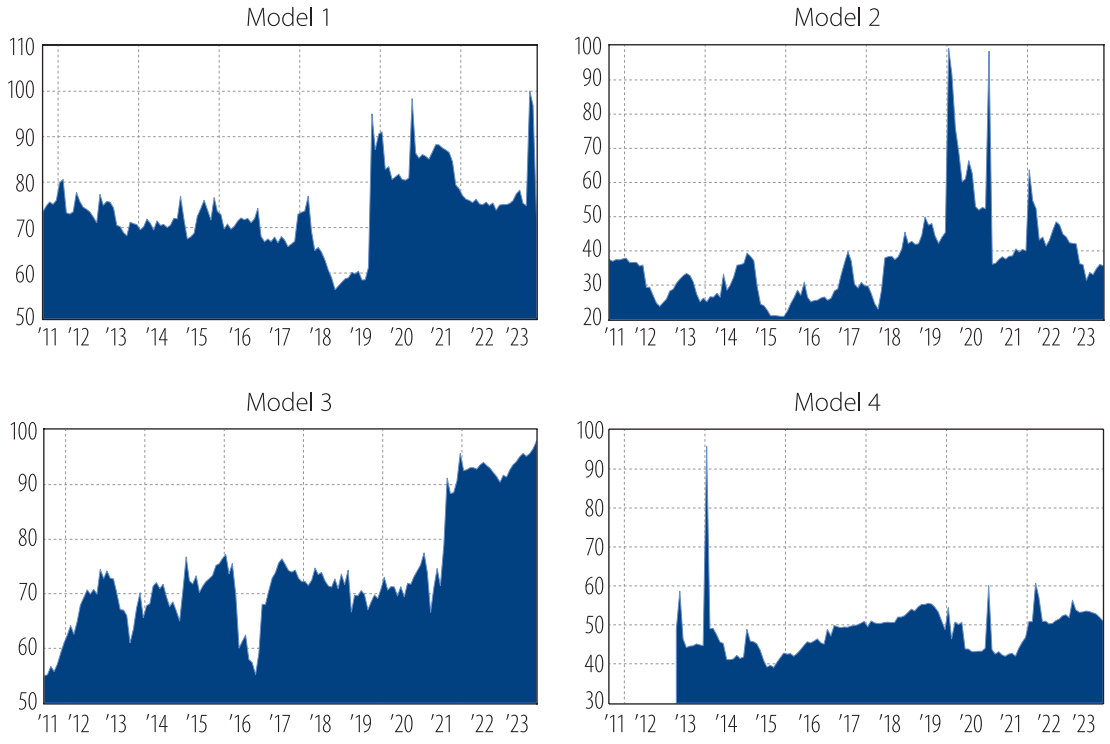
High inflationary oscillations reduce the expectations of workers in the labour market of Montenegro, Western Balkans and EMU, following our explanation of the adjustment mechanism: $P^e \sim P$ and $A^e \sim A$. The reason is that the economy is affected by a shock of one standard deviation in the management factors, management expectations decrease by more than the real management factor, creating a negative gap in the labour market.

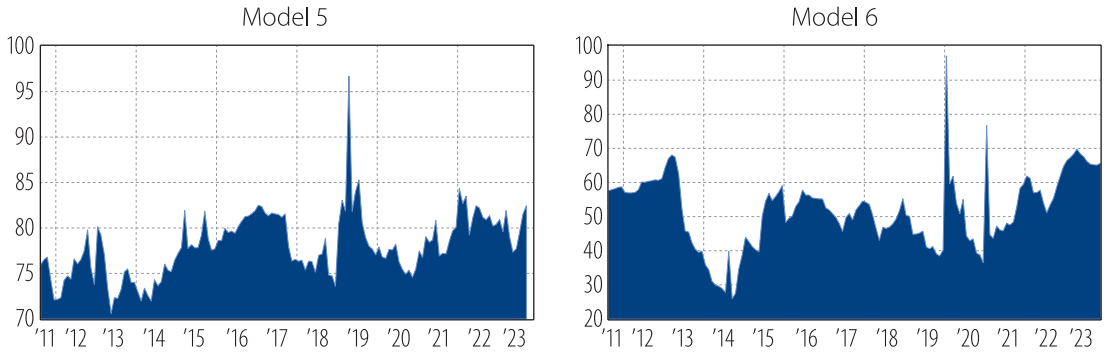
Model 6 confirms previous conclusions from the decomposition analysis that the current account remains a volatility spillover problem. The current account directly affects GDP with 13%, as seen in Figure 1, model 6. A pairwise relationship between inflation and interest rate is also noticeable.

3.5.1. Dynamic policy analysis

The previous analysis is static and does not address the dynamics of inflation. In Graph 8, we show the overall dynamic connectedness of volatility for all models.

Graph 8 – Dynamic connectedness





Source: author's calculations.

Note: Graph 8 shows dynamic connectedness spillover.

From a bird's eye view, the overall connectedness diagrams in Graph 8 have some revealing patterns. We notice three main cycles; (a) one starts in mid-2011 and ends in mid-2017, (b) the second cycle from mid-2019 to the first quarter of 2020, and (c) the third cycle starts in the first quarter of 2020 and lasts until the end in 2023. The first cycle coincides with the global financial crisis: the correlation index of total volatility jumped in all models. The second wave coincides with the 2019–2020 political protests, increasing the dynamic volatility index in all models.

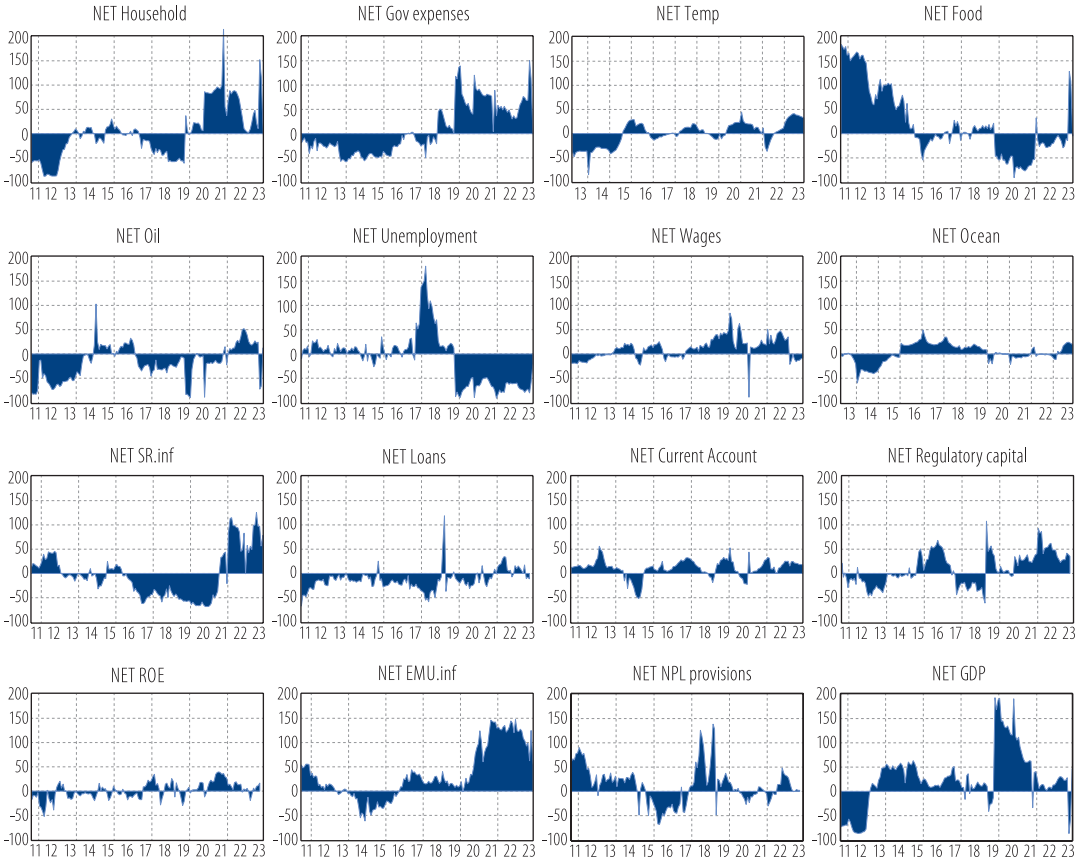
The third boom corresponds to the health crisis of the COVID-19 pandemic and inflation. Whenever the overall connectedness rose to a higher level, it always returned to the 45%–55% range. The dynamic analysis of the overall connectedness gave us a clearer understanding of the factors and policies that influence contagion volatility in the period from July 2011 to November 2023.

3.5.2. Net directional connectedness

Graph 9 shows the time series of total dynamic directional connectedness ('net' degrees) specifically for some variables of models 1–6. The difference between the directional connectedness "to" and "from" others equals the "net" directional connectivity to others as shown in Graph 9. As connectedness "from" others is smoother, the variation in the plots for "net" connectedness to others resembles variation in charts "for" others.

In Graph 9, we notice that idiosyncratic shocks always affected individual institutions and their policies, and these shocks were transmitted to other institutions. These policy shocks became more frequent and each time affected more institutions than before the inflation increased and therefore were passed on to others in greater quantities than before. In times of crisis and relatively more than in non-crisis times, there are a few sectors that receive very little and a few sectors that transmit very much.

Graph 9 – Total "net" directional dynamic connectedness



Source: Author's calculations

We notice that the net dynamic connectedness of the household, government expenditures, food prices, EMU inflation, inflation in Serbia, GDP, fixed capital and unemployment has increased to 150-200%. These variables transmit the net spillover to the Montenegrin market. This implies that these sectors receive less volatility connectedness than they transmit and are therefore considered volatility multipliers, representing a high risk of market destabilization. Household consumption, government expenditure and EMU inflation created and transmitted a large volatility spillover connectedness. The above variables show us that they predicted the arrival of inflation, even from the middle of 2020.

In January 2021, the volatility of EMU inflation exceeded 124%, which was a clear sign that inflation had started and would not be easy to curb. As demand increased, producers began to meet the market, increasing volatility pressure. The current account deficit persistently maintained a volatility spillover relationship of around 40%. The results provided policymakers with a net-directed dynamic relationship, with a wide range of variables affecting the volatility relationship.

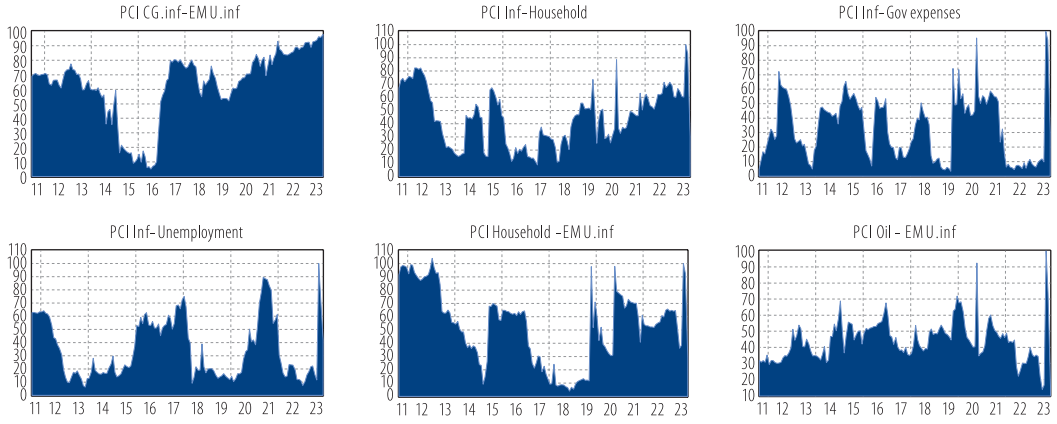
3.5.3. Dynamic policy pairwise connectedness

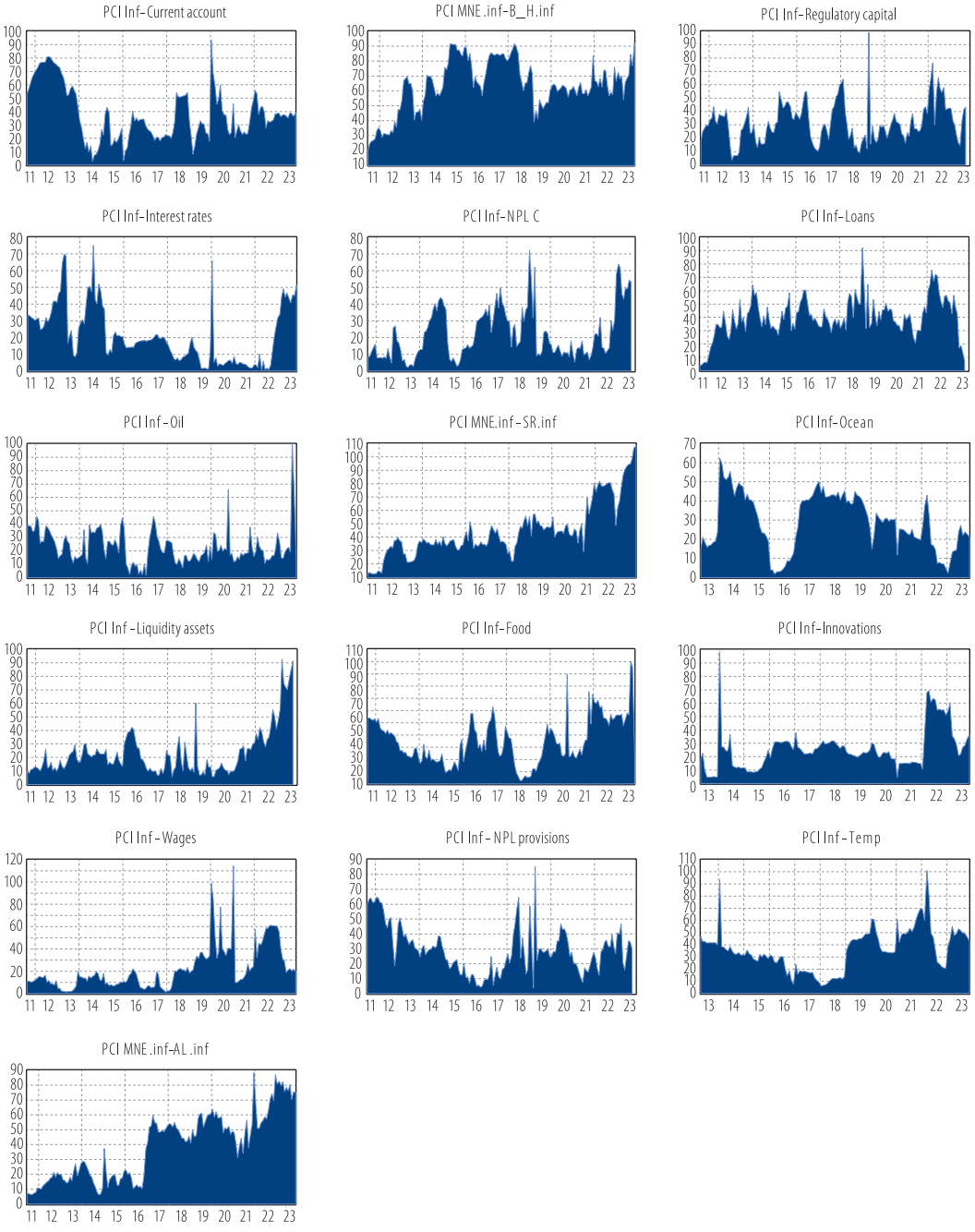
Pairwise connectedness analysis is even more important in the case of a rolling-dynamic sample window because it helps us identify how policy measures of connectedness among institutions' actions vary over time. How these shocks lead to dynamic volatility between pairs is crucial to any policy analysis.

Unfortunately, given that there are six models and 29 institutions in our analysis, presenting a volatility diagram (for each of the 10,176 measure/policy diagram pairs) is a nearly impossible task to achieve within the scope of this paper. Thus, we identify problematic political decisions. The dynamic relationship between inflation in Montenegro and inflation in the EU, Serbia, Bosnia and Herzegovina, and Albania is high from mid-2017 to the beginning of the era of the COVID-19 pandemic. Also, the dynamic pairwise connectedness between food inflation, innovation inflation, liquidity inflation, temperature inflation and wage inflation is over 60%. This indicates that citizens of Montenegro consume mostly all products from the European Union. In other words, the production of goods and services that would meet the needs and expectations of citizens and businesses in Montenegro would be of great importance. We notice that government expenditure has a very similar pattern to the previous two dynamic pairwise interconnections. The message is clear: when the Government expands its investments beyond a certain limit, then the expectations of citizens, companies and institutions are too high, creating cost pressure and demand, which results in an increase in inflation. This matches the results of Cochrane (2021), highlighting the background of the concept of fiscal inflation. So far, we have come to a very important implication that the dynamics of realization of government expenditures is important.

Food prices have a dynamic relationship paired with inflation volatility in months of high volatility. In the context of a complex network, connections are not binary (existing or not existing) but are weighted against the economic interaction under consideration. Moreover, the links represent the volume of trade, capital invested, climate change and so on, and their weight can change over time.

Graph 10 – Dynamic pairwise connectedness





Source: Author's calculations

Inflation in the EU and countries of the Western Balkans has similar trends. Spillover effects started to emerge in early 2019 although the link in the pair "EU inf-inflation" reached 93% in December 2021, as seen in Graph 10 (first chart on the left). The percentages are obtained by identifying Choleski factor and generalized identification (Del Negro and Shorfeide, 2011). The relevance of pairwise connectedness measures is transferred to "rolling-sample windows" (Inoue et

al., 2017). Pairwise connectedness analysis is even more important in the case of a moving sample window, as it helps us identify how the connectedness of swing measures across financial institutions varies. During times of crisis, individual institutions are likely to be more susceptible to frequent volatility shocks. How these shocks lead to volatility correlations across inflation pairs is crucial to any crisis analysis and this was an early sign of what would begin to happen in February 2022. We note that the normal spillover of "EU inf-inflation" is around 20%, which could be taken for consideration by Montenegrin policy makers as an early threshold. Another indicator of the contagion spillover is the "inf-inf Serbia" pair, which reached 84% in November 2021. We have come to a very important implication: the first signs of contagion spillover appear in relation to the European Union and continue in Montenegro and the threshold is less than 20%. If the spillover is above 20%, it is a sign that spiral inflation is coming to Montenegro, leaving enough time for policymakers to prepare for counter-inflationary actions. Moving on, we notice that the pair connection: a) inf-liquidity, b) inf-NPL, c) and inf-oil price have very identical movements. This implies that as the wave of oil prices comes, less income is available that consequently weakens the paying power to repay loans. As a result, there is an increase in NPLs and a decrease in liquidity.

Also, the second implication is that all foreign investments are not beneficial and policy makers should focus on creating policies that attract green investments and that the focus should be the synchronization of ESG models of clean energy. Another implication from the pair "inf-current account" shows that export potential analysis and product diversification are very important for commercial banks to understand the connectedness that products, markets and suppliers/customers have with unrealized export potential for Montenegro. On the other hand, the diversification of exports would provide banks with regular monthly loan payments, with an impact on employment, opportunities for building regional value chains, tourism and the choice of strategic products.

3.6. Recommendations

Considering Montenegro's need for a well-defined integration avenue, we recommend that regulatory authorities take the following essential steps to narrow the gap and, consequently, stimulate economic growth: (1) engage in collaborative efforts with nations that have advanced integration frameworks, forming an initial proactive strategy and actively participate in international agreements to address global challenges such as climate change, social inequality, and inflationary shocks, (2) formulate and enforce comprehensive sustainable-growth regulations and standards that compel businesses and commercial banks to disclose their collaborative practices and performance, (3) provide tax incentives, subsidies, or grants to enterprises that embrace sustainable and socially responsible practices, (4) develop educational programs and training initiatives aimed at cultivating a skilled workforce proficient in sustainable techniques and technologies, thereby bolstering economic competitiveness, (5) enhance corporate governance regulations to ensure transparency, accountability, and ethical conduct within the corporate sector, diminishing the risk of financial crises and corporate misconduct, and (6) establish mechanisms for monitoring and reporting the progress of sustainable-growth initiatives and their influence on macroeconomic factors.

4. Conclusion

We present a novel macroeconomic approach that includes inflation and sustainable growth policy modelling. Our main findings, which were obtained by estimating seven models, using combination and Bayesian connectedness, support the inclusion of inflationary policies in macroeconomic connectedness prediction models. Notably, the introduction of the seven policy models firmly reduces the likelihood of misclassifying a clear net contagion spillover distributor as healthy. We identify six structural VAR and BVAR models and combine them with equal and inverse MSE weighting approaches. Bayesian VAR combinations show the best performance.

Our novel findings indicate that Montenegro should address the disparities in approaches to inflation and growth policies since the growing domestic and international imbalances have a very high cost, de-anchoring investor expectations, disrupting markets, destabilizing key macroeconomic factors, and historically running and leading to high risky shocks. The results also indicate that strategies for sustainable growth and inflationary stability should not be only based on conventional presumptions.

The results underscore the formidable obstacle posed by imbalances in fiscal policies, expectations, demand and supply, labour inputs, governance indicators, global supply, foreign markets, and economic inequality. This working paper recommends the necessary methodological tools, combining forecasts in order for the creators of macroprudential policies in Montenegro to fight more effectively with the challenges of maintaining price stability. The results of the work suggest the use of high-dimensional dynamic models for forecasting inflation.

Dynamic network connectedness of variables and volatility spillovers of shocks are of great importance. This methodology successfully demonstrates measures of connectivity at all levels, from the whole system down to pairs, which captures different strengths of different connections and dynamic variation in connectivity. Model 1 identifies that food and energy prices are the main sources of volatility spillovers. The dynamic network connectivity of model 3 reveals that inflation in the EMU transmits high volatility to the Montenegrin economy. Model 4 shows that extreme weather and imported innovations are not healthy for maintaining price stability. The results of model 5 indicate that the stability of non-performing loans is of great importance. This methodology has the ability to predict crises: an approach that effectively combines VAR theory and connectedness topology theory, recognizing that variance decompositions of VARs form weighted directional network connections, characterizing connectivity in those networks, and a twist that characterizes connectedness in VAR.

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Annex

Annex 1: Decomposition of model 5