NATURAL RESOURCES AS A KEY FACTOR IN FORECASTING GDP IN EUROPE

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Abstract: *A Mixed-Frequency Bayesian Vector Autoregressive (MF-BVAR) model is developed in this work to forecast GDP growth in Europe. To improve forecast accuracy, the model incorporates data on natural resources, macroeconomic variables, and monetary policy instruments. The dynamic interaction between these factors is captured by the model through the integration of mixed-frequency data and Bayesian inference. Furthermore, we employ a Bayesian framework to integrate prior distributions and revise them with observed data, ensuring our model remains robust and adaptable to new information. By including data on natural resources, forecasting errors as determined by metrics such as Theil inequality coefficient and Root Mean Standard Errors (RMSE) can be reduced. The findings show how well the model predicts GDP growth, giving economists and policymakers important information.*

Keywords*: mixed-frequency Bayesian VAR, GDP growth forecasting, performance, monetary policy tools, Brent and precious metals prices.*

JEL Classification*: E37, C11, C53, Q4, O13.*

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1. **Introduction**

In the field of economic forecasting, Mixed-Frequency Bayesian Vector Autoregression (MF-BVAR) models have gained importance, particularly for predicting GDP growth (Ghysels, 2016; Cordoni et al., 2024). Because these models are designed to handle data gathered at various intervals, including quarterly and monthly, it is possible to analyze economic aggregates in a more rapid and sophisticated manner.

The use of natural resources, such as oil and precious metals, could offer a pertinent contrast to conventional monetary policy measures, such as M1, interest rates, inflation, and unemployment, in the context of GDP growth forecasting. Because of their effects on trade balances, investment flows, and production costs, natural resources directly affect economic activity. As an example, changes in the price of oil can have a substantial impact on the building expenses across many industries, which in turn can affect the growth of the economy as a whole. Precious metals, such as gold, silver, and so forth, similarly frequently act as a hedge against inflation and economic unpredictability, influencing investment choices and market stability.

On the other hand, central banks employ traditional monetary instruments to control economic activity and uphold financial and price stability. We can include the money supply, interest rate, and inflation as examples of these tools. In order to improve the forecast quality as measured by various metrics commonly used in the related literature (i.e., root mean square error (RMSE) and Theil's inequality coefficient).

Our analysis has two objectives. First, it illustrates the benefit of employing mixed frequency models to evaluate GDP growth forecasting mistakes more precisely. Second, we investigate how natural resources might enhance forecasts by lowering errors through the use of several indicators.

The paper is organized as follows: Section 2 outlines and justifies our MF-BVAR specifications. In the following section, we present the datasets and discuss our findings. it concludes with a final section that summarizes the key points.

2. **Selection of the model and the datasets**

The specification used in this study belongs to the VAR family and this latter is often used by central banks to assess the impact of their policies on growth and previsions (Goldman and Zhelyazkova, 2024). Indeed, VAR method analyses the relationship between variables and the famous Granger causality test assesses the variables forecasts. Besides, the Impulse Response Function (IRF) studies the behaviour of one variable after a shock in another. Indeed, the monetary policy is not neutral and have significant impacts on growth and unemployment. One of the conventional prudential tools of the central banks is the interest rate. For instance, during financial crises and the COVID-19 crisis, the ECB did not hesitate to decrease the interest rate below zero to avoid a systemic crisis. This period is characterized by a rapid development of VAR specification literature (Guo, 2024). The variables introduced in several models are different and provide very interesting conclusions, namely mixed frequency are relevant to analyse forecasts and interlinkage of variables.

After having briefly justify our choice to use MF-VAR models, we focus on the famous model of Schorfheide and Song (2013). They develop a vector autoregression (VAR) model dedicated to time series, which are observed at mixed frequencies, namely, quarterly and monthly.

The MF-VAR model studies the joint dynamics of quarterly GDP, which is obtained from monthly indicators. The specification is described by the following paragraphs.

In a nutshell, the MF-VAR is represented as a state-space model where the state-transition equations are given by a VAR at months and the assessment equations describe the observed series to the underlying, potentially unobserved monthly time series that are stacked in the state vector. To deal with the high dimension of parameters, the MF- VAR approach utilizes Minnesota prior and estimated Bayesian methods (Schorfheide and Song, 2020).

Hence, a complex development in econometric modeling is the Mixed-Frequency Bayesian Vector Autoregressive (MF-BVAR) model. Without requiring the aggregation of high-frequency data to lower frequencies, it expands the conventional Bayesian VAR framework to handle data available at varied frequencies, such as monthly and quarterly. This capacity is especially useful for financial and economic analysis, as variables of interest frequently appear at different temporal resolutions.

The MF-BVAR model functions based on the idea that weighted averages of unobserved lower-frequency observations (like quarterly data) can be used to represent higher-frequency variables (like monthly data). Such models are able to fully utilize the richness of the data that is accessible, capturing more complex economic dynamics. The robustness and adaptability of the MF-BVAR model to shifting economic conditions are improved by utilizing Bayesian inference to update these beliefs based on new data and include previous knowledge.

The MF-BVAR model's capacity to increase forecast accuracy is one of its greatest benefits. The granularity and timeliness provided by high-frequency data may be lost in traditional models that only use low-frequency data. The MF-BVAR model can produce more accurate and fast forecasts by incorporating both, which is essential for practitioners and policymakers who must make decisions quickly.

Another important advantage of the MF-BVAR model is its adaptability in handling mixed-frequency data. Its versatility allows it to effortlessly mix many data types without requiring them to be standardized to a single frequency. This characteristic makes the model particularly effective in complex economic systems where data availability and frequency may differ significantly.

A noteworthy strength of the MF-BVAR model is its Bayesian foundation. Forecasts using Bayesian approaches are more believable and trustworthy because they incorporate past knowledge and estimate uncertainty. This method is especially helpful in economic forecasting, where expert judgment and uncertainty play important roles.

3. Empirical results: Main results

This section aims to explain our choice of data and highlight the key findings from the MF-BVAR specifications.

Although all of the factors included in the specification are considered to be drivers of economic growth and monetary policies may be seen as an indirect means of fostering growth, the choice of variables is related to the literature (Amaral et al., 2022; ECB Economic Bulletin Issue 4, 2024).

Table 1. Variables

Variables	Period	Frequency	Sources
GDP	1999Q1-2024Q2	Quarters	European Central Bank (ECB-SDW) (https://data.ecb.europa.eu/)
Inflation rate (INF)	1999M01-2024M08	Months	European Central Bank (ECB-SDW) (https://data.ecb.europa.eu/)
Strict Money aggregate (M1)	1999M01-2024M07	Months	European Central Bank (ECB-SDW) (https://data.ecb.europa.eu/)
Short interest rate (SIR)	1999M01-2024M08	Months	European Central Bank (https://data.ecb.europa.eu/)
Unemployment rate (UN)	1999M01-2024M07	Months	European Central Bank (https://data.ecb.europa.eu/)
Oil prices (Brent)	1999M01-2024M04	Months	European Central Bank (https://data.ecb.europa.eu/)
Precious metals (PREC)	1999M01-2024M07	Months	European Central Bank (https://data.ecb.europa.eu/)

Source: ECB Data Portal.

To prevent biases (in terms of harmonization, definition, sources, etc.), we utilize the same data providers. The database was chosen in accordance with conventional literature, which holds that these factors influence GDP-based economic growth (Mojon and Peersman, 2001; Barsoum and Stankiewicz, 2015; Amaral et al. 2022; Guo, 2024).

To find the optimal model, which is defined by well-behaved residuals and a low error prediction, we run two distinct specifications. Thus, Model 1 considers GDP growth along with all the variables of the monetary policy tools (M1, short interest rate, inflation rate); Model 2 includes GDP, variables related to natural resources, and inflation.

Table 2. Empirical Results

GDP	RMSE	Theil's inequality coefficient
Model 1	0.013091	0.485020
Model 2	0.012773	0.436779

Source: Authors

Theil inequality coefficient and RMSE measurements show a decline in mistake predictions. In other words, Model 2 performs better than Model 1. The assumption that natural resources directly contribute to GDP growth is supported by these empirical findings.

4. Conclusion

In conclusion, MF-BVAR models have proven to be a highly beneficial tool for projecting GDP growth on a worldwide scale, particularly when combined with other natural resource prices, including those of precious metals and oil. These resources directly and significantly affect trade, investment flows, and manufacturing costs in the economy. Compared to the variables included in monetary policy instruments, the inclusion of these variables in MF-BVAR models enables a more thorough and accurate description of economic dynamics. These datasets are still necessary to manage development and stability in the economy. Their ability to forecast economic activity, however, may occasionally be limited by their indirect influence. Natural resources, on the other hand, have an immediate and palpable impact on the economy, which makes them useful predictors in forecasting models.

Although MF-BVAR models are useful for economic forecasting, they are not perfect, particularly when it comes to natural resources with highly volatile prices. Therefore, utilizing more advanced methods to simulate the volatility and non-linear interactions could help improve the accuracy of MF-BVAR models for natural resources. To better understand the effect of natural resource pricing on GDP growth, for example, non-linear transformations or the use of GARCH models to handle volatility could be used.

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