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Nowcasting GDP in Romania: A Dynamic Factor Model Approach

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Abstract. *This paper explores the use of dynamic factor models for nowcasting gross domestic product in Romania, focusing on their potential to enhance short-term forecasting accuracy and support economic policy decisions. Nowcasting models have become essential in macroeconomic analysis due to their ability to integrate high-frequency data and address delays in official statistical releases. The study builds on the growing body of research demonstrating the effectiveness of factor models in capturing latent economic dynamics through large datasets. The methodology applies a dynamic factor model framework, grouping variables into four categories: Global, Soft, Real, and Labor factors. The model is estimated using the Expectation Maximization algorithm, and common factors are extracted through Kalman filtering. Monthly and quarterly indicators from January 2007 to December 2024, including trade, industrial production, and labor market data, are employed. The research questions center on the accuracy of short-term gross domestic product projections and the relative contribution of different factor categories. The findings reveal that the model effectively captures economic trends, with strong correlations between model estimates and actual data. This study underscores the significance of dynamic factor models in real-time economic assessment for emerging markets. By addressing publication delays and integrating diverse data sources, the proposed approach offers valuable insights for policy-making and macroeconomic analysis, contributing to the ongoing development of advanced forecasting techniques.*

Keywords: dynamic factor model, nowcasting, gross domestic product, macroeconomic forecasting, Romanian economy.

Introduction

The development of very short-term forecasting models for macroeconomic variables (*nowcasting*) as part of central banks' analysis and forecasting processes is a natural undertaking, justified on the one hand by the need to assess, for the purpose of monetary policy decisions, the most recent estimates of the current macroeconomic situation, and on the other hand by the publication lags of statistical data and the frequent revisions these data undergo as new information is collected or becomes available. Short-term forecasting models have the capacity to mitigate these constraints arising from delays in collecting, compiling, and publishing official statistical indicators, while also integrating extensive data series, many of which are updated at very high frequency.

Nowcasting is a relatively recent approach in econometrics, whose emergence and use have been facilitated both by the expansion of available econometric tools and techniques, alongside increasing computational capabilities, and by the growing number of statistical indicators collected or calculated, or the availability of large datasets (big data). In general, nowcasting models are employed for real-time estimation or very short-term forecasting of lower-frequency macroeconomic variables, with GDP and its components being the most commonly cited examples in the literature. Nevertheless, numerous central banks also use similar models for estimating monthly-frequency variables, such as inflation, confidence indicators, and labor market indicators.

The main advantage, and rationale, for developing such models within central banks lies in their ability to rapidly produce and update estimates of current variables or very short-term forecasts, thereby facilitating a more informed monetary policy response. Additionally, these

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procedures can be used to validate or update expert judgment assumptions that are subsequently incorporated into the standard or main econometric forecasting models. They can also enable the restructuring of data series, for instance by generating a monthly GDP estimate.

The econometric challenges of such an approach arise primarily from the difficulties in integrating statistical indicators with different frequencies and handling a large number of asynchronously published data series, for which standard estimation techniques are unsuitable - not least due to the dimensionality issue. In economies with vast databases or where numerous surveys are available, choosing the most relevant indicators becomes critical, since including too many variables may distort the economically meaningful signal. Furthermore, because nowcasting is essentially a statistical method, it does not, unlike the standard forecasting suite used by central banks, reveal or model the economic significance of the relationships between variables.

Literature review

Forecasting current economic conditions - commonly referred to as *nowcasting* - has become a focal point in both academic research and professional practice, particularly among central banks in advanced economies such as the United States and the euro area (Federal Reserve Bank of New York, n.d.; Banbura et al., 2010). The Federal Reserve Bank of New York's nowcasting platform, for instance, employs a dynamic factor model (DFM) estimated via Bayesian techniques and Kalman filtering, thus continuously integrating incoming data as "news" into GDP growth projections (Federal Reserve Bank of New York, n.d.). In a similar vein, Banbura et al. (2010) stress that the key to nowcasting is to absorb timely monthly indicators that inform quarterly GDP estimates.

Research on advanced economies has also highlighted various methodological innovations. Aastveit et al. (2014) propose a density combination approach in real time, underscoring how sequential data releases refine GDP nowcasts. Richardson et al. (2021) demonstrate that machine-learning algorithms can outperform both simple autoregressive benchmarks and DFMs, particularly in improving the Reserve Bank of New Zealand's official forecasts. Proietti et al. (2021) focus on nowcasting multiple GDP components in Italy using extensive monthly data, while Marcellino and Sivec (2021) illustrate the effectiveness of mixed-frequency factor models and neural networks in a small open economy such as Luxembourg.

In emerging markets, Cepni et al. (2019) show that dimension-reduction and machine-learning techniques - such as sparse principal component analysis, elastic net, and least angle regression - improve real-time GDP predictions in Brazil, Mexico, South Africa, and Turkey. Within Central and Eastern Europe, Romania has become a subject of growing interest. Additionally, Armeanu et al. (2017) utilize a generalized dynamic factor model (GDFM) comprising 86 economic and non-economic variables, reporting superior forecast accuracy relative to simpler principal component approaches.

Much of this work on DFMs and related methods builds upon Stock and Watson (2016), who offer a foundational survey on dynamic factor models, factor-augmented vector autoregressions (FAVARs), and structural vector autoregressions. Although DFMs remain the most established nowcasting technique, recent studies also underscore the value of shrinkage, model combinations, and machine-learning approaches (Cepni et al., 2019; Richardson et al., 2021). The present paper adopts the DFM methodology (Federal Reserve Bank of New York, n.d.; Banbura et al., 2010) while acknowledging these complementary methods, aiming to improve the assessment of current economic conditions in Romania and enhance short-term GDP projections.

In this paper, we adopt the same methodology for short-run GDP forecasting, following Banbura et al. (2010) in modeling the correlation between GDP growth and a broad set of monthly and quarterly indicators. Moreover, the Federal Reserve Bank of New York's nowcasting platform—whose open-source code implements a similar DFM framework—further demonstrates the practical feasibility of integrating a wide array of data in near-real time to refine GDP estimates (Federal Reserve Bank of New York, n.d.).

Methodology

The methodology used for short-term GDP forecasting is that proposed by Banbura, Giannone, and Reichlin (2010). These authors estimate a *dynamic factor model* (DFM), which highlights the correlation between GDP growth and a wide set of monthly and quarterly economic indicators. The core assumption underpinning the DFM is that the evolution of all observable variables can be explained by a small number of unobservable common factors. Once estimated, these factors can be used as regressors to model the variable of interest.

Next, the modeling approach for monthly variables, for quarterly variables, as well as the unified model, is presented.

Modeling the monthly variables

$$x_t^M = \Lambda_M f_t + \varepsilon_t^M \quad (1)$$

$$f_t = \beta_p f_{t-1} + u_{t,} \qquad u_t \sim N(0, Q) \quad (2)$$

$$\varepsilon_{i,t}^M = \alpha_{i,M} \varepsilon_{i,t-1}^M + e_{i,t}^M, \qquad e_{i,t}^M \sim N\left(0, \sigma_{i,M}^2\right) \quad (3)$$

where x_t^M denotes the set of monthly variables, Λ_M s the matrix of common factor loadings, and f_t is the vector of common factors[1] (the common component is given by their product $\Lambda_M f_t$). The term ε_t^M represents the vector of idiosyncratic errors[2] associated with the monthly-frequency indicators, while β_p and $\alpha_{i,M}$ are the autoregressive coefficient matrices for the common factors and the idiosyncratic components, respectively. Moreover, $u_{t,}$ and $e_{i,t}^M$ enote the errors linked to these processes, and Q as well as $\sigma_{i,M}^2$ sare the corresponding variance-covariance matrices of those errors.

The variables are grouped into four categories, namely:

$$f_t = (f_t^G, f_t^S, f_t^R, f_t^L)'$$

f_t^G – the *Global* factor: includes all variables used in the model.
f_t^S – the *Soft* factor: comprises indicators derived from specialized surveys.
f_t^R – the *Real* factor: vcaptures variables describing the evolution of the real sector.
f_t^L – the *Labor* factor: encompasses labor market indicators.

Modeling the quarterly variables

Incorporating quarterly variables into the model requires constructing partially observable monthly data series. Specifically, the observed values of the quarterly variables appear in the row corresponding to the last month of each quarter, while the values for the intervening months remain unobservable.

[1] The common factors are modeled using a first-order vector autoregression (VAR).
[2] They are modeled as a first-order autoregressive (AR) process.

Thus, the quarterly variables ($ex: GDP_t^Q, t = 3,6,9, \dots$) can be expressed as the sum of their unobservable monthly values (GDP_t^M):

$$GDP_t^Q = GDP_t^M + GDP_{t-1}^M + GDP_{t-2}^M, \quad t = 3,6,9, \dots$$

We define: $Y_t^Q = 100 * \log(GDP_t^Q)$ and $Y_t^M = 100 * \log(GDP_t^M)$ and assume that the unobservable monthly GDP growth rate $y_t^M = \varDelta Y_t^M$, follows the same common factor model used for the other monthly variables.

$$y_t^M = \varLambda_Q f_t + \varepsilon_t^Q \qquad (4)$$

$$\varepsilon_{j,t}^Q = \alpha_{j,Q}\varepsilon_{j,t-1}^Q + e_{j,t}^Q, \qquad e_{j,t}^Q \sim N\left(0, \sigma_{j,Q}^2\right) \qquad (5)$$

here y_t^M denotes the set of unobservable monthly variables, ε_t^Q, represents the vector of idiosyncratic terms associated with these variables, $e_{j,t}^Q$ are the errors corresponding to the idiosyncratic components, and $\sigma_{j,Q}^2$, is the variance-covariance matrix of these errors.

To correlate the unobservable monthly data y_t^M with the observable quarterly data, we construct the partially observable monthly series as follows:

$$y_t^Q = \begin{cases} Y_t^Q - Y_{t-3}^Q, & for \quad t = 3,6,9,12 \\ unobservable, & for\ any\ other\ t \end{cases}$$

It follows:

$$\mathrm{y}_t^Q = \mathrm{Y}_t^Q - \mathrm{Y}_{t-3}^Q \simeq (\mathrm{Y}_t^M + \mathrm{Y}_{t-1}^M + \mathrm{Y}_{t-2}^M) - \left(\mathrm{Y}_{t-3}^M + \mathrm{Y}_{t-4}^M + \mathrm{Y}_{t-5}^M\right)$$
$$= \mathrm{y}_t^M + 2\mathrm{y}_{t-1}^M + 3\mathrm{y}_{t-2}^M + 2\mathrm{y}_{t-3}^M + \mathrm{y}_{t-4}^M, \qquad t = 3,6,9, \dots \qquad (6)$$

By substituting Equation (4) into Equation (6), we obtain:

$$\mathrm{y}_t^Q = \varLambda_Q f_t + \varepsilon_t^Q + 2\left(\varLambda_Q f_{t-1} + \varepsilon_{t-1}^Q\right) + 3\left(\varLambda_Q f_{t-2} + \varepsilon_{t-2}^Q\right) + 2\left(\varLambda_Q f_{t-3} + \varepsilon_{t-3}^Q\right) + \varLambda_Q f_{t-4} + \varepsilon_{t-4}^Q$$
$$= \varLambda_Q f_t + 2\varLambda_Q f_{t-1} + 3\varLambda_Q f_{t-2} + 2\varLambda_Q f_{t-3} + \varLambda_Q f_{t-4} + \left(\varepsilon_t^Q + 2\varepsilon_{t-1}^Q + 3\varepsilon_{t-2}^Q + 2\varepsilon_{t-3}^Q + \varepsilon_{t-4}^Q\right)$$

After estimating the common factors and their corresponding coefficients, the short-term GDP estimate and forecast will be determined by the common component:

$$\boldsymbol{\tilde{y}_t = \varLambda_Q f_t^G + 2\varLambda_Q f_{t-1}^G + 3\varLambda_Q f_{t-2}^G + 2\varLambda_Q f_{t-3}^G + \varLambda_Q f_{t-4}^G}$$

The unified model

We define $X_t = \left(x_t^{M'}, y_t^{Q'}\right)'$.

The unified model, which encompasses Equations (1)–(6), can be expressed in matrix form as follows:

$$X_t = CZ_t$$
$$\mathrm{Z_t} = \mathrm{AZ_{t-1}} + \eta_t \qquad \eta_t \sim \mathrm{N}\left(0, \Sigma_\eta\right) \qquad (7)$$

where the first equation represents the *measurement equation*, with X_t being the set of observable variables and C the coefficient matrix for Z_t, which denotes the set of unobservable variables (including common factors and idiosyncratic terms). The second equation represents the *transition equation*, where A is the autoregressive coefficient matrix, η_t the model errors, and $\varSigma_\eta$ the corresponding error variance-covariance matrix.

The model parameters, $\theta = \left(\varLambda_M, \varLambda_Q, \beta_p, \alpha_{i,M}, \alpha_{j,Q}, Q, \sigma_{i,M}, \sigma_{j,Q}\right)$, are estimated via the maximum likelihood method using the Expectation Maximization (EM) algorithm. Once the model parameters have been estimated, the common factors are extracted via the Kalman filter. The implementation is carried out in Matlab using an open-source code base provided by the New York Fed.

Data description

The dataset includes both monthly and quarterly frequency variables, covering the period from January 2007 to October - December 2024 for monthly data and up to Q3 - Q4 2024 for quarterly data. The model is re-estimated each time an indicator is updated. A total of 23 variables were included in the model, consisting of 19 monthly variables and 4 quarterly variables. Table 1 provides a detailed description of the data used and its source. The selection of this dataset was driven by its predictive capacity for GDP in Q4 2024, as determined through successive iterations of indicator combinations.

Table 1. Data description

Variable name	Frequency	Unit of measurement	Transformation	Category	Source
Number of employees	monthly	Thousands of people	Difference (level chg.)	Global, Labor	INSSE
Hiring perspectives (employment outlook)	monthly	Index	Levels (no chg.)	Global, Soft	European Commission
Real sector net wage	monthly	RON	Percentage chg.	Global, Labor	INSSE
Unemployment rate	monthly	Percentage (%)	Difference (level chg.)	Global, Labor	INSSE
Unit labor cost in industry (ULC)	monthly	RON	Percentage chg.	Global, Labor	INSSE
Monthly inflation rate based on Consumer Price Index (CPI)	monthly	Index, MoM (%)	Levels (no chg.)	Global	INSSE
Economic Sentiment Indicator (ESI)	monthly	Index	Levels (no chg.)	Global, Soft	European Commission
Retail turnover volume (excluding the trade with motor vehicles and motorcycles)	monthly	Index (fixed base)	Percentage chg.	Global, Real	INSSE
Motor vehicles and motorcycles trade	monthly	Index (fixed base)	Percentage chg.	Global, Real	INSSE
Market services provided to the population	monthly	Index (fixed base)	Percentage chg.	Global, Real	INSSE
Wholesale trade	monthly	Index (fixed base)	Percentage chg.	Global, Real	INSSE
Market services rendered mainly to enterprises	monthly	Index (fixed base)	Percentage chg.	Global, Real	INSSE
Construction works	monthly	Index (fixed base)	Percentage chg.	Global, Real	INSSE
Industrial production index	monthly	Index (fixed base)	Percentage chg.	Global, Real	INSSE
Volume indices of industrial new orders	monthly	Index (fixed base)	Percentage chg.	Global, Real	INSSE
Exports	monthly	Mln. EUR	Percentage chg.	Global, Real	INSSE
Imports	monthly	Mln. EUR	Percentage chg.	Global, Real	INSSE
Narrow money supply (M1)	monthly	Mln. RON	Percentage chg.	Global	NBR

Variable name	Frequency	Unit of measurement	Transformation	Category	Source
Non-government credit	monthly	Mln. RON	Percentage chg.	Global	NBR
Real GDP	quarterly	Volume indices, QoQ (%)	Levels (no chg.)	Global, Real	INSSE
Final consumption	quarterly	Volume indices, QoQ (%)	Levels (no chg.)	Global, Real	INSSE
Gross fixed capital formation	quarterly	Volume indices, QoQ (%)	Levels (no chg.)	Global, Real	INSSE
Capacity utilization rate in industry	quarterly	Percentage (%)	Difference (level chg.)	Global, Real	Eurostat

Source: Authors' own research.

Results and discussions

As a result of correlating the observable quarterly data with the unobservable (estimated) monthly data, the resulting common component will exhibit a monthly frequency.

$$\widetilde{y}_t = \Lambda_Q f_t^G + 2\Lambda_Q f_{t-1}^G + 3\Lambda_Q f_{t-2}^G + 2\Lambda_Q f_{t-3}^G + \Lambda_Q f_{t-4}^G$$

To estimate and forecast the quarterly GDP dynamics, we extract from the monthly common component the values corresponding to the final month of each quarter. Subsequently, from the quarterly dynamics, we derive the GDP growth rate expressed in annual terms. Table 2 presents the data related to GDP dynamics and its estimation and projection. Figure 1 illustrates the quarterly GDP dynamics along with its estimation and forecast, while Figure 2 shows the GDP growth rate in annual terms, including its short-term estimation and projection.

Table 2. Romania's GDP growth rate: effective data and nowcasting estimates

		Q1 2024	Q2 2024	Q3 2024	Q4 2024
Quarterly dynamics (QoQ%)	*Effective data GDP*	-0.4	0.1	0.0	
	Projection - Common Component	*0.5*	*0.8*	*0.1*	*1.0*
Yearly dynamics (YoY%)	*Effective data GDP*	2.0	0.8	-0.1	
	Projection - Common Component	*1.6*	*1.9*	*2.0*	*2.3*

Source: Eurostat and authors' own calculations.

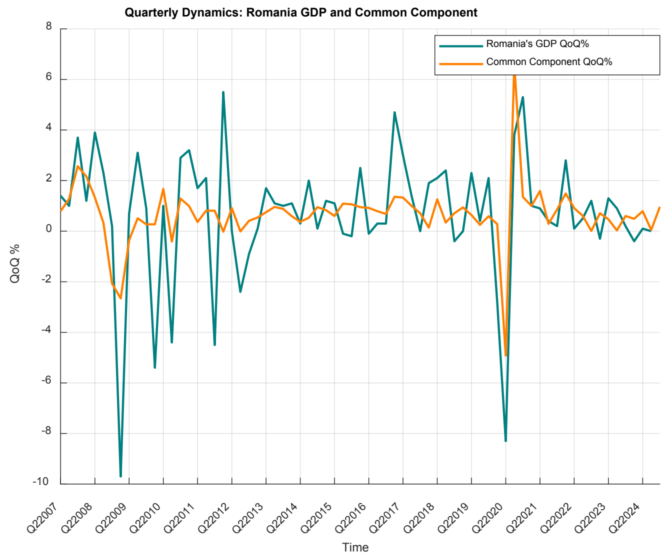

Figure 1. Quarterly dynamics: Romania's GDP and Common Component

Source: Eurostat and authors' own calculations.

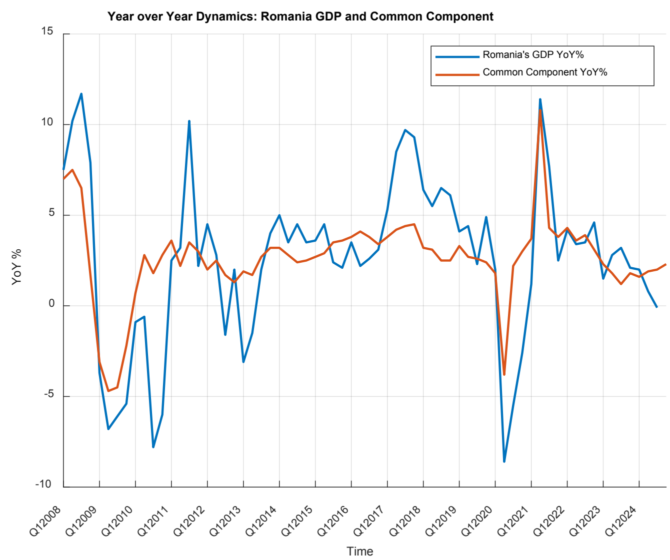

Figure 2. Yearly dynamics: Romania GDP and Common Component

Source: Eurostat and authors' own calculations.

The results indicate that the estimation of the common component using the dynamic factor model (DFM) captures economic activity reasonably well in terms of both direction (expansion or contraction) and magnitude of change. However, as observed in Table 2, there are instances, such as in Q1 2024 (quarterly dynamics), where discrepancies arise, including differences in sign - the model indicates an economic expansion, whereas the actual data shows a contraction.

Figures 1 and 2 illustrate the evolution of Romania's GDP and the common component derived from the model, presented for both quarterly and annual dynamics. These figures reveal a relatively high correlation between the two variables, with coefficients of 60% for quarterly variations and 75% for annual variations. This suggests that the model demonstrates a fairly strong forecasting ability for economic activity.

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Table 3: Factor Loadings for Monthly Series

	Global	Soft	Real	Labor
Number of employees	0.2	0.0	0.0	0.5
Hiring perspectives (employment outlook)	0.2	0.7	0.0	0.0
Real sector net wage	0.2	0.0	0.0	0.2
Unemployment rate	0.0	0.0	0.0	-0.8
Unit labor cost in industry (ULC)	-0.3	0.0	0.0	0.4
Monthly Inflation Rate based on Harmonized Consumer Price Index (HICP)	0.0	0.0	0.0	0.0
Economic Sentiment Indicator (ESI)	0.1	0.7	0.0	0.0
Retail turnover volume (excluding the trade with motor vehicles and motorcycles)	0.3	0.0	0.2	0.0
Motor vehicles and motorcycles trade	0.3	0.0	0.2	0.0
Market services provided to the population	0.3	0.0	0.1	0.0
Wholesale trade	0.2	0.0	0.3	0.0
Market services rendered mainly to enterprises	0.2	0.0	0.2	0.0
Construction works	0.1	0.0	0.2	0.0
Industrial production index	0.3	0.0	0.2	0.0
Volume indices of industrial new orders	0.3	0.0	-0.4	0.0
Exports	0.3	0.0	-0.4	0.0
Imports	0.3	0.0	-0.5	0.0
Narrow money supply (M1)	0.1	0.0	0.0	0.0
Non-government credit	0.1	0.0	0.0	0.0

Source: Authors' own research.

Table 4: Quarterly Loadings Sample (Global Factor)

	f1_lag0	f1_lag1	f1_lag2	f1_lag3	f1_lag4
Real GDP	0.1	0.1	0.2	0.1	0.1
Final consumption	0.0	0.1	0.1	0.1	0.0
Gross fixed capital formation	0.0	0.1	0.1	0.1	0.0
Capacity utilization rate in industry	0.0	0.0	0.0	0.0	0.0

Source: Authors' own research.

Table 5: Autoregressive Coefficients on Factors

	AR Coefficient	Variance Residual
Global	0.1	3.9
Soft	0.9	0.3
Real	-0.5	0.6
Labor	-0.3	0.2

Source: Authors' own research.

The results of the factor loadings presented in Table 3 highlight the varying contributions of the four factors - Global, Soft, Real, and Labor—to macroeconomic variables. The Global Factor shows consistent loadings across trade and production-related variables, such as retail turnover volume (0.3), exports (0.3), and industrial production index (0.3), emphasizing its broad applicability in capturing overall economic trends. These results indicate that the Global Factor predominantly reflects fluctuations in economic output, trade, and industrial activity. Similarly, Soft Factor loadings are concentrated in sentiment-driven variables such as the Economic

Sentiment Indicator (ESI, 0.7) and hiring perspectives (0.7), underscoring the factor's relevance in explaining shifts in confidence and labor market expectations.

The Real Factor, which captures short-term production dynamics, exhibits both positive and negative loadings. For instance, negative loadings on exports (-0.4) and volume indices of industrial new orders (-0.4) point to its sensitivity to declines in trade and industrial activity. This aligns with the factor's role in explaining short-term reversals in economic conditions. The Labor Factor, on the other hand, is driven by employment-related variables, such as number of employees (0.5) and unemployment rate (-0.8), reflecting its utility in analyzing labor market dynamics.
The quarterly loadings in Table 4 further corroborate the importance of the Global Factor in explaining GDP dynamics. Significant lagged loadings, such as 0.2 at lag 2 for real GDP, reflect the persistence of global macroeconomic conditions in influencing economic activity over time.

The autoregressive coefficients in Table 5 provide further insights into the persistence and variance of each factor. The Soft Factor demonstrates the highest persistence, with an autoregressive coefficient of 0.9 and a low residual variance of 0.3, indicating that sentiment-driven factors evolve gradually over time. Conversely, the Global Factor, while still significant, exhibits a lower persistence (0.1) and a higher residual variance (3.9), reflecting its responsiveness to short-term shocks. The Real Factor shows a negative autoregressive coefficient (-0.5), highlighting its tendency toward reversals and volatility, consistent with its role in capturing short-lived dynamics. The Labor Factor also exhibits moderate negative persistence (-0.3) and a low variance residual (0.2), suggesting shorter adjustment periods in labor market conditions compared to sentiment-driven factors.

The idiosyncratic components, detailed in the appendix, reveal additional nuances about specific variables. Variables such as the Economic Sentiment Indicator (ESI) and real GDP have very low residual variances (0.0 and 0.1, respectively), indicating that they are well-captured by the common factors. Conversely, variables such as the monthly inflation rate (HICP) and narrow money supply (M1) exhibit higher residual variances (0.9 and 1.0, respectively), suggesting additional unexplained variability or noise. Furthermore, the autoregressive coefficients of key economic variables such as exports (-0.4) and imports (-0.5) reinforce the idea that trade dynamics are more prone to short-term reversals, aligning with the negative autoregressive pattern observed in the Real Factor.

Overall, these results demonstrate the robustness of the dynamic factor model in capturing broad economic trends while highlighting areas where further refinements, such as incorporating additional indicators or addressing high residual variances, could enhance its explanatory power. This detailed analysis underscores the interplay between common factors and idiosyncratic components in explaining the complexities of macroeconomic fluctuations.

Conclusion

The dynamic factor model (DFM) presents a robust framework for nowcasting GDP in Romania, successfully correlating high-frequency monthly data with quarterly economic indicators. By leveraging a broad array of variables categorized into Global, Soft, Real, and Labor factors, the model effectively captures the complexities of economic activity. The Global Factor's consistent influence across trade and production metrics underscores its utility in representing macroeconomic conditions, while the Soft Factor highlights the critical role of sentiment in shaping short-term dynamics.

Despite its strengths, the model encounters limitations, particularly in reconciling certain discrepancies between observed and forecasted data. For instance, the Q1 2024 forecast illustrates a divergence in sign, signaling an expansion where a contraction was observed. These differences suggest areas for refinement, including the incorporation of additional variables and techniques to address high residual variances in specific indicators, such as inflation and money supply.

Overall, the paper underscores the value of DFMs as a critical tool for central banks, enabling real-time economic assessments that support informed decision-making. By continuing to refine these models and integrating complementary approaches, such as machine learning, researchers and policymakers can enhance their capacity to navigate the complexities of macroeconomic forecasting in both advanced and emerging economies.

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Appendix

Table 1a. Autoregressive Coefficients on Idiosyncratic Component

	AR Coefficient	Variance Residual
Number of employees	0.8	0.4
Hiring perspectives (employment outlook)	0.1	0.1
Real sector net wage	-0.1	0.8
Unemployment rate	-0.3	0.9
Unit labor cost in industry (ULC)	-0.3	0.5
Monthly Inflation Rate based on Harmonized Consumer Price Index (HICP)	0.3	0.9
Economic Sentiment Indicator (ESI)	1.0	0.0
Retail turnover volume (excluding the trade with motor vehicles and motorcycles)	-0.4	0.4
Motor vehicles and motorcycles trade	-0.2	0.4
Market services provided to the population	0.1	0.6
Wholesale trade	-0.3	0.6
Market services rendered mainly to enterprises	-0.3	0.8
Construction works	-0.3	0.9
Industrial production index	-0.3	0.4
Volume indices of industrial new orders	-0.4	0.4
Exports	-0.4	0.2
Imports	-0.5	0.2
Narrow money supply (M1)	0.1	1.0
Non-government credit	0.5	0.7
Real GDP	-0.8	0.1
Final consumption	-0.9	0.1
Gross fixed capital formation	-0.7	0.1
Capacity utilization rate in industry	-0.8	0.1

Source: Authors' own research.

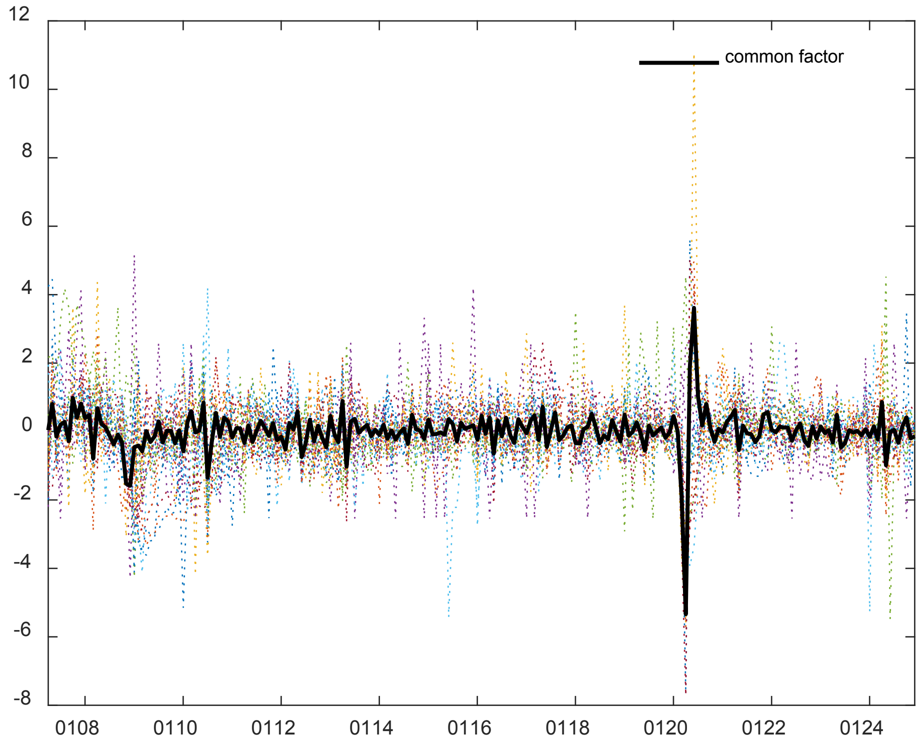

Figure 1a. Common factor and standardized data

Source: Authors' own calculations.