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Forecasting Moldova's monthly exports using autoregressive models with seasonal dummies

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ABSTRACT

Exports significantly influence Moldova's economic stability and regional integration, particularly due to its agriculture-driven economy characterized by pronounced seasonality. This study evaluates the forecasting accuracy of autoregressive integrated moving average (ARIMA) models, enhanced with seasonal dummy variables, for predicting Moldova's monthly exports. It systematically compares traditional ARIMA methods, ARIMA with seasonal dummies, and modern techniques such as Gated Recurrent Unit (GRU) neural networks. Forecast performance is assessed using Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Theil's U-statistic, and the Cost-Value Ratio (CVR). Results demonstrate that combining forecasts from multiple ARIMA models significantly improves predictive accuracy, with weighted combinations based on MAPE reducing forecast errors by approximately 10%. The findings highlight the effectiveness and adaptability of combined forecasting models, emphasizing their value for small, open economies like Moldova's that are susceptible to external shocks and seasonal fluctuations. This research provides robust empirical evidence supporting the adoption of combined econometric forecasting methodologies in economic policymaking and strategic planning.

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Agriculture & Environmental Sciences; Food Laws & Regulations; Statistics for Social Sciences

1. Introduction

Exports are of pivotal importance to small and open economies, with far-reaching consequences for economic growth, macroeconomic stability, and social development. As the primary source of international financial flows, exports play a crucial role in Small Open Emerging Economies by providing the necessary foreign currency to finance imports of goods and services and maintaining balance in the current account. By increasing exports, countries can stimulate domestic production, leading to job creation and an improved standard of living (Wan et al., 2022).

Furthermore, the development of export sectors has been shown to aid in the diversification of the economy and the reduction of dependency on a single sector or internal economic fluctuations. Exports enable local producers to access international markets, which in turn encourages investments in modern technologies and practices, thereby enhancing the global competitiveness of products and services. Additionally, an export-oriented economy can attract foreign direct investments, as international companies are often interested in investing in countries with access to large external markets. Consequently, exports can function as a catalyst for sustainable economic growth and enhance the economy's resilience against external shocks.

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The fundamental characteristics of Small Open Emerging Economies include a strong dependence on external economic conditions, vulnerability to price fluctuations in global markets, and limited internal resources for stimulating exports (Menna & Tobal, 2018).

Export forecasts furnish the government and economic institutions with invaluable data for the development of appropriate trade, fiscal, and monetary policies. By comprehending future trends, authorities can implement measures to stimulate productive sectors and facilitate access to external markets. Both domestic and foreign investors rely on economic forecasts to make informed investment decisions. Positive export projections have the capacity to attract investments in sectors with growth potential, thereby fostering the development of industry and agriculture.

It can thus be concluded that the export of goods should constitute a fundamental component of the structural econometric model of the Republic of Moldova (Ganciucov et al., 2007), which is classified as a Small Open Emerging Economy. Therefore, it is necessary to develop such a model and to update it periodically based on annual data, ensuring its applicability for medium-term macroeconomic forecasts (Toacă et al., 2015).

In the context of both internal and global economic instability, the identification of relevant econometric relationships for model variables is becoming increasingly challenging, which in turn affects the accuracy of forecasts. A significant support mechanism for generating annual macroeconomic forecasts is the use of higher-frequency statistical data, such as monthly or quarterly figures. The Nowcasting method (Furukawa & Hisano, 2022; Giannone et al., 2006, 2008; Kunovac & Špalat, 2014; Modugnoy et al., 2016; Nguyen et al., 2024) utilises these high-frequency data sources to generate high-quality forecasts.

In light of the pivotal function of external financial flows, particularly exports, in the economic advancement of Small Open Emerging Economies, the present study aspires to furnish a decision-making framework for economic and policy formulation through the medium of monthly export forecasting. The objective of this research endeavour is to develop an efficacious export forecasting instrument that takes into account the seasonal characteristics of Small Open Emerging Economies, employing the Republic of Moldova as a case study. The overarching ambition of this research is to contribute to the development of a structural econometric model that is tailored to the specific dynamics of such economies.

In order to achieve the stated objective, the following key objectives will guide the research:

1. The identification of appropriate methods for forecasting monthly exports in a Small Open Emerging Economy.
2. The application of the selected method to the economy of the Republic of Moldova in order to assess its effectiveness and practical relevance.

The structure of the present study is delineated as follows: Firstly, the context of the research and its objectives are outlined in the introduction. Secondly, the literature review analyses studies related to the methods used for forecasting export volumes. Thirdly, the materials and methods present the methodologies applied in the study. Fourthly, the results showcase the findings obtained from the application of the methods described in Section 3. Fifthly, the discussion focuses on the analysis and interpretation of the obtained results. Finally, the conclusions summarise the key findings and contributions of the study.

2. Literature review

Contemporary theory of international trade explores a wide range of economic issues, analysing the relationships and causality between various economic processes. A significant portion of traditional trade theory focuses on the causes and consequences of trade development (Ghauri et al., 2020), incorporating models such as the Ricardian and Heckscher-Ohlin frameworks. The process of global economic integration has led to the inclusion of open-economy characteristics in most macroeconomic models.

Recent trade theory advancements have broadened the scope of trade determinants by incorporating monopolistic competition and market failures, with a particular emphasis on intra-industry trade.

Further theoretical advancements include gravity growth models (Anderson, 2010; Capoan, 2023), endogenous growth models (Chirwa & Odhiambo, 2018; Fine, 2000; Onyimadu, 2015), and the theory of competitive advantage (Alimohammadi et al., 2014). Integrating exports into econometric models enables a more comprehensive evaluation of economic evolution and sectoral interactions at both national and international levels (Karakaya & Cooke, 2002). These methodological approaches provide a complex perspective on economic development and support the adaptation of long-term economic strategies.

As the primary objective of this study is the monthly forecasting of Moldova's exports, both qualitative and quantitative methods can be used. Qualitative methods are particularly useful when statistical data are scarce, relying on expert judgement (Collopy et al., 2001) and scenario analysis (Bacciotti, 2020). In the case of Moldova's exports, however, monthly statistical data have been available since January 2005, allowing the application of quantitative methods based on mathematical models, statistical techniques and numerical data.

The use of econometric methods for macroeconomic forecasting is widely recognised in both academic research and practical applications. The choice of forecasting techniques is mainly influenced by the research objective and the availability of statistical data. Structural econometric models not only facilitate the generation of accurate forecasts, but also allow a detailed analysis of the influence of exogenous factors on endogenous variables.

Time Series Models are a powerful statistical tool for analysing and forecasting data collected or recorded at successive time intervals. These models are particularly effective when the primary objective is to identify patterns, trends and relationships within data over time. Time series forecasting methods can be divided into three main groups (Liu et al., 2021):

- Classical forecasting methods: Including ARIMA (AutoRegressive Integrated Moving Average) models, which capture trends and seasonality in time series.
- Machine learning forecasting models: Using advanced algorithms such as decision trees, support vector machines and gradient boosting for predictive analysis.
- Hybrid forecasting methods: Combining traditional statistical models with machine learning techniques to improve forecasting accuracy.

Among machine learning techniques, Artificial Neural Network (ANN) has shown strong performance in time series forecasting. However, due to the complexity and amount of data required (Liu et al., 2021), overfitting often occurs. As a result, ANNs are not suitable for time series forecasting when dealing with small data samples.

Given the need to forecast macroeconomic indicators, in particular exports, it is essential to identify a forecasting method that is suitable for the economic conditions of the Republic of Moldova. The academic literature presents several models for export forecasting.

ARIMA is a widely used model for stationary data or data that can be made stationary by differencing. It is easy to use and interpret, making it well suited for short-term forecasting. One of the main advantages of this model is its ability to incorporate seasonal components. However, some of its main disadvantages include its inability to capture structural changes and economic shocks, and its sensitivity to the choice of parameters (p, d, q) (Liu & Wang, 2024).

Elena Bobeica et al. (2015) applied a dynamic panel data model to forecast exports in euro area countries. Panel data models are efficient for analysing datasets with spatial and temporal characteristics, as they take into account individual differences and dynamic behaviour over time. These models provide more accurate forecasts in the presence of heterogeneous data and are suitable for datasets with missing values. However, they require large datasets and can suffer from multicollinearity and autocorrelation problems, making the interpretation of results more complex.

Recent research has increasingly relied on structural models for forecasting macroeconomic indicators, especially exports (Bin & Tianli, 2020; Dai, 2023). Structural models are used to analyse and predict macroeconomic processes, taking into account economic policies. In addition, these models allow the study of the impact of economic shocks and policy decisions on the economy. However, the challenges associated with these models include high data quality requirements and complex parameter construction and calibration.

3. Materials and method

The separate analysis and forecasting of a single indicator within a macroeconomic model is essential for understanding how that indicator influences and is influenced by other economic factors. This involves the use of econometric methods to study trends in a given indicator. If the main objective of the study is to generate forecasts, the Auto Regressive Integrated Moving Average (ARIMA) technique can be used to obtain qualitative and robust results (Bretschneider et al., 1989; Sahu & Mishra, 2013). For macroeconomic indicators with a monthly or quarterly frequency, it is recommended to use dummy variables to capture seasonality or other structural changes. Alternatively, a combination of ARIMA models and dummy variables can improve forecasting accuracy (Ghauri et al., 2020). The ability to use different theories to perform analytical tasks is beneficial for the advancement of science (Armstrong, 2001a), in this case for the development and improvement of forecasting methods. Model selection is usually done by ex-post forecasting, which involves splitting the historical time series into training and validation data sets. The predictive performance of the model can be evaluated using statistical measures such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) to ensure that the selected model provides a robust and reliable forecast.

In forecasting analysis, the establishment of a baseline model is crucial for assessing the performance of more complex methods. As a benchmark, this study uses the Seasonal Naïve Model, which assumes that the value of exports in a given month is equal to that of the same month in the previous year. This simple but efficient model serves as a baseline that allows us to quantify the added value of econometric models such as ARIMA and those that incorporate seasonal dummy variables.

It is common practice to estimate several models that are considered reasonable (Armstrong, 2001b), followed by hypothesis validation. T. Alam Alam (2019) mentions that the most appropriate models for forecasting total exports and imports of the Kingdom of Saudi Arabia are artificial neural networks, ARIMA(0,1,1) and ARIMA(1,1,2). According to the results of Ghauri et al. (2020), ARIMA or Box-Jenkins techniques provide the best forecast values for exports due to their lower MAE values compared to AR models with dummy variables. Seasonal models, such as seasonal ARIMA, use specific parameters that reflect cyclical patterns and provide more accurate forecasts for time series affected by seasonal variations. By incorporating seasonal variables, econometric models can adjust and improve their forecasting ability, ensuring a more accurate estimation of long-term trends. In Khan's study, an ARIMA(0,1,1)(1,0,0) (Chirwa & Odhiambo, 2018) model was used to analyse seasonality and forecast time series (Khan, 2011). This model integrates a first-order moving average term and a first-order seasonal autoregressive term, thus capturing both non-seasonal and seasonal components of the data. A similar result was obtained in the determination of the forecasting model (Mladenovic et al., 2016) for monthly exports of Serbia, where the identified model is ARIMA(1,1,1)(1,2,1) (Chirwa & Odhiambo, 2018). The ARIMA model proposed by Amoussou A. G. and Medenou A. could be useful for forecasting export values and assessing both realised and unrealised export potential of products (Amoussou & Medenou, 2021). Among the total ARIMA(p,d,q) models estimated for fish export forecasting in Indonesia according to the MAPE indicator, ARIMA(2,2,4) was selected (Handayani et al., 2024).

The use of the ARIMA model in modelling and forecasting macroeconomic indicators is widely used because of its ability to capture the dynamics of time series and deal with trends, seasonality and shocks in the data. On the other hand, the inclusion of dummy variables in econometric models allows the impact of structural or seasonal events to be captured. The combination of ARIMA and dummy variables improves the accuracy of the model by allowing adjustments to be made to account for structural and seasonal changes in macroeconomic data. Used together, these tools provide *robust models for short- and medium-term economic forecasting*, helping policymakers to anticipate fluctuations and adjust economic policy accordingly.

Considering that a significant share (61%) of Moldova's exports consists of agri-food products (Stratan et al., 2024), which are seasonal by nature, it is crucial to forecast international financial flows on a monthly basis, as they fluctuate significantly. For this reason, ARIMA was chosen as the primary forecasting method.

Nevertheless, we acknowledge that the trade-off between theoretical coherence and practical relevance is a common challenge in empirical econometric applications. On the one hand, theoretical coherence ensures that econometric models are constructed in line with established economic theories, thus providing a solid and rational basis for analysis. However, purely theoretical models can sometimes be overly simplistic or rigid, failing to capture the complex realities of economic dynamics. Practical relevance, on the other hand, emphasises the use of real data and empirical approaches that are best suited to specific circumstances.

In order to better reflect observed realities and to fulfil the objectives of this study, we aim to adapt the models. This involves modifying certain variables or using alternative techniques that are not always consistent with traditional economic theory. This trade-off reflects the need to balance practical applicability with theoretical rigour, ensuring that research findings are both academically sound and useful in real-world contexts.

The data used for this study consists of the monthly export of goods from the Republic of Moldova for the period 01/2005–06/2024 (NBS, 2024). For the analysis, the natural logarithm was used to stabilise the variance, while exponential smoothing was used to reduce fluctuations. Before applying the MA, AR, and ARIMA methods, the stationarity of the data series was tested using the Phillips and Perron (1988) and Augmented Dickey and Fuller (1979, 1981) tests.

The equation for the Augmented Dickey-Fuller (ADF) test, which is used to test the stationarity of a time series, has the following general form:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + + \delta_2 \Delta y_{t-2} + \cdots + \delta_p \Delta y_{t-p} + \varepsilon_t, \tag{1}$$

where Δy_t - the first difference of the time series, α - the constant term (intercept) in the equation, βt - the linear trend term, γy_{t-1} - the autoregressive term, which tests whether the time series has a unit root, $\delta_1, \delta_2, \ldots \delta_p$ - the coefficients on the lagged differences of the time series, ε_t - the error term.

The hypotheses tested are:

H_0: The time series has a unit root (non-stationary).

H_1: The time series is stationary (no unit root).

The Phillips-Perron (PP) test is another method used to test the stationarity of a time series and the presence of a unit root. Although it has similar objectives to the ADF test, the PP test uses a different approach to correct for autocorrelation and heteroscedasticity. The general form of the PP test equation is:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \varepsilon_t \tag{2}$$

The ARIMA(p,d,q)(P,D,Q)[s] model is an extension of the ARIMA(p,d,q) model that includes seasonal components. It is used to model time series that exhibit both seasonality and long-term trends.

The general equation for the seasonal ARIMA model is as follows

$$\Delta_{y_t}^d = \alpha + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{i=1}^{P} \Phi_i \Delta^D y_{t-is} + \sum_{j=1}^{Q} \Theta_j \varepsilon_{t-js} + \varepsilon_t, \tag{3}$$

where y_t - the value of the time series at time t, $\Delta_{y_t}^d$ - non-seasonal difference of order d applied to make the series stationary, α - the constant term, ϕ_i - non-seasonal autoregressive coefficients of order p, θ_j - non-seasonal moving average coefficients of order q, Φ_i - seasonal autoregressive coefficients of order P, capturing seasonality over several periods of s (seasonal frequency, e.g., 12 for monthly data), Δ^D - seasonal differencing of order D, applied to remove seasonal components, Θ_j - seasonal moving average coefficients of order Q, applied to seasonal residuals, ϵ_t - the error (residual) term at time t.

This comprehensive description highlights the role of each component in the ARIMA (p,d,q) (P,D,Q) [s] model, which integrates both non-seasonal and seasonal elements to provide a better fit to time series with periodic patterns and long-term trends.

A *dummy* variable is a binary variable that takes the value 1 if a particular event occurs and 0 if it does not. These variables are used to model the impact of events that have a temporary or structural effect on a time series. In monthly time series, dummy variables are used to represent each month separately.

The general form for defining a *dummy* variable is

$$D_i = \begin{cases} 1, \textit{for month } i \textit{ of each year} \\ 0, \textit{for other months of each year} \end{cases}$$

For monthly time series, dummy variables can be defined for each specific month, allowing the model to capture seasonal effects or structural changes that may affect the series in different months.

In this study, the quality of forecasts was assessed using the ex-post method, with the aim of validating and calibrating the forecasting models to ensure that they provide reliable estimates for future periods. The error of the forecast values was calculated using the *Mean Absolute Percentage Error* (MAPE) coefficient:

$$MAPE = \frac{1}{m}\sum_{t=1}^{m}\frac{\left|y_t - \hat{y}_t\right|}{y_t} * 100 \tag{4}$$

where y_t - the actual value at time *t*, $\check{y}_t$ - the predicted value at time *t*, *m* - the number of observations.

MAPE measures the accuracy of a forecasting model by expressing the error as a percentage, making it useful for evaluating the predictive performance of the model and comparing different models. Lewis (1982) created a table with typical MAPE values (Table 1).

Several other statistical metrics besides MAPE were employed to assess the forecastings accuracy of the models:

The *Mean Absolute Error (MAE)* measures the average absolute error, irrespective of the error direction.

$$MAE = \frac{1}{m}\sum_{t=1}^{m}\left|y - \hat{y}\right|5) \tag{5}$$

Root Mean Squared Error (RMSE) penalizes larger errors more significantly than Mean Absolute Error (MAE) due to the squared differences:

$$RMSE = \sqrt{\frac{1}{m}\sum_{t=1}^{m}\left(y - \hat{y}\right)^2} \tag{6}$$

Theil's U statistic (U-Statistic) is a relative measure that compares the model forecast to a reference forecast (usually the *naïve forecast*).

$$U = \frac{\sqrt{\frac{1}{m}\sum_{t=1}^{m}\left(y - \hat{y}\right)^2}}{\sqrt{\frac{1}{m}\sum_{t=1}^{m}y^2} + \sqrt{\frac{1}{m}\sum_{t=1}^{m}\hat{y}^2}} \tag{7}$$

Interpretation of Theil's U-statistic results:

U < 1: the model forecast is better than the naive forecast.

Table 1. Interpretation of the MAPE coefficient.

MAPE value (%)	Interpretation
<10	Highly accurate forecast
10 to 20	Good forecast
20 to 50	Reasonable forecast
>50	Poor forecast

Source: Lewis, 1982.

U = 1: the model forecast is equally accurate as the naive forecast.

U > 1: the model forecast is more accurate than the naive forecast.

The *Cost -Value Ratio (CVR)* provides an economically grounded evaluation of forecast utility.

$$CVR = \frac{\sqrt{\frac{1}{m}\sum_{t=1}^{m}\left(y-\hat{y}\right)^2}}{\frac{1}{m}\sum_{t=1}^{m}y_t} \tag{8}$$

The CVR expresses the average forecast error relative to typical export values. A lower CVR indicates that the model generates errors with a lower economic cost, which is a critical factor in trade policy decision-making processes.

Together, these indicators provide a more comprehensive understanding of each model's forecasting performance. While MAPE captures relative forecasting errors and RMSE emphasizes larger errors, Theil's U statistic facilitates comparison against a baseline naïve forecast. Additionally, a Diebold-Mariano test was conducted to evaluate the statistical significance of the models' performance differences. Incorporating CVR into forecast evaluation is important because it provides an economic context to our analysis. CVR quantifies the financial impact of forecast errors relative to estimated correct export values. Thus, statistical accuracy and economic efficiency are considered for each model.

The results confirm that the weighted combined forecasting method significantly outperforms individual models in terms of not only MAPE but also other statistical criteria, thus validating its robustness.

4. Results and discussion

4.1. Descriptive statistics

Descriptive statistics provide a summary of the data set, which may represent either a sample or a population. Table 2 presents these statistics for Moldova's exports. The mean export value of 5.17 reflects the average level during the period analysed, while the median of 5.20, which is very close to the mean, indicates a relatively balanced distribution. Exports recorded a maximum value of 6.03 and a minimum value of 4.13, with a range of 1.91 and a standard deviation of 0.42, indicating a moderate variation around the mean.

The skewness coefficient of -0.21 indicates a slightly negative skewness, meaning that the data distribution is slightly concentrated to the right. With a kurtosis coefficient of 2.47, close to the normal value of 3, the distribution can be considered approximately normal.

The Jarque-Bera test recorded a statistic of 4.44, with an associated probability of 0.11, indicating that there is insufficient evidence to reject the hypothesis that the data follow a normal distribution at the 5% level of significate.

Table 2. Descriptive statistics.

Statistics	Total export
Mean	5.166572
Median	5.204552
Maximum	6.031646
Minimum	4.125520
Std. Dev.	0.424946
Skewness	−0.206139
Kurtosis	2.465651
Jarque-Bera	4.441153
Probability	0.108547
Sum	1208.978
Sum Sq. Dev.	42.07496
Observations	234

Source: Authors' calculations.

4.2. Stationarity test

The monthly evolution of goods exports is a non-stationary time series, but it becomes stationary after the application of first-order differencing (Figure 1).

In both tests, at the original level of the series (without differencing), the *p*-value are higher than the usual significance threshold of 0.05 (Table 3), indicating that the null hypothesis (H0) cannot be rejected, confirming that the series has a unit root. After applying the first difference to the series, the *p*value become very small (below 0.05 in both tests), indicating that the null hypothesis (H0) can be rejected and that the series becomes stationary after the first differencing, or that the series is integrated of order I (1).

4.3. Model identification

Based on the analysis of autocorrelation (AC), partial autocorrelation (PAC) and seasonality in the data (Table 4), several model variants can be proposed to capture the dynamics of monthly exports.

At lag 1, the autocorrelation is negative (-0.120) and relatively small, indicating a modest dependence between consecutive observations. At lag 2, the autocorrelation decreases significantly (-0.386) and is

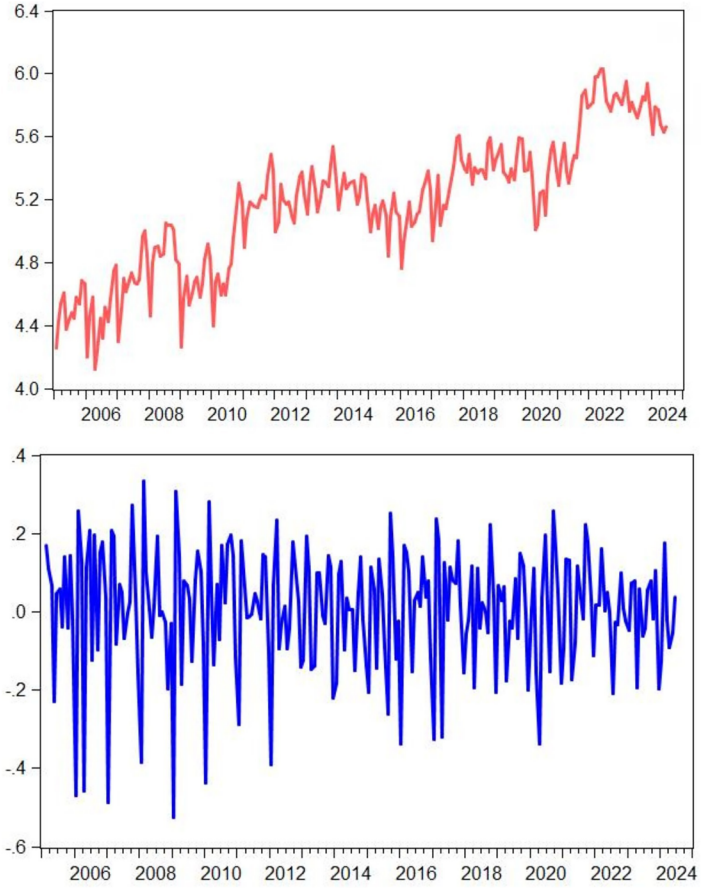


Figure 1. Monthly goods exports of the Republic of Moldova from 01/2006 to 6/2024 (in Log Form)—Non-stationary and stationary series. The diagram showing the evolution in red highlights the non-stationary time series. The diagram showing the evolution in blue highlights the stationary time series.

Table 3. Results of the augmented Dickey-Fuller and Philips-Perron tests.

Augmented Dickey-Fuller (ADF)		Philips-Perron (PP)	
Level	1st diff	Level	1st diff
−1.60 (0.48[1])	−4.33 (0.0005)	−2.66 (0.08)	−21.98 (0.00)

Source: Authors' calculations.

Table 4. Results of the ACF and PACF.

Lag	AC	pAC	Q-Stat
1	−0.120	−0.120	3.4076
2	−0.386	−0.406	38.724
3	0.012	−0.124	38.761
4	0.119	−0.072	42.121
5	0.049	0.024	42.707
6	−0.154	−0.137	48.425
7	−0.024	−0.045	48.561
8	0.151	0.045	54.081
9	−0.026	−0.030	54.250
10	−0.319	−0.320	79.290
11	0.003	−0.175	79.292
12	0.584	0.433	163.93
13	−0.111	0.019	166.99
14	−0.280	0.060	186.57
15	−0.018	−0.062	186.65
16	0.158	0.055	192.96
17	0.033	−0.063	193.24
18	−0.185	−0.065	201.96
19	−0.006	−0.029	201.97
20	0.208	0.081	213.12
21	−0.107	−0.101	216.05
22	−0.331	−0.173	244.43
23	0.021	−0.189	244.55
24	0.473	0.062	303.22
25	−0.036	0.045	303.56
26	−0.278	−0.023	324.03
27	−0.027	−0.025	324.23
28	0.167	−0.037	331.66
29	−0.020	−0.138	331.76
30	−0.143	−0.053	337.30
31	0.045	0.000	337.85
32	0.156	−0.050	344.46
33	−0.084	0.021	346.40
34	−0.301	−0.085	371.35
35	0.015	−0.110	371.41
36	0.505	0.138	442.28

supported by the PAC value (-0.406), indicating the possible presence of a second order autoregressive component (AR(2)).

At higher lags, fluctuations in AC are observed, with significant values at lag 12 (0.584) and lag 24 (0.473), indicating the presence of annual seasonality in the data (as the series consists of monthly observations with a 12-month cycle). The presence of seasonality at 12-month intervals suggests the need for a seasonal ARIMA model, of the form ARIMA(p,d,q)(P,D,Q) (Chirwa & Odhiambo, 2018).

The low-order lags (2 and 8) may indicate the need to include non-seasonal components, such as AR(2). An ARIMA(2,d,q)(1,D,0) (Chirwa & Odhiambo, 2018) model could integrate both the short-term dynamics and the observed annual seasonality.

Alternative model options include ARIMA(2,1,0) and ARIMA(1,1,2). Given the structure of the data, an ARIMAX(1,1,1) or ARIMAX(1,1,2) model with seasonal dummy variables could allow for adjustments for seasonal effects and further improve forecast accuracy.

4.4. Estimation of econometric forecasting models for Moldova's exports

After several evaluations, four models were selected that met the requirements of the econometric tests. The residuals of these models are normally distributed, and the absence of autocorrelation was confirmed.

1. Model with dummy variables

$$\begin{aligned} D(LEXP)_t = {} & -0.21 - 0.25D2006M01 + 0.37(@MONTH = 2) + 0.32(@MONTH = 3) \\ & + 0.084(@MONTH = 4) + 0.22(@MONTH = 5) + 0.25(@MONTH = 6) \\ & + 0.23(@MONTH = 7) + 0.19(@MONTH = 8) + 0.30(@MONTH = 9) \\ & + 0.34(@MONTH = 10) + 0.26(@MONTH = 11) + 0.10(@MONTH = 12) \end{aligned} \tag{9}$$

2. ARIMA Model (2,1,0)

$$D(LEXP)_t = 0.007 - 0.37D2006M01 - 0.21D(LEXP)_{t-1} - 0.42D(LEXP)_{t-2}, +0.1642D(LEXP)_{t-3} \quad (10)$$

3. ARIMA Moldel (1,1,2)(2,0,0):

$$D(LEXP)_t = 0.003 + 0.57D(LEXP)_{t-1} + 0.34 - 0.35 + 0.45D(LEXP)_{t-12} + 0.22D(LEXP)_{t-24} \quad (11)$$

4. ARIMA Moldel (1,1,2) and Dummy Variables

$$\begin{aligned} D(LEXP)_t = & -0.23 + 0.38(@MONTH = 2) + 0.37(@MONTH = 3) + 0.098(@MONTH = 4) \\ & + 0.23(@MONTH = 5) + 0.26(@MONTH = 6) + 0.24(@MONTH = 7) \\ & + 0.204(@MONTH = 8) + 0.31(@MONTH = 9) + 0.35(@MONTH = 10) \\ & + 0.27(@MONTH = 11) + 0.11(@MONTH = 12) - 0.32D(LEXP)_{t-1}, -0.22 - 0.35\,\varepsilon_{t-2} \end{aligned} \quad (12)$$

Forecast quality testing was tested using the ex-post method, which assesses the performance of a forecasting model by comparing predicted values with actual values. The training set (in-sample), used for model estimation, covers the period from 01/2005 to 12/2022. The test set (out-of-sample), used for ex-post evaluation, covers the period from 01/2023 to 06/2024. The MAPE coefficient was calculated to determine the quality of the forecasts (Table 5). A MAPE value below 10% indicates that the ex-post forecasting model has high accuracy, with minimal errors between predicted and actual values, making the model suitable for practical use, such as short- or medium-term forecasting of Moldova's monthly export trends. In addition to the four estimated econometric models, a Seasonal Naïve model was also evaluated and used as the baseline model. The Seasonal Naïve model assumes that monthly values of exports are equal to those of the same month of the previous year, thus capturing only the recurring seasonality without modeling the internal structure of the series.

The ex-post forecast evaluation for the Seasonal Naïve model, carried out over the same test period (01/2023–06/2024), yielded a MAPE of 10.86%, slightly above the threshold defining a 'highly accurate forecast' (MAPE < 10%). This result confirms that while the baseline model is able to reflect simple seasonal components, the advanced models used in this study provide superior forecast accuracy.

Each model has its strengths and weaknesses, and aggregating the forecasts from all four models can reduce the errors specific to each individual model. The effectiveness of using aggregated forecasts has been widely discussed in the literature. Clemen (1989) shows how forecast combinations, such as simple averages and weighted averages, outperform individual models by reducing forecast errors over different time series. Dudek (2023) presents advanced techniques that use machine learning to combine forecasts from multiple models to improve accuracy in managing complex seasonality. The article by S. Lis and Chlebus, (2023) emphasizes that simple forecast combination methods can be surprisingly effective.

The authors compare various forecast combination techniques, such as arithmetic mean, with single models (e.g. GARCH), and the results show that during periods of high market uncertainty, including crises such as COVID-19, simple combination methods, such as averaging or minimum VAR, often outperform more complex approaches. This underscores the power of simplicity in forecast aggregation, both for researchers and practitioners (Makridakis & Winkler, 1983; Welch et al., 1998). The study suggests that combining models helps capture more volatility and improves forecast

Table 5. Ex-post forecast quality based on MAPE.

Ex-post forecast according to model	MAPE (%)
Baseline (Seasonal Naïve)	10.86
Model 1	8.872494
Model 2	9.743336
Model 3	8.193955
Model 4	9.268454

Source: Authors' calculations.

accuracy compared to using individual models, especially during periods of instability, such as the current uncertainty surrounding the evolution of Moldova's exports.

Two forecasting combination methods were used in this study: simple averaging and weighted forecasting. In the case of weighted forecasting (Table 6), a model that provides a more accurate forecast (with a lower MAPE) is given a higher weight in the final combination. Thus,

$$Final_{forcast} = \omega_1 M1_{forecast} + \omega_2 M2_{forecast} + \omega_3 M3_{forecast} + \omega_4 M4_{forecast} \quad (13)$$

where $M1_{forecast}$ - Forecast obtained from model *i*, ω_i - Weight of the forecast from model i, $i = 1,2,3,.4$ și $\omega_1 + \omega_2 + \omega_3 + \omega_4 = 1$.

The forecasts obtained from the four models and the combined forecasts are shown in Figure 2.

The lower MAPE values for both the average (7.14) and weighted (7.07) forecasts indicate that combining the models improves forecast accuracy compared to using the individual models. This highlights the effectiveness of forecast aggregation in reducing errors and improving forecasting performance.

Using the above-outlined methodology, the research was expanded by calculating several additional forecasting metrics: mean absolute error (MAE), root mean squared error (RMSE), Theil's U statistic, and cost-value ratio (CVR). Additionally, three more variants of weighted combined forecasts were calculated, each corresponding to one of these metrics. These metrics provide a more robust evaluation of forecasting accuracy, with each highlighting different aspects of deviation from actual values. Table 7 presents the values of the four indicators used to evaluate the quality of forecasts and compares individual and combined forecasting models.

Based on the values presented in Table 7, the relative ranks of each model were calculated according to the statistical indicators used: MAPE, MAE, RMSE, Theil's U, and CVR.

The average of these ranks was used to obtain an aggregated score reflecting each model's overall performance. This approach provides a synthetic comparison of all the tested methods and facilitates their classification into an overall ranking, as presented in Table 8.

The formula used to calculate the average score is:

$$Overal_{rank\,i} = \frac{1}{5}\left(Rank_{mape\,i} + Rank_{mae\,i} + Rank_{rmse\,i} + Rank_{Theil\,i} + Rank_{CVR\,i}\right), i = \overline{1,10} \quad (14)$$

Table 6. Weights of the models used in the combined forecast.

Model	MAPE	1/mAPE	Weight
M1	8.872494	0.112708	0.253119
M2	9.743336	0.102634	0.230496
M3	8.193955	0.122041	0.27408
M4	9.268454	0.107893	0.242305

Source: Authors' calculations.

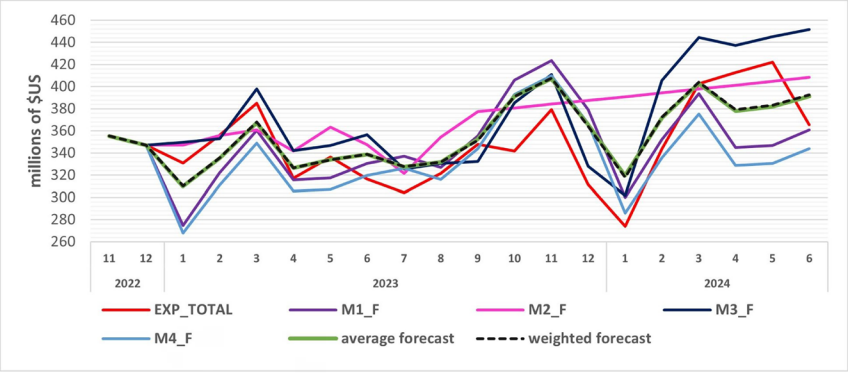


Figure 2. Ex-post forecast of Moldova's monthly exports.

Table 7. Forecasting model performance based on statistical indicators.

Model	MAPE (%)	MAE	RMSE	Theil's U	CVR
Model 1	8.87	31.19	39.72	0.0568	0.099
Model 2	9.74	31.47	41.63	0.0575	0.104
Model 3	8.19	28.47	34.7	0.0477	0.087
Model 4	9.26	33.42	42.39	0.0617	0.106
Seasonal Naïve	10.86	69.08	78.31	0.1242	0.196
Combined Avg	7.14	24.27	28.79	0.0406	0.072
Combined Weighted with MAPE	7.07	24.07	28.43	0.0400	0.071
Combined Weighted with MAE	7.09	24.08	28.47	0.0401	0.071
Combined Weighted with RMSE	7.06	23.98	28.29	0.0398	0.071
Combined Weighted with Theil's U	7.042	23.91	28.212	0.0397	0.071

Source: Authors' calculations.

Table 8. Individual model ranks and aggregated scores.

Model	Rank MAPE	Rank MAE	Rank RMSE	Rank theil's U	Rank CVR	Average score	Overall rank
Combined Weighted with Theil's U	1	1	1	1	10	2.8	1
Combined Weighted with RMSE	2	2	2	2	9	3.4	2
Combined Weighted with MAPE	3	3	3	3	7	3.8	3
Combined Weighted with MAE	4	4	4	4	8	4.8	4
Model 3	6	6	6	6	1	5	5
Combined Avg	5	5	5	5	6	5.2	6
Model 1	7	7	7	7	1	5.8	7
Model 2	9	8	8	8	1	6.8	8
Model 4	8	9	9	9	1	7.2	9
Seasonal Naïve	10	10	10	10	5	9	10

Source: Authors' calculations.

The results in Table 7 confirm that combined forecasting methods outperform individual models. A comparative analysis of the aggregated scores shows that the combined models perform very similarly to one another and significantly better than the individual models.

According to this evaluation, the best-performing model is the Combined Weighted, with weights calculated using Theil's U. It occupies the first position in the overall ranking despite having a very weak CVR. Furthermore, the minimal differences between the combined models indicate methodological stability and the high efficiency of the forecast aggregation strategy, regardless of the weighting criterion employed.

In contrast, the average score for the four individual models and the seasonal naïve model is 8.00, confirming the superiority of the combined forecasting approach. These results support the idea that aggregation reduces model-specific errors, providing more stable and precise estimates. However, Model 3 is noteworthy as it is the best among the individual models, ranking first in CVR and being the most economically efficient.

To complement the traditional econometric models, a Gated Recurrent Unit (GRU) neural network was implemented and tested on the same dataset. The GRU model yielded a Mean Absolute Percentage Error (MAPE) of 7.07%, indicating a high level of predictive accuracy. Despite this strong performance, the GRU model operates as a black box, which limits its interpretability and practical use in policy-oriented contexts. Consequently, ARIMA models combined with dummy variables remain better suited for macroeconomic forecasting where transparency and explainability are essential.

Forecasting macroeconomic indicators is a crucial task for economists and analysts. In *small open emerging markets*, including Moldova, vulnerabilities are generally greater than in advanced economies. Moldova's situation is further complicated by the ongoing armed conflict between Russia and Ukraine, which had a negative impact on the country's macroeconomic performance.

Therefore, macroeconomic forecasting, especially in the short term, is essential for macroeconomic decision making. As exports are the main source of international financial flows for Moldova, their

continuous monitoring is necessary. In this context, export forecasting plays a key role in shaping macroeconomic policies, ensuring informed decision-making, and maintaining economic stability.

Based on the results obtained, we can conclude that each of the estimated models captures specific trends in the evolution of monthly exports. ARIMA models effectively capture dynamic relationships and recurring seasonality in monthly exports, while dummy variable models are ideal for identifying simple seasonality patterns and the effects of discrete events.

The combination of these two methods can improve forecasting accuracy by integrating both short-term dynamics and seasonal or structural effects. However, this approach may lead to overlap or redundancy in the capture of seasonality, which could affect the performance of the model. Another problem is that dummy variables may be correlated with the seasonal components captured by ARIMA, leading to collinearity between variables. This, in turn, affects coefficient estimation, leading to model instability and reduced interpretability.

Integrating ARIMA with dummy variables adds additional terms, which increases the risk of overfitting, especially in small data sets. As a result, the statistical significance of coefficients may become inconsistent. This challenge led to the use of multiple models, each of which demonstrated high predictive accuracy. The combination of individual models helped to reduce model-specific errors, thereby increasing the robustness of the estimates.

This approach exploits the strengths of different models and provides a more comprehensive and accurate representation of economic trends. Since the objective of the study is to apply ARIMA models and dummy variables to analyse monthly export trends in Moldova, several model iterations were tested. As a result, four statistically significant models were estimated, which are valid for short-term forecasting, as shown by the ex-post analysis.

5. Conclusions

For a small and open emerging economy like the Republic of Moldova, exports represent one of the main sources of foreign exchange earnings, which are crucial for financing essential imports of goods and services. Given Moldova's dependence on imported energy, technology, and equipment, export earnings must ensure a balanced current account and maintain financial stability.

Moldova's balance of payments has faced persistent challenges throughout its independent history, particularly in terms of current account deficits. While remittances and external assistance have helped offset some imbalances, the country's economy remains highly vulnerable to external shocks, such as energy price fluctuations and geopolitical tensions.

Econometric models are a powerful tool for forecasting exports, providing essential support for decision making and trade policy development. However, their use requires careful data validation and systematic model updates to improve forecast accuracy and ensure reliable economic projections.

In this study, several econometric methods were used to forecast Moldova's exports, including autoregressive models and the use of seasonal dummy variables to capture the seasonality of exports. The selected methods were validated by residual diagnostic tests and by assessing the quality of the forecasts using ex-post evaluation methods.

ARIMA models were used to capture short-term dynamics and seasonality in the export time series. Another approach to accounting for month-specific seasonal effects was the use of dummy variables, which allowed adjustments in the econometric models to reflect seasonal effects such as agricultural cycles and fluctuations in international market demand. A combination of autoregressive models and dummy variables was also used.

The ex-post forecast accuracy of the estimated models was high; however, the combined forecasts were more accurate than any individual model. To evaluate forecasting models more broadly, highlighting not only their statistical performance, but also their economic efficiency, which is crucial for practical compliance in international trade, the Cost-Value Ratio (CVR) indicator was integrated. The results suggest that, despite superior statistical performance, combined models offer less economic value than individual models.

At the same time, it is important to highlight a number of limitations in the chosen methods for forecasting Moldova's monthly exports, which warrant further discussion:

- The statistical data used for export forecasts cover a long period (2005–2024), but potential gaps or inaccuracies in historical reporting may affect the quality of econometric models.
- Although the monthly data sets are comprehensive, they remain limited compared to the requirements of complex models, such as those combining ARIMA and dummy variables, which may increase the risk of overfitting.
- The models do not always account for major structural changes or economic shocks, such as the COVID-19 pandemic or the Russia-Ukraine armed conflict, which had a significant impact on exports.
- The models are calibrated specifically for the Moldovan economy, which means that their results may not be directly applicable to other economies with different characteristics.
- The models were validated using ex-post forecasting, which may limit their relevance in predicting entirely new or unprecedented economic scenarios.
- Exploring new forecasting methods, such as ARIMAX or machine learning approaches, could improve forecasting accuracy, especially when dealing with complex datasets.

Future research aims to overcome the limitations identified in this study by improving existing models and exploring more advanced forecasting methods that better capture the complexity and dynamics of Moldova's foreign trade.

Note

1. MacKinnon one-sided p-values.

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The authors report there are no competing interests to declare.

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Data availability statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study. Data available on reasonable request from the corresponding author, Liliana Staver (liliana.condratchi@ase.md).

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