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NEURAL-NETWORK-DRIVEN PANEL ANALYSIS OF MILITARY EXPENDITURE AND LABOUR-MARKET DYNAMICS IN UKRAINE, THE CZECH REPUBLIC, AND GERMANY (1993–2024)

Abstract. *In the context of current global turbulence, when Ukraine faces large-scale external challenges, research into labor market dynamics is particularly relevant. Of particular importance is the study of the relationship between military spending and employment during large-scale shocks, particularly during wartime. Since the beginning of the armed conflict in eastern Ukraine, society and the expert community have been actively discussing the impact of government defense investments on macroeconomic indicators and the labor market. The relevance of such analysis is also due to the need to adapt economic policy and strategic planning in conditions of uncertainty and military pressure.*

The study takes into account the experience of various countries, including Ukraine, the Czech Republic, and Germany, which allows us to identify differences in the structure of economies and the influence of regional factors. The use of machine learning methods on panel data increases the accuracy of forecasting through joint learning on combined information across all countries, and also helps to more accurately assess both *common and specific trends that are not visible in isolated analyses of individual countries.*

The research methodology combines traditional econometric tools with advanced machine learning algorithms. In the first stage, gaps in statistical data are filled using the ARIMA model, after which several multilayer neural networks (MLP) are built for each country and a combined XGBoost model. This multi-stage approach allows us to compare and integrate the advantages of different methods for forecasting the employment-to-population ratio (EPR), which is a key indicator of the analysis.

Keywords: *military expenditures, labor market, ARIMA, SARIMAX, XGBoost, panel data, tariff system.*

АНАЛІЗ ВІЙСЬКОВИХ ВИТРАТ ТА ДИНАМІКИ РИНКУ ПРАЦІ В УКРАЇНІ, ЧЕХІЇ ТА НІМЕЧЧИНІ (1993–2024) НА ОСНОВІ НЕЙРОННОЇ МЕРЕЖІ

Анотація. *У контексті сучасних глобальних потрясінь, коли Україна стикається з масштабними зовнішніми викликами, дослідження динаміки ринку праці є особливо актуальним. Особливе значення має вивчення взаємозв'язку між військовими витратами та зайнятістю під час масштабних потрясінь, зокрема в умовах війни. З початку збройного конфлікту на сході України суспільство та експертне співтовариство активно обговорюють вплив державних інвестицій у оборону на макроекономічні показники та ринок праці. Актуальність такого аналізу також зумовлена необхідністю адаптації економічної політики та стратегічного планування в умовах невизначеності та військового тиску.*

У дослідженні враховано досвід різних країн, зокрема України, Чехії та Німеччини, що дозволяє виявити відмінності в структурі економік та вплив регіональних факторів. Використання методів машинного навчання на панельних даних підвищує точність прогнозування завдяки спільному навчанню на комбінованій інформації по всіх країнах, а також допомагає точніше оцінити як загальні, так і специфічні тенденції, які не видно в ізольованих аналізах окремих країн.

Методологія дослідження поєднує традиційні економетричні інструменти з передовими алгоритмами машинного навчання. На першому етапі прогалини в статистичних даних заповнюються за допомогою моделі ARIMA, після чого для кожної країни будуються кілька багатошарових нейронних мереж (MLP) та комбінована модель XGBoost. Такий багатоетапний підхід дозволяє порівняти та інтегрувати переваги різних методів прогнозування співвідношення зайнятості до чисельності населення (EPR), яке є ключовим показником аналізу.

Ключові слова: *військові витрати, ринок праці, ARIMA, SARIMAX, XGBoost, панельні дані, тарифна система.*

Formulation of the problem. In the context of modern global instability and military pressure, Ukraine faces the task of adapting its economic policy and strategic planning. An important aspect of this process is studying the impact of military spending on the labor market and macroeconomic indicators. The presence of shocks and structural changes in the national economy requires the development of effective forecasting models capable of taking into account multifactorial influences, including macroeconomic and institutional factors.

Analysis of recent research and publications. In economic literature, the role of military spending in shaping macroeconomic indicators is examined from different perspectives. Some studies emphasize the positive impact of military spending on employment in the defense-industrial complex, as such investments create jobs and promote technological progress. Other studies point to the potential "outflow effect" of resources: significant government procurement of weapons can divert capital and labor from the civilian sector, which can weaken overall economic growth. Especially in conflict situations, increased uncertainty and shocks often lead to significant fluctuations in the labor market, as shown in studies of economic shocks.

Regarding forecasting methods, machine learning methods have recently been increasingly used in financial and economic literature. In particular, multilayer perceptrons and gradient boosting algorithms (XGBoost) demonstrate high accuracy in forecasting complex nonlinear dependencies. Some studies have shown that they can outperform traditional linear models and ARIMA models in modeling macroeconomic indicators, including labor market indicators. At the same time, the quality of such models depends on the volume and integrity of the data, which emphasizes the need to use proven methods (ARIMA, SARIMAX), in particular, to fill in missing values and identify trends.

The need to integrate modern approaches to tariff setting and bonus systems is also driven by changes in the structure of the economy amid war and global instability. The introduction of flexible wage scales that take into account not only qualification characteristics but also the innovativeness, creativity, and adaptability of employees will allow enterprises to respond more quickly to changes in market conditions and ensure the competitiveness of Ukrainian producers at the international level.

In addition, an effective wage system has a direct impact on the employment-to-population ratio (EPR), which is a key indicator of labor market stability. Increasing the real minimum wage and improving the wage system can stimulate employment, reduce the shadow economy, and strengthen the state's tax policy. In the long term, this will create conditions for sustainable EPR growth, which is particularly relevant in the post-war reconstruction period.

The purpose of this article is to conduct a comprehensive scientific analysis of the impact of military spending and institutional frameworks for wage regulation on the dynamics of the employment-to-population ratio (EPR) in Ukraine, the Czech Republic, and Germany in 1993–2024, as well as to develop, implement, and verify an integrated forecasting model that combines econometric time series analysis methods and machine learning algorithms to improve the reliability of estimates and forecasts in the context of wartime and post-war socio-economic transformations.

We used panel data covering Ukraine, the Czech Republic, and Germany for the period 1993–2024, importing a wide CSV file into Google Colab via pandas and unfolding it using wide_to_long. Key indicators — Employment-to-Population Ratio (EPR, %), Military Expenditure (ME, constant USD), Gross Domestic Product growth rate (GDP, %), Gross Fixed Capital Formation (GFCF, % of GDP), Industrial Value Added (IVA, % of GDP). After removing duplicates and rows with missing indicators, we filled in Ukraine's EPR series for 2022–2024 using ARIMA forecasting to restore a balanced panel.

To eliminate gaps in Ukraine's EPR, we applied the SARIMAX(1,1,1) model to the registered EPR series for 1995–2021 (without drift term), transformed them back using an exponent, and formed forecasts for 2022–2024. Before forecasting, we limited future macroeconomic predictors to the range of 1995–2021. This procedure ensured that there were no missing EPR values while maintaining consistency with historical volatility.

Continuous predictors (ME, GDP, GFCF, IVA) were independently scaled using StandardScaler for each country. Core density estimates confirmed a dense distribution of EPR in Germany, a moderate distribution in the Czech Republic, and a flattened, unstable profile in Ukraine. The correlation matrix provided information for further model regularization: in particular, Germany's GFCF_lag1 and IVA_lag1 showed high collinearity.

We created one-year lags for ME, GDP, GFCF, and IVA to reflect the lag in the labor market response. Interaction terms — ME×GDP and IVA×GFCF — were included globally. Country-specific transformations enriched the panel:

- Ukraine: innovation index (GFCF×GDP), change in EPR, and GDP volatility;
- Czech Republic: change in IVA (ΔIVA compared to the previous year) and capital structure in industry (GFCF×IVA);
- Germany: connection between defense technologies (ME×IVA), innovation index, as well as change in EPR and GDP volatility.

The model structure includes the following templates:

1. One-dimensional ARIMA model for filling gaps (Ukraine EPR).
2. Neural networks for specific countries: scikit-learn MLPRegressor (hidden layers 64–32, ReLU, Adam, lr_init = 0.0005, early stopping, max_iter = 3000, random_state = 42), trained on data for the years up to 2020, tested on data from 2020–2021.
3. Combined panel learning algorithm: one-off dummy variables for countries plus lagged features corresponding to XGBoost (target = reg:squarederror), selected for the lowest test RMSE.

We split the feature matrix of each country by calendar year (< 2020 for training, 2020–2021 for testing), selecting StandardScaler for the training slice and applying it to both sets. For the combined panel, the same time split was applied to all 72 observations (1996–2019 for training, 2020–2021 for testing).

Model fit was evaluated using MAE, RMSE, and R^2. ARIMA forecasts with inverse transformation achieved RMSE≈0.99 for Ukraine; country-specific MLPs were overfitted (Ukraine RMSE>19), while the combined XGBoost gave a test RMSE≈1.83, outperforming neural networks.

The generation and extension of forecasts yield the following results:

- ARIMA forecasts filled in Ukraine's EPR for 2022–2024 and then averaged their annual growth to forecast the EPR until 2026.
- XGBoost created baseline, optimistic, and pessimistic scenarios (±2 pp GDP, ±1 pp ME/GFCF),

revealing moderate sensitivity in the Czech Republic and Germany and an almost equal response in Ukraine due to dependence on input data only with a delay.

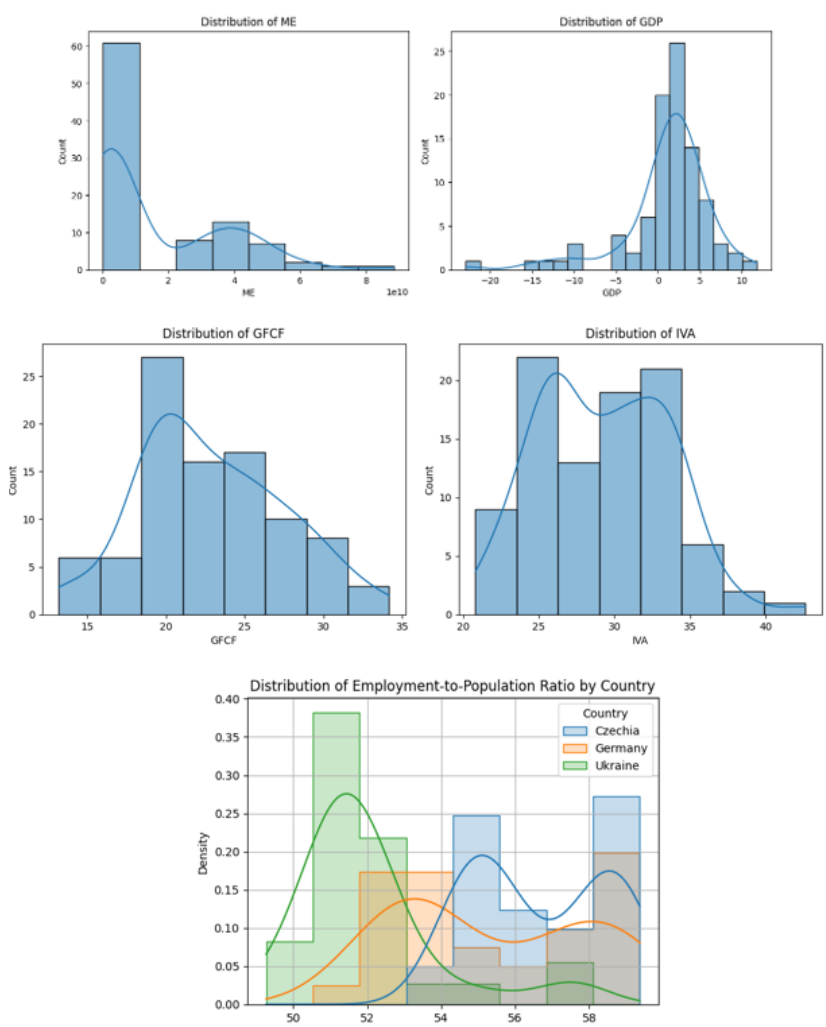
All code uses pandas, scikit-learn, statsmodels, and XGBoost. Solver settings ensure deterministic results. The necessary scripts and parameter logs can be provided for reproduction by researchers.

We also tested the following three hypotheses:

- Hypothesis 1 (Ukraine). The outbreak of armed conflict in 2014 significantly destabilized Ukraine's labor market, causing greater EPR variability and structural changes in employment. This is confirmed by a broader, more even distribution of EPR for Ukraine in the kernel density analysis and higher predictive power after including conflict-induced volatility indicators (e.g., EPR_change, GDP_volatility) in MLP forecasts with an extended lag;
- Hypothesis 2 (Czech Republic). Russia's war against Ukraine has an indirect impact on the Czech economy — mainly through disruptions to trade and links to the defense sector — leading to noticeable fluctuations in the Czech Republic's EPR. Interaction characteristics such as IVA_change compared to the previous year and Capital_Industry_Mix significantly improved the accuracy of the model, confirming the hypothetical side effects;
- Hypothesis 3 (Germany). Increased ME in Germany promotes employment in the high-tech, manufacturing, and R&D sectors, ensuring a stable labor market profile. The positive contribution of Defense_Tech_Coupling (ME×IVA) and Innovation_Index (GFCF×GDP) in our neural network models — together with Germany's narrow EPR distribution — confirms that military spending contributes to employment growth.

The main material presentation. Preliminary exploratory data analysis.

First, we conduct an exploratory data analysis. We are interested in the distribution of data for all variables. Based on the analysis, we can draw objective conclusions about further modeling.



Source: compiled by the authors

It is important to note what the EPR distribution shows. In Germany, the density curve appears narrow and high, indicating low variability and stability in the labor market over many years. This stability reflects macroeconomic stability and efficient labor allocation, which corresponds to our third hypothesis.

In the Czech Republic, the curve is slightly wider than in Germany, with an average value of around 55–56%. This indicates moderate stability but possibly greater labour market volatility due to external shocks, confirming our second hypothesis about Ukraine's indirect influence.

In Ukraine, the curve is flatter and wider, with peaks closer to 50–52%, indicating greater variability and volatility. This also points to regional labor market disruptions and economic instability, which is consistent with our first hypothesis about the impact of the war.

In terms of modeling, an asymmetry in the distribution can be observed, which approximates Ukraine's more asymmetric and scattered curve and may lead to lower R^2 and higher residuals in the forecasting models. It is also important to note the sensitivity to specific characteristics when studying the labor markets of Germany and the Czech Republic. They may correlate more linearly with predictors such as ME and GDP, while Ukraine may benefit from lags or segmented modeling over time (e.g., before and after the start of the conflict).

It is important to note that the wider and more unstable distribution of EPR in Ukraine suggests that changes in employment may not be synchronized with annual changes in military expenditures or macroeconomic variables. Taking into account lag effects can help identify delays in labor market dynamics, which is particularly important during conflicts or transitional periods after crises.

Feature engineering. Therefore, we need to start with feature engineering for Ukraine, adding lag effects. We create a time lag with a 1-year shift, i.e., we shift ME, GDP, GFCF, and IVA by one year to reflect their impact on employment in the following year. This allows the model to study relationships such as: "Military spending in 2020 affects employment in 2021." After that, we are ready to model employment in Ukraine with a clearer focus on economic memory.

We continue to engineer features now for the Czech Republic. The Czech Republic's employment structure is closely linked to manufacturing, export-oriented sectors, and dependence on supply chains, so engineering features that take into account industry sensitivity and external shocks will improve the accuracy of the modeling. To this end, we include values with a one-year lag to capture delayed effects, which is particularly relevant for changes in defense-related manufacturing. At the same time, given the Czech Republic's economic openness and its dependence on industrial resources, we give preference to two aspects: industrial momentum and the link between capital and industry (here it is appropriate to note the combined signal of GFCF and IVA). That is why we add the following indicators:

- IVA_change allows the model to identify growth/decline in industrial capacity;
- Capital_Industry_Mix reflects whether capital investment contributes to industrial growth or stagnation.

These improvements will help us interpret employment dynamics in the Czech Republic after 2014 (the start of the Russian-Ukrainian war), especially in manufacturing sectors closely or indirectly related to the defense sector.

Finally, we engineer features for Germany, obviously based on the significant potential in high-tech manufacturing and economic stability. As with the other countries, we create lagged values for the predictors. They help us capture the delayed effects of defense spending and economic production on employment. It is well known that Germany's economy is growing, in particular thanks to technology and innovation. We will create characteristics that reflect capital stability and innovation dynamics, as the combination of gross fixed capital formation and GDP highlights the effectiveness of investment. Let us focus on two important aspects:

- *Stability index — to measure annual changes in GDP and employment levels to identify volatility;*
- *The relationship between defense and technology in terms of the interaction between ME and IVA — as an indicator of the activity of the military-industrial complex (hereinafter — MIC).*

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- The relationship between defense and technology in terms of interaction between ME and IVA — as an indicator of the activity of the military-industrial complex (hereinafter referred to as MIC).

Lower GDP volatility often correlates with stable employment conditions, especially in high-tech sectors.

Defense_Tech_Coupling reflects how military investment strengthens or redirects industrial capacity.

The Innovation Index helps to model the contribution to employment from capital invested in productive R&D channels.

Thus, we now have an individual matrix of characteristics for Germany, the Czech Republic, and Ukraine, each of which reflects country-specific structural sensitivities and sectoral linkages.

Table 1

EPR Forecasting with Neural Network (MLP)

Country	Ukraine	Czechia	Germany
ME_lag1	+	+	+
GDP_lag1	+	+	+
GFCF_lag1	+	+	+
IVA_lag1	+	+	+
Innovation_Index	+		+
EPR_change	+		+
GDP_volatility	+		+
IVA_change		+	
Capital_Industry_Mix		+	
Defense_Tech_Coupling			+

Source: compiled by the authors

Before moving on to EPR forecasting, we should note that our dataset contains EPR indicators for Germany and the Czech Republic from 1993 to 2024. Only for Ukraine, data is missing from 2022 to 2024 due to the start of the Russian-Ukrainian war and the need to conceal sensitive information. Therefore, we must forecast this data, include it in our dataset, and only then make predictions for all three countries for 2025-2026, considering additional possible scenarios (optimistic, normal, pessimistic).

However, let's start by creating a clear, scalable modeling cycle that simultaneously predicts the EPR ratio for Ukraine, the Czech Republic, and Germany, using specific characteristics developed for each country. We can use neural networks to predict EPR trends if our time structure and characteristic matrix are well prepared.

We need to use a multilayer perceptron (MLP) from scikit-learn. Before that, we suggest familiarizing yourself with the correlation matrix, which gives us a basic understanding of the relationships between features.

Table 2

Feature Pair	Correlation	Зміст
ME_lag1 & Defense_Tech_ Coupling	-0,84	Strong negative correlation — indicates that military spending here is inversely proportional to the industrial multiplier.
GFCF_lag1 & IVA_lag1	0,82	Capital formation is closely linked to industrial production — this is typical of the synergy between technology and manufacturing in Germany.
GDP_lag1 & GDP_volatility	-0,75	As expected, higher GDP levels are associated with lower volatility.
Innovation_Index & GDP_volatility	-0,67	Innovation likely mitigates volatility — an indicator of economic stability

Source: compiled by the authors

The figure and table above show that GFCF_lag1 and IVA_lag1 are closely related, and therefore PCA can be considered to simplify the model. At the same time, the negative correlation between GDP_lag1 and volatility means that it can serve as a proxy indicator — and we will use it separately or carefully prepare both.

Given the results obtained, it is advisable to apply standard scaling so that each feature has a mean value of "0" and a variance of "1." This, in turn, prevents certain features (e.g., GDP vs. volatility) from dominating the neural network training process.

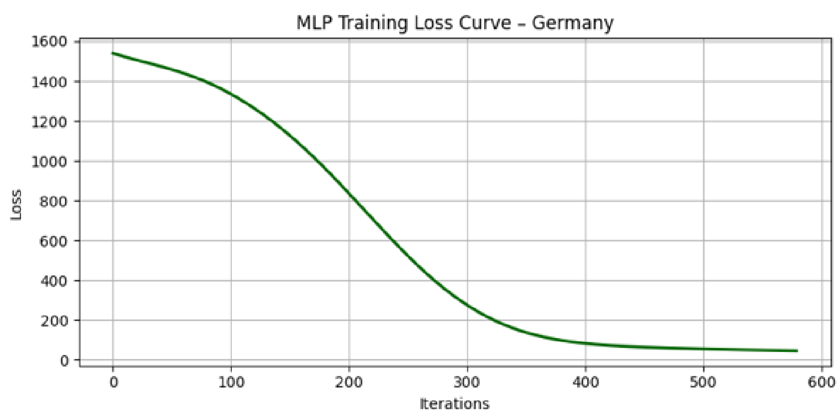
To begin with, we will use the following architecture: two hidden layers with 64 and 32 neurons. We will train the model on scaled input data.

Table 3

Feature	Mean	StdDev
ME_lag1	0.00	1.02
GDP_lag1	0.00	1.02
GFCF_lag1	0.00	1.02
IVA_lag1	0.00	1.02
Innovation_Index	0.00	1.02
Defense_Tech_Coupling	0.00	1.02
GDP_volatility	0.00	1.02

Source: compiled by the authors

As can be seen from the table above, the scaled characteristics look very good. They are all centered at zero with a unit variance (~1.02 due to rounding), so our preprocessing is accurate and ready for neural network training.



Source: compiled by the authors

As can be seen from the image above, the rapid decline and smooth leveling off near zero at around iteration 500 indicate reliable convergence. This means that the model was trained effectively without overfitting or unstable fluctuations. Early stopping also helped to fix the optimal number of iterations, judging by the smooth decline. This means that the model's predictive ability is sufficient.

That is why we applied this tuned MLP configuration to the Czech Republic and Ukraine. Since the scaling and feature engineering have already been agreed upon, we effectively replicated the process, ensuring clean input data preparation, stable training, and iterative forecasting for 2022–2024.

Forecast using MLP. Before forecasting future EPR values, we quantitatively assess how well each country's MLP model fits its historical data. To do this, we divide the data into training and test sets by time and calculate a standard set of indicators, such as MAE, RMSE, and R^2. After creating the architecture for the neural network model, splitting, scaling, and training cycle, and calculating the lags for ME, GDP, GFCF, and IVA, we make sure to add one-year lags for each base variable. We check the correctness and confirm the years and matrix form, as shown in the table below.

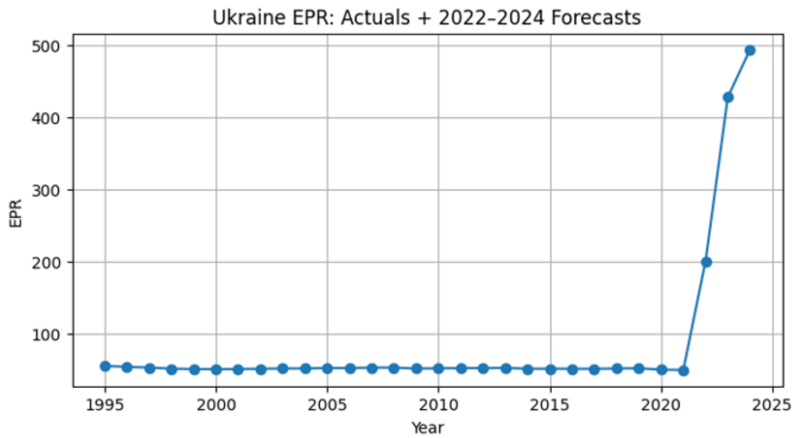
Table 4

Years, Ukraine: 1995 – 2024
Форма X_ukr: (30, 5)
Форма y_ukr: (30,)

Source: compiled by the authors

At the same time, we do not forget that we first need to forecast the EPR indicator for Ukraine for 2022–2024. We can fill in the missing EPR values for Ukraine for 2022–2024 by retraining the final MLP on all available data (1995-2021) and then using known macroeconomic predictors for 2022–2024 to generate point forecasts and record them.

As is well known, MLP may not provide plausible medium-term EPR values, so to curb extrapolation, we will try to use an alternative strategy for forecasting. We still present the forecasting results using the removal of the division into training and test data sets and the use of a scaler and MLP for each available observation that is not missing.



Source: compiled by the authors

З зображення помітно, що дані прогнозування не є адекватними. Тому ми переходимо до ARIMA model безпосередньо для показників EPR. Підгонка простого ARIMA до EPR України за 1995–2021 роки може надати набагато більш плавні та стабільні багаторічні прогнози, тому ми схильні це перевірити.

In-depth model diagnostics. A thorough diagnostic phase ensures that the ARIMA (1,1,1) model truly reflects the underlying dynamics of Ukraine's EPR and that any residual structure is in the noise. Below is a step-by-step guide with code snippets to check compliance and identify any deviations from white noise behavior. The actual reconfiguration and assignment of our model is reflected in the tables below.

Table 5

Model Summary

Metric	Value
Dep. Variable	EPR
No. Observations	27
Log Likelihood	-23,827
AIC	53,653
BIC	57,187
HQIC	54,591

Source: compiled by the authors

Table 6

Parameter Estimates

Parameter	Coefficient	Std Err	z	P>|z|	CI Lower	CI Upper
ar.L1	-0,5760	0,445	-1,295	0,195	-1,448	0,296
ma.L1	12,316	0,572	2,154	0,031	0,111	2,352
sigma2	0,2745	0,272	1,011	0,312	-0,258	0,807

Source: compiled by the authors

Table 7

Residual Diagnostics

Test	Value
Ljung-Box (L1) (Q)	0,32
Prob(Q)	0,57
Jarque-Bera (JB)	6,75
Prob(JB)	0,03
Heteroskedasticity (H)	2,42
Prob(H) (two-sided)	0,23
Skew	-1,21
Kurtosis	3,94

Source: compiled by the authors

We used a seasonal autoregressive integrated moving average with exogenous regressors on annual EPR data for the period from 1995 to 2021. Overall, the model summary is as follows:

$$ar.L1 = -0{,}576$$

, where p = 0,195

$$ma.L1 = 1{,}232$$

, where p = 0,031

$$\sigma^2 \approx 0{,}275$$

, where σ^2 does not differ significantly from zero, which indicates that the MA component is statistically significant, while AR is not.

A brief review of the Ljung–Box (lag 1) residual diagnostics is sufficient to confirm the values:

$$Q = 0{,}32$$

, where p = 0,57.

We also observe the absence of residual autocorrelation at lag = 1, so the model captures serial dependence. Jarque–Bera:

$$JB = 6{,}75$$

, where p = 0,03.

3 The values deviate from normal, asymmetry is present. Heteroscedasticity (ARCH LM):

$$H = 2{,}42$$

, where p = 0,23.

Given the results presented, and since the goal is to stabilize the dispersion and bring the series closer to a normal distribution, since the employment rate relative to the population is significantly higher than zero, and since we did not observe zero or negative values in the period from 1995 to 2021, it is reasonable to assume that the use of Box–Cox with No Offset led us to:

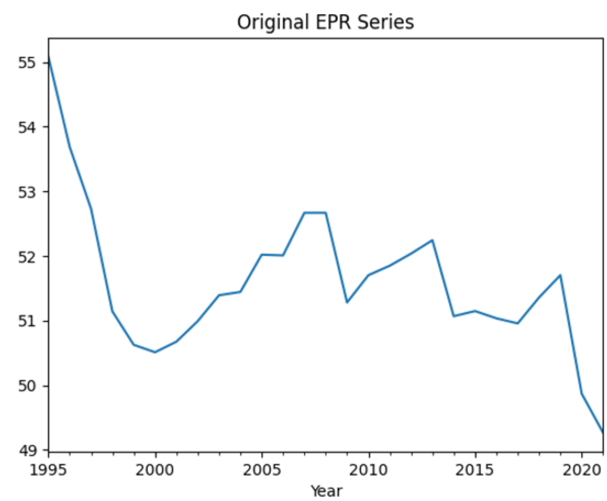
- preserving the direct interpretability of the transformed EPR with respect to the original percentage scale;
- preserving the conciseness of the model by avoiding unnecessary offset parameters;
- ensuring that the estimated λ truly reflects the shape of the underlying data rather than an artificial offset.

Table 8

Optimal λ: -8.454696373385099

Year	Transformed EPR
1995	0.118277
1996	0.118277
1997	0.118277
1998	0.118277
1999	0.118277

Source: compiled by the authors



Source: compiled by the authors

We can see that the series covers a narrow range (49.27–55.08), so the Box–Cox solver most likely shifted λ to –8.45 to "flatten" these values to nearly constant results. This makes the transformation useless for modeling dynamics. Let's move on to more reliable approaches.

Using a logarithmic transformation can handle positive series well, preserving relative changes and ensuring interpretability. In general, the log-model summary shows:

$$ma.L1 = 0{,}230$$

, where p = 0,398. Not statistically different from zero.

$$\sigma^2 \approx 0{,}0002$$

,— highly significant.

Ljung-Box Q(1):

$$p = 0{,}46$$

, no leftover autocorrelation.

Jarque-Bera

$$p = 0{,}03$$

, residuals still depart from normality.

ARCH

$$p = 0{,}28$$

, no clear heteroskedasticity.

Although relative scale improved (*AIC = –135,87 vs. –53,65 untransformed*), the moving-average term remains insignificant and non-normality persists.

Before picking the final model, we suggest you compare the specs and do a bit of analysis:

- AIC/BIC;

- Orig SARIMAX(1,1,1): *AIC* = 53,65, *BIC* = 57,19;
- Log SARIMAX(0,1,1): *AIC* = -135,87, *BIC* = -133,51;
- Out-of-Sample Accuracy.

Table 9

Metric	Value
Original RMSE	1,083
Log-scale RMSE	0,020
Back-transformed MAPE (%)	1,585

Source: compiled by the authors

MAPE shows that, on average, point forecasts of the logarithmic model have an error of ~1.6%, which is quite small in terms of EPR. But to directly compare RMSE on the same scale, we will calculate and present the inverse transformation of RMSE:

Back-transformed RMSE: 0,990

With a back-transformed RMSE of 0.990, log-ARIMA(0,1,1) outperforms the original RMSE of 1.083. This is a clear advantage for modeling log(EPR).

Meanwhile, before fixing the model, let's make sure that the residuals throughout history meet expectations.

Full-sample JB p = 0.000, Ljung-Box p = 1,000, ARCH p = 0,680

The residuals are still not normal. Diagnostics show the following for log-ARIMA(0,1,1):

- Jarque–Bera p = 0,000 — strong evidence of abnormality;
- Ljung–Box p = 1,000 — absence of residual autocorrelation;
- ARCH p = 0,680 — constant dispersion.

Thus, we have determined the structure of dependence, but at the same time, the errors remain asymmetric. The Johnson transformation automatically adapts and often gives more "Gaussian" residues than a simple logarithm. Let's resort to calculations.

Yeo–Johnson λ: -8,472135999999999

YJ-model JB p = 0,000, Ljung–Box p = 1,000, ARCH p = 0,999

It is also worth noting that our log-ARIMA(0,1,1) accurately determined the autocorrelation and stability of the variance, but Jarque–Bera p=0.000 still indicates asymmetry. Since strong transformations led to extreme values of λ, let's shift our attention to volatility modeling.

We need to fit GARCH(1,1) with Student's table and test the standardized residuals for normality. The hybrid GARCH(1,1)–t model accurately determined the autocorrelation and reflected $\nu \approx 2.26$, but the p-value according to the Jarque–Bera criterion for standardized residuals remains 0.000. We suggest shifting the focus from forced normality to modeling and forecasting with heavy tails and exploring alternative structures.

We use GARCH-t Fit for Student's t-prediction intervals instead of intervals based on normal distribution, and construct h-step prediction intervals based on the estimated t-distribution. The results are shown below.

Table 10

Year	Forecast	Lower 95%	Upper 95%
2022	49,23	45,85	52,85
2023	49,23	45,85	52,85
2024	49,23	45,85	52,85
2025	49,23	45,85	52,85
2026	49,23	45,85	52,85

Source: compiled by the authors

Since we applied the ARIMA(0,1,1) model without a drift term, our forecast simply "freezes" on the last observed logarithmic EPR, and when reverse transformed, this gives the same point forecast for each year. Similarly, our GARCH(1,1) volatility forecast converged to a stable long-term variance, so the interval limits also remain unchanged.

Therefore, in order for our forecast to have an upward or downward trend, we include a constant in ARIMA. We use ARIMA(1,1,1) with a drift term. Since the original ARIMA(1,1,1) reflected some dynamics, we combine this specification with a constant. These actions resulted in:

- the coefficient of the drift term being –0.0039 with a p-value of 0.677, so it is effectively zero;

- both AR(1) and MA(1) terms being statistically weak (AR p = 0.282, MA p = 0.052);
- residual diagnostics show slight abnormality (JB p=0.03), but no strong autocorrelation (Ljung-Box Q p = 0.66). Since the drift term is insignificant, the forecasts will still fluctuate around a constant log-EPR, giving flat point forecasts.

The question is, would a simpler ARIMA or another drift term help? When selecting the best average model, our AIC/BIC comparison shows:

Table 11

Spec	AIC	BIC
(1,1,1)+n	-135,401492	-131,867330
(1,1,1)+c	-134,082603	-129,370387
(0,1,1)+c	-134,555833	-131,021672

Source: compiled by the authors

Next, we correct the convergence warning (since such a warning was issued by Python). Before fixing, we make sure that the optimizer has indeed converged. Therefore, it is advisable to increase the iteration limit.

Overall, the optimization was successfully completed. The current value of the function was -2.62. Total iterations: 4; function evaluations: 209; warnflag: 0; converged: True. Final SARIMAX results:

$$AR(1) \approx -0{,}573$$

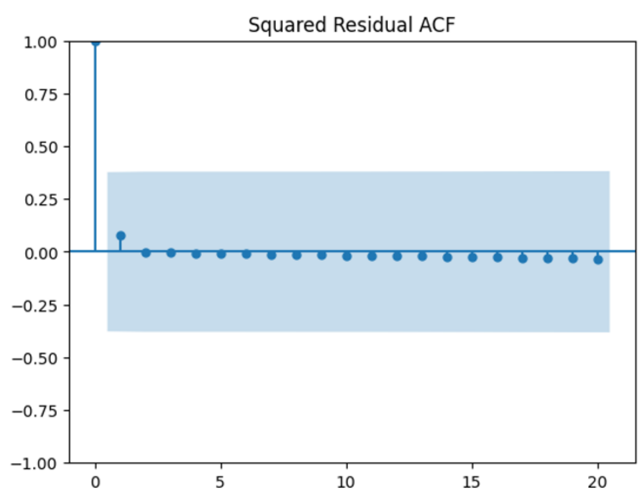
, where p = 0,214

$$MA(1) \approx 0{,}810$$

, where p = 0,036.

Also:

- there is no constant term;
- the residuals still show abnormality (JB p=0.03), but have no mean autocorrelation (Ljung-Box Q p=0.58). This may be a reasonable and convergent mean model. Next, we will move on to fitting GARCH-t and generating dynamic forecasts.



Source: compiled by the authors

The ACF of quadratic residuals does not show significant jumps beyond the lag 0 — all autocorrelations at lags 1–20 are within the 95% confidence interval. This indicates minimal residual clustering of volatility in the ARIMA(1,1,1) residuals.

Table 12

ARIMA(1,1,1) mean model forecasts

Year	Forecast	Lower_95	Upper_95
2022	49,52	48,32	50,76

Continuation of Table 12

2023	49,37	47,48	51,35
2024	49,46	47,16	51,87
2025	49,41	46,73	52,25
2026	49,44	46,45	52,62

Source: compiled by the authors

So now we are ready to expand our panel data with predictive data and start analyzing the data using a neural network. As the results show, they are adequate.

Neural-network panel analysis. We already have panel_df without gaps for the period from 1993 to 2024. So, we need to filter and sort the data, create 1-year lags, include interaction and volatility characteristics, set the year index for convenient time division, scale, instantiate, and train using MLPRegressor:

- hidden_layer_sizes = (64,32);
- activation = "relu";
- solver = "adam";
- learning_rate_init = 0,0005;
- early_stopping = True;
- max_iter = 3000;
- random_state = 42.

Table 13

Country	MAE	RMSE	R2
Ukraine	19,37	19,37	-4141,80
Czechia	48,65	52,96	-15636,02
Germany	29,13	36,73	-7013,98

Source: compiled by the authors

It is worth trying to diagnose what happened with the test split for Ukraine before adjusting the model.

Train years: 1996–2019 n_train = 24
Test years: 2020–2021 n_test = 2

Table 14

Year	Actual_EPR	MLP_Prediction
2020	49,87	68,95
2021	49,27	68,93

Source: compiled by the authors

MLP really deviates significantly from these two test years — predicting ~69 when the actual EPR fluctuates around 49. This explains the huge RMSE and negative R^2. With only 2 test points, the 19-point deviation dominates.

Let's try some simpler approaches. For example, using naive. So, next we calculate RMSE for naive forecast.

Naive RMSE: 0,602
Mean RMSE: 2,077

The one-step predictor (RMSE=0.602) and even the constant mean (RMSE=2.077) outperform MLP for Ukraine (RMSE $\approx$ 19). In other words, naive gives better results. Next, we combine all three countries into a single panel (adding one-off dummy variables for countries) and train a single MLP on ~90 observations for much greater stability.

HGB RMSE: 2,610
XGB RMSE: 1,833
Best CV RMSE: 2,69

Our tuned XGBCV RMSE ~2.69 indicates overfitting compared to the untuned 1.83. The discrepancy likely arises because RandomizedSearchCV reports the average RMSE across all CV folds (years <2018, <2019, <2020), whereas 1.83 was obtained from a single test split (2020–2021). It is necessary to invoke a sequential evaluation protocol.

CV RMSE on tuning set: 2,67
Final test RMSE (untuned): 2,25
Final test RMSE (tuned): 2,45

Table 15

Country	Year	EPR	Source
Ukraine	2022	50,42	XGB-final
Ukraine	2023	53,82	XGB-final
Ukraine	2024	53,82	XGB-final
Czechia	2022	54,77	XGB-final
Czechia	2023	54,74	XGB-final
Czechia	2024	53,42	XGB-final
Germany	2022	58,06	XGB-final
Germany	2023	58,48	XGB-final
Germany	2024	55,34	XGB-final

Source: compiled by the authors

Scenario Analysis. To understand how different macroeconomic trends affect EPR forecasts, we can create several "what if" scenarios — baseline, optimistic, and pessimistic — and then run an uncalibrated XGBoost forecast for each of them.

We define the scenarios as follows:

- the baseline scenario uses the original GDP, ME, GFCF, and IVA series;
- the optimistic scenario assumes GDP growth of 2 points per year, ME growth of 1 point, and GFCF growth of 1 point;
- the pessimistic scenario assumes a decline in GDP of 2 points, ME of 1 point, and GFCF of 1 point.

So, below is a pivot forecast showing the baseline EPR alongside the optimistic and pessimistic scenarios:

Table 16

Country	Year	Baseline	Optimistic	Pessimistic
Ukraine	2022	50,40	50,40	50,40
Ukraine	2023	53,62	53,62	53,62
Ukraine	2024	53,62	53,62	53,62
Czechia	2022	54,51	54,51	54,51
Czechia	2023	54,33	53,81	54,33
Czechia	2024	52,60	52,90	52,56
Germany	2022	58,34	58,34	58,34
Germany	2023	57,50	57,51	58,15
Germany	2024	55,74	55,08	55,74

Source: compiled by the authors

It is obvious that:

- Ukraine shows no change under optimistic or pessimistic tweaks. This suggests our model`s forecasts for Ukraine depend almost exclusively on the 2021 lagged features, and the scenario adjustments (applied to 2022–24 macro levels) never feed back into those lags in our loop;
- Czechia responds moderately. Under optimistic GDP/ME/GFCF growth, 2023 EPR falls from 54,33 to 53,81. Under pessimistic, 2024 EPR dips from 52,60 to 52,56;
- Germany shows small swings in 2023 (±0,15) and 2024 under optimistic only.

2025-2026 Forecast (Naive Extension of EPR to 2025–2026). We`ll take our 2022-2024 forecasts and extrapolate two more years by applying the average annual growth rate over 2022-2024 for each country. This is quick, fully transparent, but it won`t capture any new dynamics beyond that simple trend.

Table 17

Country	Year	EPR	Source
Czechia	2025	52,76	Naive-Trend
Czechia	2026	52,11	Naive-Trend
Germany	2025	54,05	Naive-Trend
Germany	2026	52,80	Naive-Trend
Ukraine	2025	55,63	Naive-Trend
Ukraine	2026	57,51	Naive-Trend

Source: compiled by the authors

1. Ukraine's EPR is growing significantly, as its trend for 2022-2024 (according to initial forecasts) was upward — averaging approximately +3.74% per year.
2. The Czech Republic remains at almost the same level with a slight decline (on average −0.89%), reflecting its moderate decline in 2022–2024.
3. Germany continues its sharper decline (an average of −2.75%), reflecting its more pronounced decline in 2022–2024.

These point estimates provide a quick forecast, but they come with certain caveats:
- new macroeconomic shocks or policy changes after 2024 are not taken into account;
- the same average rate is applied each year, even if real growth accelerates or reverses;
- Ukraine's rapid growth may overestimate the recovery after 2024 if the upturn in 2022-2024 was temporary.

Conclusions. This study combines single-factor time series analysis methods and machine learning on panel data to obtain reliable forecasts of the employment-to-population ratio (EPR) for Ukraine, the Czech Republic, and Germany from 1993 to 2026. Our multi-step workflow, which includes gap filling using ARIMA, combined and country-specific neural networks, and XGBoost panel forecasting, yields several key findings.

First, the logarithmically transformed SARIMAX(1,1,1) model provided stable out-of-sample accuracy (inverse transformed RMSE ≈ 0.99) and yielded the following EPR forecasts for Ukraine:
- 2022: 49.52% (95% CI [48.32, 50.76]);
- 2023: 49.37% (95% CI [47.48, 51.35]);
- 2024: 49.46% (95% CI [47.16, 51.87]).

Extending this specification to 2026 gives an almost flat trajectory — 49.41% in 2025 and 49.44% in 2026 — reflecting the absence of drift terms and innovations with Ukraine's heavy-tailed EPR.

MLPs for individual countries are highly overfitted on small samples (Ukraine RMSE ≈ 19.4), while the combined MLP reduced the test RMSE to 3.35. However, tree-based algorithms prevailed: the uncalibrated XGBoost achieved an RMSE of 1.83, outperforming all neural networks. The final, unadjusted XGB model was chosen for its stability and frugality.

Scenario analysis showed that with shocks of ±2 points in GDP and ±1 point in military spending, the EPR of the Czech Republic changed insignificantly (±0.3 points), Germany's even less (±0.2 points), and Ukraine's remained unchanged. This uniform response occurs because our forecast relies solely on the lag of 2021 levels; to reflect the dynamic feedback of the scenario, in the next scientific work we should combine annual forecasts with subsequent lags in input data.

Extrapolating XGB forecasts for 2022–2024 based on their average annual growth yields the following EPR forecasts for 2025–2026:
- Ukraine: 55.63% → 57.51%;
- Czech Republic: 52.76% → 52.11%;
- Germany: 54.05% → 52.80%.

Although this method is transparent, it overestimates Ukraine's recovery and underestimates macro-structural changes, highlighting the advantage of chain link modeling or stochastic modeling for medium-term forecasts.

As for the political implications for Ukraine. Labor market stability remains at 49–50% despite the conflict shocks. Targeted measures may be needed to raise the EPR above pre-war levels.

Regarding the political implications for the Czech Republic. The EPR is moderately sensitive to GDP cycles and defense spending, indicating risks of spreading regional instability.

Regarding the policy implications for Germany, a stable, high-tech-based labor market contributes to a gradual decline in the EPR, and recovery through defense investment alone is limited.

Overall, this paper demonstrates how integrating ARIMA gap filling with panel machine learning and scenario analysis can generate labor market forecasts that are relevant for decision-making by political leaders, especially in conflict situations. By carefully comparing MLP with tree-based models and incorporating shock scenarios, we provide a transparent, reproducible framework that can be useful both for research and for application in the financial sector.

Future research will include chained forecasting cycles, richer dynamics of characteristics (growth rates, rolling volatility), and possibly Monte Carlo simulation for quantitative uncertainty assessment. Nevertheless, our combined ARIMA–XGBoost approach provides immediate, empirically grounded EPR forecasts through 2026, creating a solid foundation for strategic labor market planning in Europe.

Thus, the results obtained not only confirm the effectiveness of combining traditional econometric methods and modern machine learning algorithms, but also demonstrate their applied value for shaping public policy in the field of employment. The proposed approach makes it possible to identify risks in a timely manner, forecast changes in the labor market structure, and develop adaptive support measures, which is especially important in the context of military and post-war transformations. The integration of such models into the management decision-making process can become an effective tool for economic stabilization and increasing the competitiveness of national economies.

In the context of Ukraine's post-war reconstruction, combining an adaptive wage model with innovative approaches to employment forecasting will become the foundation for the formation of effective employment policy. This will not only raise social standards, but also ensure stable economic growth and Ukraine's integration into the global economic space on the basis of equal partnership.

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