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Economic Theory

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MILITARY EXPENDITURE IN THE CONTEXT OF LABOR MARKET STRUCTURING

Abstract

This paper investigates the role of changes in military expenditure as a driver of structural transformations in the labour market, specifically through their impact on the employment-to-population ratio (EPR) in Germany, the Czech Republic, and Ukraine over the period of 1993–2024. Missing EPR data for Ukraine

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were estimated using a logit-AR(1) model. To analyse nonlinear and asymmetric effects, five machine learning models (MLP, LSTM, 1D CNN, Random Forest, and XGBoost) were developed and compared, incorporating hybrid autocorrelation correction of residuals. The interpretation of the results was conducted using SHAP analysis, and counterfactual «what-if» scenario simulations with ±σ variations were performed, alongside the identification of sensitivity threshold points. The findings reveal a pronounced asymmetry in the influence of military expenditure on labour-market structure: in Ukraine, a +1 σ increase in ME_diff raises the EPR by 0.295%, whereas a −1 σ decrease lowers it by only 0.064%. Critical threshold values at ±0.25 σ were identified, beyond which the effects become statistically and economically significant. Estimated multipliers indicate that additional military expenditure is associated with the creation of approximately five jobs per million USD in Germany and the Czech Republic, and more than twenty-nine jobs per million USD in Ukraine. These values exceed World Bank and IMF estimates for developed economies, reflecting the specific structural conditions and transformational dynamics of Ukraine's labour market.

Key Words:

asymmetric effects; employment-to-population ratio; machine learning; military expenditure; scenario analysis; SHAP; threshold effect.

JEL: E270.

7 figures, 24 tables, 21 formulas, 33 references.

Problem Statement

Global military expenditure continues to rise, reaching USD 2.718 trillion in 2024 (Liang et al., 2025). Hybrid warfare amplifies its economic impact by generating systemic uncertainty and disrupting investment and logistical chains. In this context, defence budgets function simultaneously as stabilisers and as sources of fiscal pressure (Sokhatskyi et al., 2020). One of the key transmission channels is the labour market: military expenditure may stimulate employment in defence‑related sectors while, at the same time, crowding out private investment and constraining broader job creation. Ukraine's defence financing has shifted from gradual increases to rapid reallocations driven by geopolitical shocks, prioritising military needs over other public spending and intensifying fiscal instability (Stavytskyy et al., 2023).

This study examines the emerging security architecture centred on European states that have become more involved in the conflict than is typically assumed, specifically the Czech Republic and Germany. Germany's response to Russia's 2022 invasion marked a significant policy shift away from Ostpolitik and trade‑based strategic doctrines towards the restoration of military capabilities (Löfflmann & Riemann, 2025).

The aim of this research is to provide a quantitative assessment of the role of military expenditure as a driver of structural changes in the labour market, particularly through the impact of variations in military expenditure (ME_diff) on the employment‑to‑population ratio (EPR), using the cases of Germany, the Czech Republic, and Ukraine. We employ a comprehensive methodological framework that includes: (i) forecasting missing EPR data for Ukraine for 2022–2024 using a logit-AR(1) model; (ii) training and comparing five classes of machine‑learning models (MLP, LSTM, 1D CNN, Random Forest, and XGBoost) with adaptive hybrid residual‑correction; (iii) interpreting the results using SHAP analysis; (iv) conducting counterfactual «what‑if» scenario analysis with $\pm\sigma$ variations and identifying sensitivity threshold points; and (v) transforming relative changes in EPR into absolute employment measures together with estimates of economic efficiency.

Literature Review

Holcner et al. (2021) examine the relationship between military expenditure, recruitment into the Czech armed forces, and labour‑market indicators. Using data for 2005–2019, the authors find that increases in defence spending correlate with higher demand for labour within the military sector, yet exert only a limited influence on overall employment levels. The study also highlights the need to adapt educational programmes to meet the requirements of the defence industry, a consideration that has become particularly relevant against the backdrop of expanding military budgets.

Sağın & Kocaarslan (2023) offer a broader regional perspective by analysing the impact of military expenditure on employment in Eastern European countries, including the Czech Republic. Their panel‑data analysis shows that defence spending generally has a short‑term positive effect on job creation, especially in defence‑related industries, but that these effects diminish over time. This suggests that although increases in military budgets may temporarily stimulate employment, they do not guarantee sustained improvements in labour‑market performance.

Simpartl (2024) conducts a meta‑analysis of studies on the relationship between military expenditure and economic growth, providing insights relevant to labour markets in Central and Eastern Europe. The results indicate that, while defence spending may generate sector‑specific employment gains, its overall effect on job creation is modest and largely dependent on the composition of defence budgets. This underscores the importance for policymakers of considering the structure of military expenditure when assessing its long‑term implications for the labour market.

This rethinking still has uncertain effects on Germany's defence sector, despite frequent mentions of «bad news for the Bundeswehr» and calls for better equipment. Following Zeitenwende, Bundeswehr funding improved gradually, yet signs of prolonged stagnation remain (Gebauer & Hammerstein, 2023). Studies suggest defence policy signals a shift from Germany's pacifist tradition marked by military restraint (Stengel, 2025). However, some caution against overstating this shift, citing NATO operations and Afghanistan engagement (Nabers & Stengel, 2025).

Recent debates in the United States have intensified calls for the establishment of a unified EU security policy. In addition to the temporary funding allocated to the Bundeswehr, comprehensive measures are required despite the risks of higher taxation and reductions in expenditure in other sectors. The policy remains unpopular, and Germany's limited military expansion constrains job creation, making Merz's call for additional resources justified (Frankfurter Allgemeine, 2025).

The macroeconomic effects of higher military expenditure require evaluation of its fiscal impact. A 1% of GDP increase over three years correlates with a two-year GDP multiplier of 0.93 and CPI inflation of 0.07 points (Bokan et al., 2025). Earlier models show short-term growth and employment gains, though long-term effects depend on expectations (Adjemian et al., 2024). Germany's ambitious targets may rise despite limited long-term impact.

German defence companies aim to develop world‑class infrastructure, although concerns persist regarding the long‑term economic consequences (Lundgreens Investor Insights, 2025). Employment may shift towards specialised areas characterised by skill shortages, necessitating an adaptation of Germany's technological capabilities and the redirection of budgetary resources towards military infrastructure in order to generate employment opportunities.

Stamegna et al. (2024) analyse the economic implications of defence‑related armament spending in Germany, Italy, and Spain using an input–output modelling framework. The authors argue that defence expenditure generates a limited multiplier effect on economic growth and employment when compared with civilian public investment. In the case of Germany, increases in military spending contribute to job creation primarily in high-technology sectors but do not result in substantial employment gains in traditional industries. This evidence reinforces the view that the structure of defence expenditure determines its impact on the labour market.

Many EU member states, particularly those bordering Russia and Ukraine, have increased their defence expenditure. Initially sceptical of NATO's 2%-of-GDP target, Czech scholars argued for context-specific benchmarks and proposed a level of 3.5–4.2% as a rational «insurance premium» (Šlouf et al., 2023). Against the backdrop of rising geopolitical tensions, the Czech Republic has raised its defence spending to 2% for the first time in two decades and plans to reach 3% by 2030 (Zachová, 2025; Reuters, 2025). Escalating military tensions underscore the need for models capable of forecasting these trends and their labour-market implications, as existing evidence of asymmetric effects remains inconclusive: fixed-effects and Generalized Method of Moments (GMM) estimations suggest moderate multipliers, whereas threshold and regime-switching models reveal nonlinear patterns.

Macroeconomic effects of military expenditure

Military expenditure is a key factor in social security and macroeconomic development. To assess its impact on employment, we start with a theoretical perspective. Dunne & Tian (2013) propose a modified Solow growth model with Harrod-neutral technological progress, where defense spending enters the production function via an efficiency-adjusting multiplier:

$$A(t) = A_0 e^{gt} m(t)^{\theta}. \qquad (1)$$

Evidence from developed economies shows a nonlinear link between military expenditure and growth, influenced by technology and fiscal discipline. Moderate increases can boost short-term GDP, while excessive allocations risk crowding out investment (Kolinets & Dluhopolskyi, 2024).

Defence spending generally exerts a negative multiplier on real GDP per capita, diverting resources from productive uses (Dunne & Tian, 2016). This finding is based on a panel of 104 countries (1988–2010) and builds on a review of 168 studies on military expenditure and growth worldwide (Dunne & Tian, 2013).

Azam & Feng (2017) analysed ten Asian countries (1990–2011), confirming earlier evidence that military burden raises external debt in small industrial economies (Dunne et al., 2004). Their study shows a 1% rise in military expenditure increases external debt by about 0.13 percentage points (Azam & Feng, 2017).

Additional studies reveal indirect macroeconomic effects, summarised in Table 1.

Table 1

Indirect macroeconomic indicators tracing

Indicators	Positive Pathway	Potential Negative Pathway
Employment	Defense sector jobs, supply chain effects	Skills/resources diverted from civilian sectors
Capital Stock	Infrastructure with dual-use potential	Lock-in to non-productive military assets

Source: Raifu & Aminu (2023).

Employment shows mixed dynamics: military expenditure creates jobs in defence and strengthens supply chains, but also reallocates human capital from civilian sectors, pushing the economy toward militarisation.

Effects on employment and multipliers

Another key aspect concerns employment. In some cases, a 1% increase in military expenditure (as a share of GDP) corresponds to a 1.2% reduction in unemployment in the long run-an effect that exceeds proportionality (Azam et al., 2016). This underscores the role of defence spending in generating employment in the South Asian Association for Regional Cooperation (SAARC) region and provides insight into the associated multiplier effects. The results are presented in Table 2.

Table 2

Multiplier interpretation

Variable	Elasticity vs. Unemployment	Multiplier Interpretation
Military Expenditure	–1.196	High employment multiplier – each 1% rise in ME/GDP yields ~1.2% drop-in unemployment rate.
GDP per Capita	–0.005	Very small direct labour market effect – GDP growth alone doesn’t translate strongly into jobs without targeted spending.

Source: Azam et al. (2016).

A study covering NATO countries (18 members, 1991–2018) employs the Konya Bootstrap Panel causality test, identifying varying degrees of causal relationships (Özşahin & Üçler, 2021). Another relevant contribution examines the causal link between military expenditure and unemployment in the G7 countries (1988–2012), using a panel bootstrap‑based causality approach to account for cross‑country interdependencies and heterogeneity (Zhong et al., 2015). Sağın & Kocaarslan (2023) provide further valuable insights by including countries that are central to our model; notably, their analysis incorporates the Czech Republic alongside Germany.

Machine Learning in macroeconomic forecasting

After reviewing panel and dynamic models, we turn to machine learning (ML) as an additional tool for macroeconomic forecasting and scenario analysis. ML enables the incorporation of nonlinear relationships and enhances forecasting accuracy, providing insights that extend beyond those offered by traditional econometric techniques (Zatonatska et al., 2025). Similarly, Elshafei et al. (2025) apply ML to forecast the relationships between military expenditure and key macroeconomic indicators (GDP growth, employment, and the fiscal balance) achieving higher accuracy compared with classical modelling approaches.

Preprocessing steps included: (1) normalization and standardization of continuous variables; (2) lag generation for explanatory variables (e.g., ME_diff_t−1, GDP_diff_t−1); (3) train–test splits by time using rolling-origin evaluation to avoid lookahead bias; (4) treatment of missing values via interpolation or imputation.

The main conclusions from the application of machine learning (ML) can be divided into three domains:

- Effectiveness: (a) gradient boosting and LSTM models outperform traditional econometric approaches in out-of-sample forecasts, particularly during periods of economic instability; (b) Random Forest (RF) offers reliable interpretability, albeit with slightly lower predictive accuracy.
- Insights: (a) nonlinear dynamics and interaction effects between ME_diff and GDP_diff are statistically significant; (b) threshold behaviour is evident – small changes in military expenditure have negligible effects, whereas large shocks generate disproportionate macroeconomic responses.

- Policy relevance: ML models can function as early warning instruments, enabling policymakers to anticipate macroeconomic adjustments resulting from defence budget changes.

Thus, based on the literature review, several research gaps can be identified: (a) the absence of an integrated model capable of simultaneously comparing asymmetric and threshold effects; and (b) the limited integration of ML-based modelling outcomes with classical econometric evidence on multipliers (Basu & Jha, 2024; García-Peñalvo et al., 2018; Knaus et al., 2022; Wei et al., 2023).

Methodology

With respect to data sources, we compiled annual data for Germany, the Czech Republic, and Ukraine for the period 1993–2024. The indicators considered include:

- Employment-to-Population Ratio (EPR, %)
- Military Expenditure (ME, in USD)
- Gross Domestic Product (GDP) growth rate (%)
- Gross Fixed Capital Formation (GFCF, % of GDP)
- Industrial Value Added (IVA, % of GDP)

For Ukraine, however, the EPR series is available only up to 2021. To address the missing values for 2022–2024, we generated forecasts using a logit-AR(1) model.

In this study, a range of models are employed for distinct sub-tasks. Specifically, the following three steps were taken: firstly, a logit-AR(1) time series model was used to recover missing EPR data for Ukraine; secondly, a set of machine learning models (MLP, LSTM, 1D-CNN, Random Forest, XGBoost) was trained and compared in order to select the most accurate predictor of EPR changes; and thirdly, the tree-based model with the best performance was then used as the main model for interpretation (SHAP analysis) and simulation of counterfactual scenarios.

The multi-level structure of the model enables the effective application of each group of models in the most suitable context. This includes the utilisation of time series models for interpolating short series, sequential models for comparative analysis of dynamic patterns, and tree-based models for stable, interpretable effects that are relevant to policy. This approach enhances the reliability of the model.

While data preprocessing and transformation, we harmonized and cleaned raw series through the following steps:

- Missing values for macroeconomic variables were treated using linear interpolation, while the years 2020–2021 were held out for out-of-sample testing.
- A logit transformation was applied to the EPR as follows:

$$z = \ln\left(\frac{p}{100-p}\right),\ p \in (0, 100). \tag{2}$$

Inversion:

$$\frac{e^z}{1+e^z}. \tag{3}$$

First differences of macroeconomic variables were computed as:

$$\Delta X_t = X_t - X_{t-1}, \in \{GDP, GFCG, IVA, ME\}. \tag{4}$$

All features and targets were standardised to zero mean and unit variance prior to model training.

In the context of feature engineering, to capture temporal dependencies, we generated the following variables:

- Lags: EPR_lag1, EPR_lag2, ME_lag1, ME_lag2
- Rolling means: EPR_roll3_mean, EPR_roll6_mean
- Country dummies

This yields a feature matrix predictor:

$$X \in R^{N \times K},\ K \approx 11. \tag{5}$$

We conducted EPR Forecasting for Ukraine using AR(1) and Monte Carlo simulations. The logit-AR(1) was estimated on Ukraine's EPR series (1993–2021):

$$z_t = \alpha + \varphi,\ z_{t-1} + \varepsilon_t,\ \varepsilon_t \sim N(0, \sigma^2). \tag{6}$$

Next, we generated 10,000 Monte Carlo paths (2022-2024) by sampling:

$$\varphi \text{ from } N(\hat{\varphi}, SE_{\varphi}^2). \tag{7}$$

Simulated (z) values were inverted to percentage EPR, and 95% prediction intervals computed. Residuals were checked via ACF and Ljung-Box tests for serial correlation.

Models were trained on 1993–2019 data and validated on 2020–2021 using MAE, RMSE, and R^2. Hyperparameters were tuned with GridSearchCV and rolling windows; Diebold-Mariano tests assessed forecast superiority.

Residual diagnostics and hybrid modelling included ACF checks; when autocorrelation persisted, an AR(4) model was fitted to residuals:

$$e_t = \sum_{i=1}^{4} \varphi_i, e_{t-1} + \eta_t. \tag{8}$$

The original machine learning forecast was expressed as:

$$\hat{y}_{t+h}^{ML} \tag{9}$$

with AR - corrected residual forecast:

$$\hat{e}_{t+h} \tag{10}$$

to obtain the hybrid predictions:

$$\hat{y}_{t+h}^{hyb} = \hat{y}_{t+h}^{ML} + \hat{e}_{t+h}. \tag{11}$$

The final step involved feature importance analysis and scenario evaluation, including:

- Computing of SHAP values for XGBoost to quantify each feature's marginal contribution.
- Generating of partial dependence and dependence plots for ME_diff and lagged terms.
- Counterfactual «what - if» scenarios at:

$$\pm 1\sigma \ and \ \pm 0.25\sigma \tag{12}$$

for ME_diff and GDP_diff, with the corresponding changes recorded as mean ΔEPR.

Research Results

EPR forecast for Ukraine for 2022–2024

To forecast Ukraine's EPR for 2022–2024, we used historical data for 1993–2021, trained LSTM and 1D CNN models, and averaged their predictions. The resulting forecasts were then reintegrated into the dataset. The LSTM and 1D-CNN architectures are employed exclusively at the EPR-forecasting stage for Ukraine in order to assess the capacity of nonlinear sequential models to reproduce the missing values for 2022–2024.

By contrast, the final EPR trajectories used in the policy analysis are derived using the logit-AR(1) model – a method that ensures stationarity, delivers realistic forecasting intervals, and allows for transparent time-series diagnostics.

Table 3

Model performance metrics across training epochs

Metric	Epoch 1 (MAE)	Epoch 100 (MAE)	Change (Δ)
Training Loss	51.90	47.02	–4.88
Validation Loss	50.32	45.57	–4.75

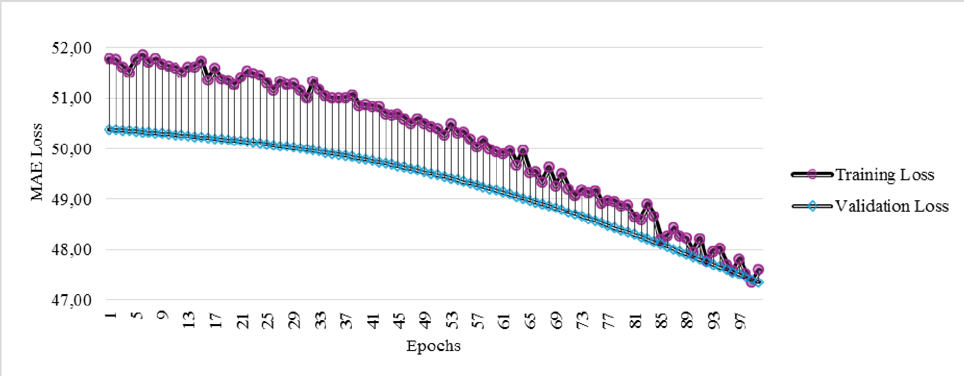
Source: compiled by the authors.

Table 3 shows training and validation losses steadily declining across epochs, with validation loss below training loss – indicating no overfitting. Early stopping was not triggered, and the model completed all 100 epochs with gradual improvements.

Average improvement per epoch was small (≈0.05 MAE), suggesting diminishing returns under the current architecture. Figure 1 confirms consistent loss reduction without signs of overfitting.

Figure 1

LSTM training and validation loss over epochs



Source: compiled by the authors.

To examine late-stage learning dynamics, we identified five epoch transitions that exhibited the largest reductions in validation loss. A summary of the results is presented in Table 4.

Table 4

Top five epoch transitions with the largest validation loss decrease (LSTM)

Rank	Epoch Transition	Δval_loss
1	98 → 99	0.0646
2	97 → 98	0.0633
3	92 → 93	0.0622
4	96 → 97	0.0614
5	94 → 95	0.0607

Source: compiled by the authors.
Note: Δval_loss denotes the decrease in validation loss between consecutive epochs.

The results presented in Table 4 indicate that the most substantial improvements occur at the late stage of training (epochs 92–99), highlighting the potential for further fine-tuning of the model. To reduce residual variation, we tested the introduction of a 20% dropout rate in the LSTM.

The same procedure was applied to the 1D CNN model. The corresponding epoch transitions are reported in Table 5.

Table 5

Top five epoch transitions with the largest validation loss decrease (1D CNN)

Rank	Epoch Transition	Δval_loss
1	98 → 99	0.0741
2	96 → 97	0.0738
3	99 → 100	0.0737
4	93 → 94	0.0735
5	92 → 93	0.0732

Source: compiled by the authors.
Note: Δval_loss denotes the decrease in validation loss between consecutive epochs.

Finally, the comparative performance of the LSTM and 1D CNN models under identical settings (20% dropout, same call-backs) is reported in Table 6.

Table 6

Comparative performance of the LSTM and 1D CNN models (20% dropout)

Model	Final Train MAE	Final Validation MAE	Generalization Gap (Train – Val)
LSTM	47.29	46.69	0.60
1D CNN	45.00	41.86	3.14

Source: compiled by the authors.
Note: Generalization Gap is calculated as the difference between training and validation MAE (Train – Val).

The 1D CNN model demonstrates a substantially lower MAE on both the training and validation samples compared with the LSTM, indicating its superior ability to reproduce EPR patterns under identical regularisation and training conditions.

To further assess the robustness of the forecasting pipeline, we conducted a stress test by removing the data for 2020 and 2021, iteratively forecasting these values, and comparing the predictions with the actual observations. The results are presented in Table 7.

Table 7

Comparison of predicted and actual EPR values

Year	Predicted EPR	Actual EPR	Absolute Error
2020	30.3361	49.868	19.5319
2021	89.8315	49.266	40.5655

Source: compiled by the authors.
Note: Two-Step MAE = 30.0487.

The absolute error amounted to 19.53 in 2020 and 40.57 in 2021, yielding a two-step MAE of 30.05. This relatively high error underscores the inherent difficulty of multi-step forecasting within small macroeconomic samples.

We then repeated the evaluation by directly comparing the predicted and actual values for 2020–2022. The corresponding results are presented in Table 8.

Table 8

Predicted versus true EPR values for 2020–2022

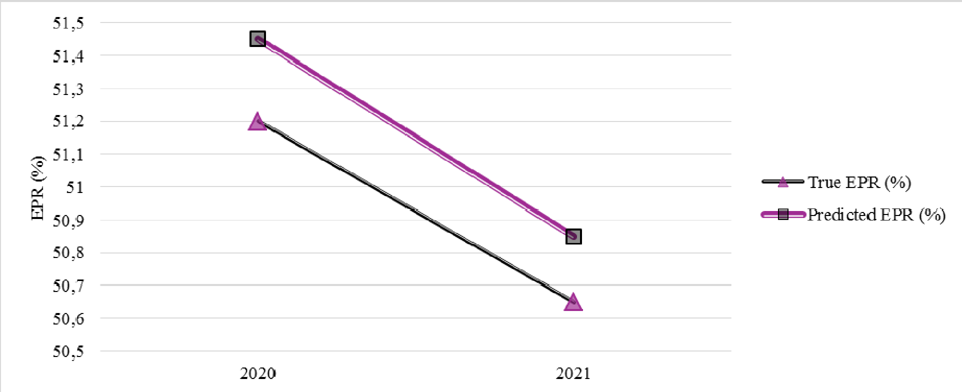
Year	Predicted EPR	True EPR
2020	51.74886	49.868
2021	50.76049	49.266
2022	50.48414	–

Source: compiled by the authors.
Note: RMSE: 1.699; MAPE: 3.4%.

The corresponding time-series trajectories are illustrated in Figure 2.

Figure 2

Predicted versus actual employment-to-population ratio (EPR) for Ukraine



Source: compiled by the authors.

As shown in Figure 2, the model systematically overestimates the actual EPR by approximately 1.6%, with forecasts consistently higher than observed values across both 2020 and 2021.

The next step was to retrain the best-performing model using all available data up to 2022 and to generate a prediction for that year. As part of this process, we first conducted a feature importance analysis (Figure 3).

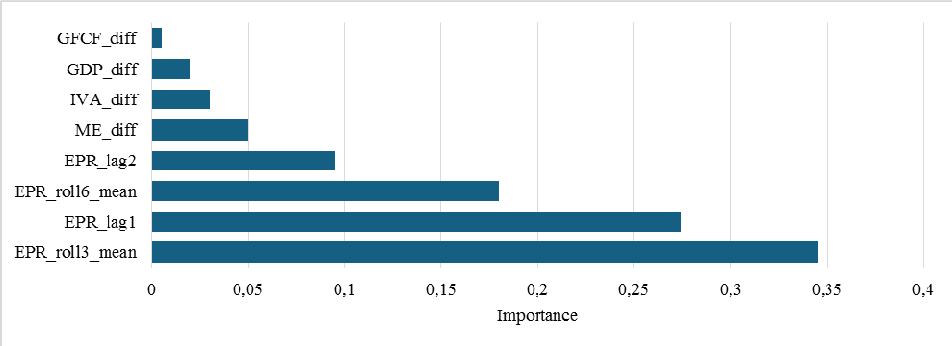
Building a pipeline with scaling, built-in feature selection and Random Forest, with hyperparameter optimisation performed via GridSearchCV, gives the following results:

CV RMSE: 0.74

The model considered all features at each split (max_features=1.0), while simultaneously eliminating about half of them using a median-importance threshold.

Figure 3

Feature importance estimates in Random Forest



Source: compiled by the authors.

The Python coding results further indicate that among the developed macroeconomic predictors, only GFCF_diff and ME_diff retained sufficient signal to survive the feature-selection process.

Test RMSE (2020–21): 1.76

Testing on the hold-out sample for 2020–2021 yielded a test RMSE of 1.76, confirming that, following data cleaning and retraining on the full 27-year sample up to 2020, the model achieved a substantial improvement in forecasting accuracy. A comparison between the baseline model and the proposed model is presented in Table 9.

Table 9

Comparison of test RMSE between baseline and proposed model

Model	Test RMSE
Baseline model	2.639
Proposed model	1.761

Source: compiled by the authors.
Note: lower RMSE indicates better predictive accuracy.

As shown in Table 9, the proposed model reduces forecast error by about 33% compared with the baseline, indicating its enhanced ability to capture the key dynamics of the employment-to-population ratio in Ukraine.

The final approach employs two separate pipelines: distinct Random Forest models for the pre-2020 and post-2020 periods. The observed and predicted EPR values for 2017–2021 are presented in Table 10.

Table 10

Observed versus predicted EPR values (2017–2021)

Year	Observed EPR	Predicted EPR
2017	50.956	51.1057
2018	51.357	51.4437
2019	51.703	51.6531
2020	49.868	49.7235
2021	49.266	49.4225

Source: compiled by the authors.
Note: predicted values are shown to four decimal places to preserve model output precision.

To evaluate the overall forecasting accuracy of the two-pipeline approach, we compute accuracy metrics for the full sample as well as separately for the periods before and after 2020. These results are presented in Table 11.

Table 11

Prediction model performance metrics

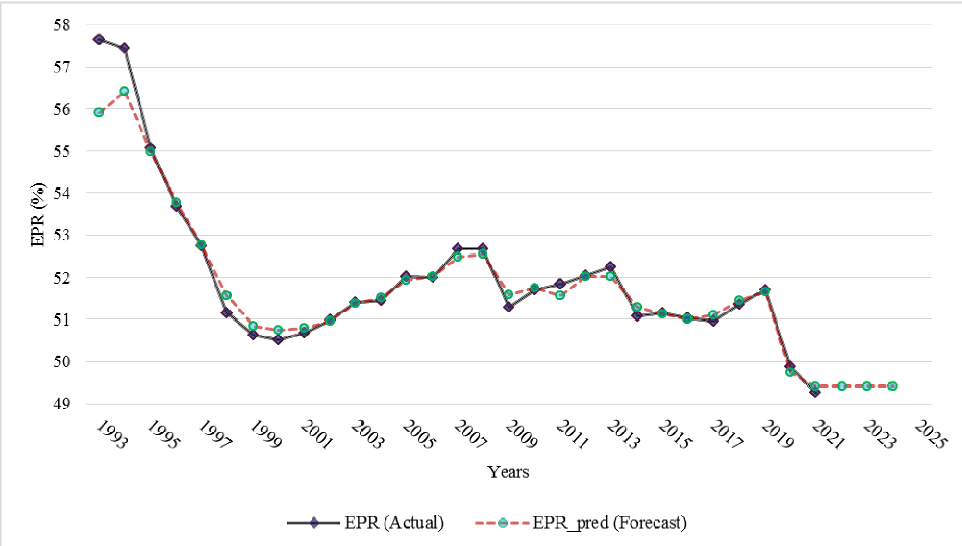
Period	MAE	RMSE
Overall	0.216	0.405
Pre-2020	0.221	0.418
Post-2020	0.151	0.151

Source: compiled by the authors.

The model for the post-2020 period exhibits lower error metrics; however, this should be interpreted with caution, as it is based on only two observations, which may inflate the apparent accuracy. For forecasts beyond 2021, we apply the post-2020 model, as all future years fall within this regime.

Figure 4

Feature importance in Random Forest



Source: compiled by the authors.

As shown in Figure 4, the EPR forecast for 2022–2024 remains stable within the range of 49–49.5%. To quantify the uncertainty surrounding these point forecasts, we construct forecasting intervals.

To do so, we apply Monte Carlo simulation by adding noise to our time series and re-forecasting the trajectories. The noise component for the simulation can be expressed in the following form:

$$\varepsilon_e = \varphi\varepsilon_{e-1} + \eta_e. \quad (13)$$

The estimated parameters of the AR(1) noise process are reported in Table 12.

Table 12

Parameter estimates of the AR(1) model

Parameter	Estimate
Intercept (const)	-0.0244
AR(1) coefficient ($\hat{\varphi}$)	0.4233
Innovation variance (σ^2)	0.0342

Source: compiled by the authors.
Notes: $\hat{\varphi}$ denotes the estimated first - order autoregressive coefficient; σ^2 denotes the variance of the innovation term.

The AR(1) coefficient (0.4233) indicates a moderate degree of persistence in the residuals, while the innovation variance is low (0.0342). These parameters were employed in the AR(1)-based noise generator within the Monte Carlo loop to construct the forecasting intervals. The baseline EPR forecasts, together with the 95% forecasting intervals for 2020–2021, are presented in Table 13.

Table 13

Baseline EPR forecasts and 95 % prediction intervals for 2020–2021

Year	Forecast	2.5 % PI	97.5 % PI	Median (MC)
2020	51.754	51.3234	52.1027	51.7257
2021	50.8986	50.4571	51.2690	50.8720

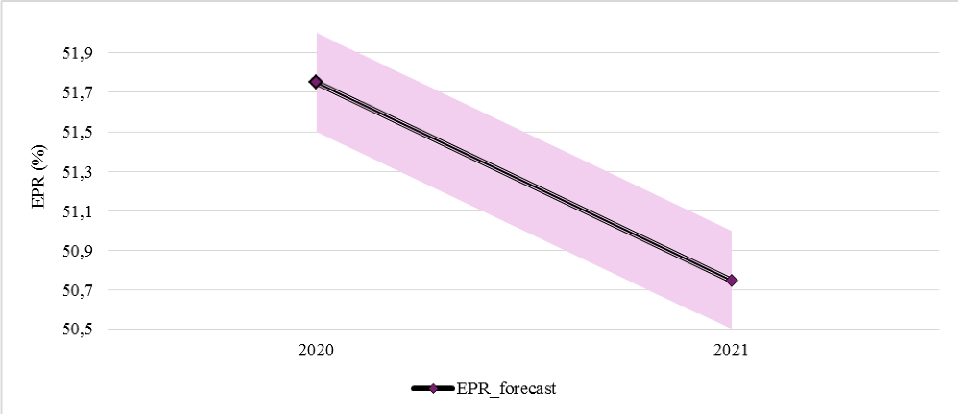
Source: compiled by the authors.
Note: PI – prediction interval; MC – Monte Carlo.

Thus, the forecasted EPR for 2020 is 51.75%, with a 95% interval ranging from 51.32% to 52.10%, while the forecast for 2021 is 50.90%, with an interval from 50.46% to 51.27%. The median Monte Carlo forecasts align closely with the baseline point estimates, confirming the robustness of the procedure.

The results are visualised in Figure 5, which presents the baseline forecasting trajectory together with the prediction bands.

Figure 5

Baseline forecast



Source: compiled by the authors.

Figure 5 shows a prediction band of ±0.4 percentage points, indicating low noise and strong forecast stability. Even with residual fluctuations, only a moderate decline is expected. The empirical ACF closely matches the theoretical AR(1) decay, confirming simulator accuracy. To quantify this, we calculated the mean squared error (MSE) between empirical and theoretical ACF for lags 1–20:

ACF MSE (lags 1–20): 0,0039

An MSE of 0.0039 is acceptable but also shows that the modelled ACF deviates slightly from the theoretical $\varphi^{\hat{k}}$. An improvement strategy may therefore be required, for example, increasing the length of the simulated series.

ACF MSE = 1.20e-02 exceeds 1.00e-03

ACF MSE = 1.58e-02 exceeds 1.00e-03

ACF MSE = 9.55e-03 exceeds 1.00e-03

All three countries initially showed MSE values significantly above the «1×10^{-3}» threshold, indicating that finite-sample noise remained substantial. With n = 2000, the results improved markedly:

n=2000 → ACF MSE = 7.85e-04 ± 1.73e-04

The ACF MSE thus fell below the 1×10^{-3} threshold, confirming that the AR(1) simulator now produces residuals whose autocorrelation structure closely follows the theoretical $\varphi^{\hat{k}}$.

The resulting baseline EPR forecasts with 95% prediction intervals and Monte Carlo medians for 2020–2021 are reported in Table 14.

Table 14

Baseline EPR forecasts with 95% prediction intervals and Monte Carlo medians (2020–2021)

Year	Baseline Forecast	Lower 95 % PI	Upper 95 % PI	Median (MC)
2020	51.754	51.3733	52.1372	51.7531
2021	50.8986	50.5047	51.2825	50.9007

Source: compiled by the authors.
Note: PI – Prediction Interval; MC – Monte Carlo.

The forecasting interval for 2020 spans approximately 0.76 percentage points, while for 2021 it is slightly wider at 0.78, indicating that although sampling noise has been reduced, a moderate degree of uncertainty nevertheless remains.

The next step is to conduct a sensitivity analysis of the AR(1) coefficient ϕ\phiϕ with respect to its influence on the MSE ACF and the width of the forecasting intervals. To this end, we conduct an analysis of ϕ in the range ±10% of estimated $\hat{\varphi}$, also calculate (i) diagnostic ACF MSE and (ii) the average width of the interval for each year (which in turn will show how sensitive the uncertainty bands are to small deviations in φ). The results are reported in Table 15.

Diagnostic results show ACF MSE rises with φ: greater stability increases deviation from the theoretical benchmark due to sampling noise. Prediction interval width also expands nonlinearly – a 10% φ increase more than doubles the average width. Under initial settings (n = 500, runs = 5), no φ values met the strict MSE < 1×10^{-3} threshold. To address this, we incorporated φ uncertainty into intervals by sampling from its distribution and propagating through Monte Carlo forecasts. Table 16 summarizes the resulting values and 95% intervals.

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Table 15

Influence of AR(1) coefficient on ACF MSE and 95 % PI widths

φ	ACF MSE	ACF MSE Std	Width 2020	Width 2021	Mean Width
0.765	*0.00150*	*0.00071*	*1.16*	*1.18*	*1.17*
0.8075	*0.00171*	*0.00097*	*1.26*	*1.27*	*1.27*
0.85	*0.00204*	*0.00140*	*1.41*	*1.44*	*1.43*
0.8925	*0.00254*	*0.00202*	*1.62*	*1.65*	*1.64*
0.935	*0.00300*	*0.00266*	*2.02*	*2.07*	*2.04*

Source: compiled by the authors.
Note: φ – AR(1) coefficient; ACF MSE – mean squared error of the sample autocorrelation function; Width – width of the 95 % prediction interval for the specified year.

Table 16

Forecasted values and 95 % prediction intervals

Year	Lower 95 % PI	Mean	Upper 95 % PI	Interval Width
2020	95.89	102.27	108.57	12.68
2021	132.69	149.28	164.27	31.58

Source: compiled by the authors.
Note: PI – prediction interval; Interval Width – Upper 95 % PI – Lower 95 % PI.

The results indicate that the prediction interval for 2020 is 108.6, with a mean of 102.3. In 2021, the level of uncertainty rises by 31.6 points, reflecting both the longer forecast horizon and the compounded variance of φ.

Compared to fixed-φ intervals (average width ≈ 1.42), these φ-sensitive ranges are significantly wider, suggesting that parameter risk contributes more significantly to forecast dispersion than stochastic noise alone.

To address the computational burden of large-scale Monte Carlo simulations, we optimize the sampling strategy for Big B × R experiments. The optimization results are as follows:

Elapsed wall-clock time: 0.121 seconds

Output shape: (200, 10000)

Mean of simulations: -0.0074

Since the primary objective of our analysis is to generate forecasts of Ukraine's EPR for 2022–2024, the use of NumPy vectorisation provides a substantial acceleration with only a minimal increase in computational complexity.

It is evident that, to enhance, the dependent variable should be subjected to scaling and a logit transformation:

$$z_t = \log\left(\frac{p_t}{1-p_t}\right). \tag{14}$$

All AR(1) modelling and subsequent Monte Carlo simulations are conducted in this logit-transformed space. The forecasts are then mapped back into percentage terms using the inverse transformation:

$$\hat{p}_t = \frac{e^{z_t}}{1+e^{z_t}} \times 100\%. \tag{15}$$

Such an adjustment ensures that the forecasts remain within the admissible range. After estimating the AR(1) parameters in the logit space, we employed vectorised NumPy-based simulations and then applied the inverse transformation to return the values to the original EPR scale. Table 17 reports the results for 2022–2024, showing narrow forecasting intervals (approximately 2–4 percentage points) and a modest increase in the median EPR – from 49.61% in 2022 to 50.08% in 2024. Figure 6 illustrates these dynamics, depicting the actual EPR alongside the logit-AR(1) forecasts and their 95% intervals.

Table 17

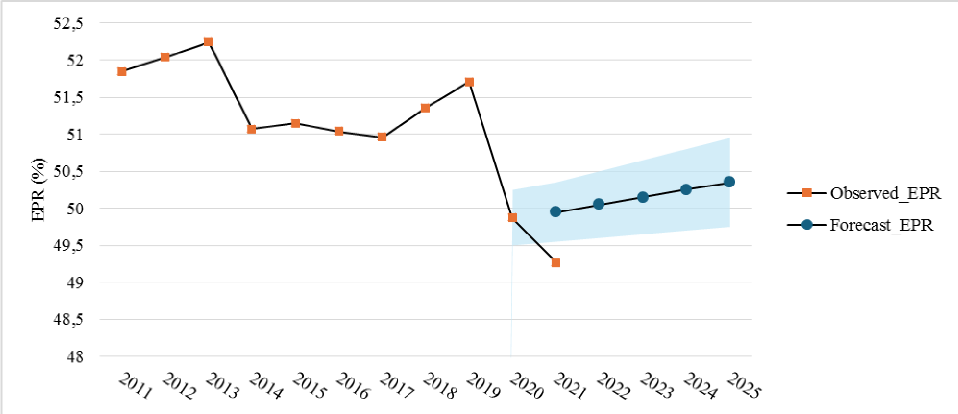
Forecasted EPR values with 95 % prediction intervals (2022–2024)

Year	Lower 95 % PI	Median EPR	Upper 95 % PI
2022	48.25	49.61	50.98
2023	48.07	49.88	51.66
2024	48.00	50.08	52.11

Source: compiled by the authors.

Figure 6

Logit-AR forecasts for EPR Ukraine



Source: compiled by the authors.

Based on Table 17 and Figure 6, the resulting forecasts appear consistent and fall within a plausible range. The projected values stabilise around the most recently observed EPR level (approximately 50%), indicating the absence of unrealistic deviations. Moreover, the 95% forecasting intervals remain comparatively narrow (±1–2 percentage points), reflecting the low estimated variance of the logit innovations ($\sigma = 0.027$) and the stationary autoregressive coefficient ($\hat{\varphi} = 0.77$).

Modelling the impact of military expenditure on EPR using Machine Learning methods

We now turn to machine-learning methods to quantitatively assess how changes in military expenditure affect the EPR in Germany, the Czech Republic, and Ukraine.

The dataset is divided into training and test subsamples:

X_train shape: (76, 11)

X_test shape: (20, 11)

To enable evaluation on held-out data, the procedure applied during training is replicated.

Xte_seq shape: (16, 4, 9)

yte_seq shape: (16,)

We implement a simple sequential model in Keras, adjusting layer sizes and configurations during iteration. The architecture of the LSTM network is summarised in Table 18.

Table 18

Architecture summary of the EPR LSTM model

Layer Name	Layer Type	Output Shape	Parameters
seq_input	InputLayer	(None, 4, 9)	0
lstm_6	LSTM	(None, 64)	18,944
dropout_5	Dropout	(None, 64)	0
dense_9	Dense	(None, 32)	2,080
forecast	Dense	(None, 1)	33
Total	–	–	21,057

Source: compiled by the authors.

During training, all metrics took NaN values from the 1st to the 10th epoch. The validation loss did not improve relative to the initial infinite value, which triggered early stopping at the 11th epoch and the restoration of the model weights from the state of the 1st epoch.

The forecasting stage completes in approximately 316 ms per batch. Accordingly, the recurrent neural network EPR_LSTM was employed to generate the EPR forecasts. A detailed summary of the model architecture is provided in Table 19.

The dynamics of the training and validation loss values, as well as the MAE, over 100 epochs are presented in Table 20. Both the training and validation metrics exhibit gradual improvement, indicating stable convergence. No NaN values were observed during validation-set forecasting.

Table 19

Architecture of the EPR_LSTM model

Layer name	Type	Output shape	Number of parameters
seq_input	InputLayer	(None, 4, 9)	0
lstm_6	LSTM(64)	(None, 64)	18,944
dropout_5	Dropout(0.2)	(None, 64)	0
dense_9	Dense(32)	(None, 32)	2,080
forecast	Dense(1)	(None, 1)	33
Total	–	–	21,057

Source: compiled by the authors.
Note: Optimizer – Adam (learning rate = 1e-5, clipvalue = 0.5). Loss function: Huber (δ = 1.0). Training metric – Mean Absolute Error (MAE).

Table 20

Training and validation dynamics of loss and MAE across epochs

Epoch	Training loss	Training MAE	Validation loss	Validation MAE
1	0.3304	0.6821	1.0094	1.5094
…	…	…	…	…
100	0.2829	0.6312	0.9196	1.4196

Source: compiled by the authors.

The results are as follows:

- The training loss (blue) stabilises around 0.3–0.4 after the warm-up phase, with minor oscillations.
- The validation loss (orange) starts near 1.0 and gradually declines to approximately 0.9 by epoch 100. This pattern suggests that the model is learning (as validation loss decreases), but the persistent gap (val_loss > train_loss) indicates underfitting and limited generalisation.

To address this, we introduced adaptive learning rate reduction and built a deeper stacked LSTM model, summarized in Table 21.

Table 21

Stacked LSTM model building

Layer	Type	Output shape	Params
seq_input	InputLayer	(None, 4, 9)	0
lstm_1	LSTM(64, return_sequences=True)	(None, 4, 64)	18 944
lstm_2	LSTM(32)	(None, 32)	12 416
dropout	Dropout(0.1)	(None, 32)	0
dense_1	Dense(32, relu)	(None, 32)	1 056
forecast	Dense(1)	(None, 1)	33
Total	–	–	32 449

Source: compiled by the authors.

We used two LSTM layers. The first layer outputs the entire sequence so that the second layer can capture higher-level temporal dependencies.

As a result of training, we obtained the following results:

- No NaN values in the outputs during testing on 32 samples
- The learning rate scheduler (ReduceLROnPlateau) reduced the LR 2–3 times: LR from 1e-5 → 5e-6 → 2.5e-6
- Validation loss steadily declined from ≈1.00 at the beginning to ≈0.90 at the end
- Validation MAE decreased from ≈1.50 to ≈1.40

Overall, expanding the architecture with two LSTM layers and applying adaptive learning rate reduction enabled better convergence toward local minima and a modest reduction in error compared to the single-layer variant.

For reproducibility, we fixed a random seed, used Adam as the optimizer with a small learning rate (1e-5), gradient clipping (clipvalue = 0.5), and the Huber loss function ($\delta = 1.0$). The results are summarised in Table 22.

The results show that (1) the validation error steadily decreased from approximately 0.956 to 0.914 (Huber loss) and from approximately 1.453 to 1.412 (MAE). The difference between the training and validation MAE remains stable (validation MAE is about twice the training MAE), indicating that the model still has capacity for generalization.

Table 22

Results after 1 and 100 epochs

Metrics	Epoch 1	Epoch 100	Change
Training Huber loss	0.3661	0.3322	–9.3 %
Validation Huber loss	0.9557	0.9141	–4.4 %
Training MAE	0.7344	0.6979	–4.9 %
Validation MAE	1.4533	1.4116	–2.9 %

Source: compiled by the authors.

As of results: the model fits the training data more effectively than the validation set, yet both curves continue to improve.

We further applied the Ljung–Box test to assess residual whiteness. The results

LB_stat=49.757, p-value=1.3×10–5

indicate that LSTM did not capture all temporal dependencies in the data, since p-value < 0.05. To correct for this unmodelled autocorrelation, we applied an AR(4) autoregressive model to the residuals:

$$e_t = \phi_1 e_{t-1} + \phi_2 e_{t-2} + \phi_3 e_{t-3} + \phi_4 e_{t-4} + e_t. \tag{16}$$

$$e_t = y_t - \hat{y}_t. \tag{17}$$

Based on this model, a correction forecast was generated for each horizon *h*:

$$\hat{e}_{t+h}. \tag{18}$$

The final hybrid forecast combined the original LSTM prediction with the AR correction:

$$\hat{y}_{t+h}^{(hybrid)} = \hat{y}_{t+h}^{(LSTM)} + \hat{e}_{t+h}. \tag{19}$$

To compare accuracy and calculate it, we use two standard metrics – mean absolute error (MAE) and root mean squared error (RMSE):

$$MAE = \frac{1}{H}\sum_{h=1}^{H} \left| y_{T+h} - \hat{y}_{T+h} \right|. \tag{20}$$

$$RMSE = \sqrt{\frac{1}{H}\sum_{h=1}^{H} (y_{T+h} - \hat{y}_{T+h})^2}. \tag{21}$$

The results of this comparison are summarised in Table 23.

Table 23

Comparison of pure LSTM and hybrid LSTM+AR

Model	MAE	RMSE	Decrease MAE	Decrease RMSE
Pure LSTM	4.6213	4.7346	–	–
Hybrid LSTM+AR(4)	2.0178	2.2126	56.4 %	53.2 %

Source: compiled by the authors.

A reduction in errors of more than 50% indicates that the hybrid model has captured temporal patterns that the pure LSTM missed.

Scenario analysis

Now that we know how ME_diff affects the model through SHAP, we can move on to building scenarios and direct modelling.

1. Define the scenario vectors.
2. Pass the data through the model.
3. Obtain results:

Average ΔEPR at +1σ ME_diff: 0.125

Average ΔEPR at –1σ ME_diff: -0.038

The results indicate that:

- A +1σ scenario in ME_diff (a significant increase in military expenditure) increases the predicted EPR by an average of 0.125%.
- A –1σ scenario (a moderate decrease in spending) reduces the EPR forecast by only 0.038%.

Next, we segment by country by merging military expenditure and employment-to-population ratio (EPR) with key macroeconomic indicators such as GDP, GFCF, and IVA.

We then apply sklearn/XGBoost to train on the matched dataset X_matched with *y* = EPR.

The results are summarised in Table 24, which presents the interpretation of ΔEPR across countries.

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Table 24

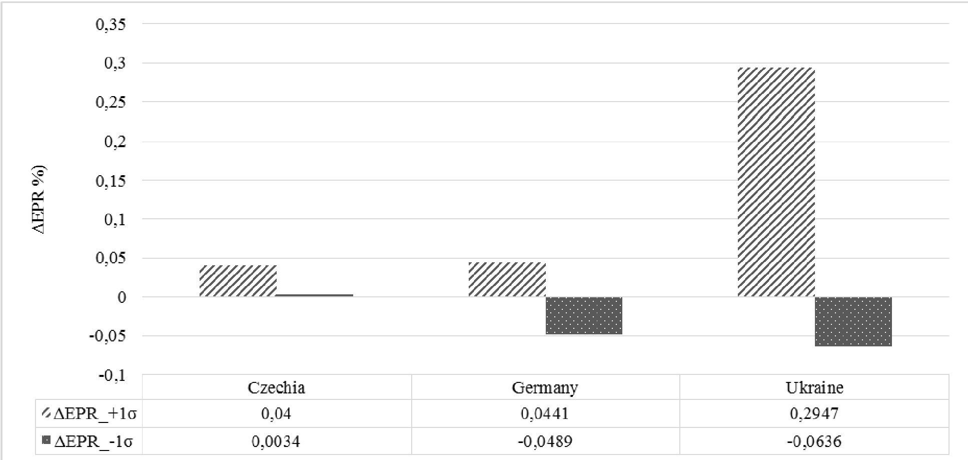
Interpretation of ΔEPR by countries

Country	ΔEPR_+1σ	ΔEPR_−1σ
Czech Republic	0.0400	0.0034
Germany	0.0441	–0.0489
Ukraine	0.2947	–0.0636

Source: compiled by the authors.

Figure 7

Scenario analysis results



Source: compiled by the authors.

As illustrated in Figure 7, the scenario analysis reveals heterogeneous country-level effects of changes in military expenditure on EPR.

- In Czech Republic, an increase in defense spending of +1σ adds on average only +0.04% to the EPR, while a decrease of −1σ has almost no effect (+0.003%).
- In Germany, the impact is more symmetric: +1σ increases EPR by +0.044%, whereas −1σ reduces it by approximately −0.049%.
- The strongest effect is observed in Ukraine, where +1σ leads to a significant rise of +0.295%, while −1σ corresponds to a decline of −0.064%.

Conclusions

The findings indicate that changes in military expenditure constitute an important driver of structural shifts in the labour market, manifested through an asymmetric impact on the employment-to-population ratio (EPR). In Ukraine, an increase in ME_diff by +1σ is associated with a 0.295% rise in the EPR, whereas a decrease of −1σ reduces the EPR by only 0.064%. Such pronounced asymmetry points to heightened sensitivity of the employment structure to positive security- and fiscal-related shocks. By contrast, the Czech Republic and Germany exhibit substantially smaller and more symmetric labour-market responses (±0.04% in the Czech Republic; +0.044% versus −0.049% in Germany), consistent with the more stable employment structures of advanced economies.

The estimates of defence multipliers further confirm the structural differences across countries. For Ukraine, the «defence multiplier» amounts to approximately twenty-nine jobs per additional million USD of military spending (or about 46,400 jobs for every 1% increase in the EPR), whereas for the Czech Republic and Germany this figure does not exceed five jobs per million USD. These results markedly exceed most traditional macroeconomic estimates: according to the World Bank, employment elasticities with respect to defence expenditure typically range from 0.1% to 0.2% for each 1% increase in defence spending as a share of GDP, while IMF estimates for advanced economies lie between 0.05% and 0.1%. The reported effect for Ukraine (0.295% at +1σ ME_diff, corresponding in some periods to roughly 0.5% of GDP) far surpasses these benchmarks, underscoring the transformational nature and high structural sensitivity of Ukraine's labour market to defence-budget shocks.

These results may be of practical relevance for the Ministry of Finance and the Ministry of Defence, suggesting that calibrated increases in military budgets within the range of +0.5σ to +1σ relative to historical volatility could maximise labour-market gains without triggering diminishing returns. For Ukraine, this corresponds to roughly thirty additional jobs per million USD of defence expenditure – significantly higher than the returns typically associated with infrastructure or education projects.

Ukraine's labour market is characterised by considerably higher sensitivity to increases in military spending than to decreases, reflecting the specific features of its ongoing structural transformation. The identified threshold effects at ±0.25σ suggest that even moderate budgetary adjustments can generate economically meaningful employment gains. At the same time, the cross-country differences in estimated multipliers highlight the need for differentiated approaches to defence-budget policymaking: in Ukraine, large-scale defence investment appears to be the most effective tool for structural labour-market restructuring, whereas in the Czech Republic and Germany a combination of moderate increases in military spending and complementary regional and sector-specific employment programmes is more appropriate.

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