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Research article

A comparative analysis of GDP determinants in Germany and Poland: Integrating econometric and machine learning perspectives

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Abstract: This study analyzed the determinants of gross domestic product (GDP) for Germany and Poland using both linear econometric models and nonlinear machine learning models (decision trees, random forests, XGBoost) on data from 1991 to 2023. By comparing the model outcomes for Germany and Poland, we identified structural differences and uncovered key predictors of economic growth, measured by gross domestic product, over 33 years. Empirical results showed that nonlinear models significantly outperformed linear ones, with XGBoost achieving the best results in Germany, while the decision tree performed best in Poland. We also conducted feature importance analysis to reveal key factors. For Germany, factors such as life expectancy, net migration, and foreign direct investment were the strongest predictors of GDP. In Poland, production volume, life expectancy, urban population, internet usage, foreign direct investment, and unemployment rate emerged as the key drivers of GDP. Our insights highlight the need for specific economic modeling strategies and show how different development paths shape national growth dynamics.

Keywords: machine learning approach; GDP; econometric approach; economic growth

JEL Codes: C53, C55, O33, O41, O47

1. Introduction

Gross domestic product (GDP) is the market value of all goods and services produced by a country or region using factors of production within a specific period. GDP not only provides accurate demand estimates but also serves as a benchmark for national economies in the drafting of macroeconomic policies. GDP data are generally more accurate and exhibit low calculation repeatability, which makes statistical analysis easier (Longo et al., 2022). Moreover, there is a strong relationship between GDP and other key macroeconomic indicators, such as inflation and unemployment rates (Ekinci et al., 2020; Richardson et al., 2021; Shiferaw, 2023; Mohamud et al., 2024; Pappas & Boukas, 2025).

By examining differences in economic structures and sectoral distributions between Poland and Germany, our study aims to uncover complex relationships that can provide insights into economic development strategies. Previous studies have often focused on traditional econometric approaches and neglected the use of machine learning to draw inferences from economic data (Bhardwaj et al., 2022; Chu & Qureshi, 2023; Srinivasan et al., 2023).

Machine learning (ML) is important for guiding national economies in analyzing and estimating economic data. Compared to other econometric methods, machine learning can analyze larger datasets and better uncover complex relationships (Gogas et al., 2015).

This study aims to determine the main factors affecting GDP by considering both structural and cyclical indicators and to reveal how these factors can be modeled with machine learning techniques. Therefore, we considered macroeconomic, demographic, technological, and environmental factors in the case of Poland and Germany and employed the following set of variables: GDP, inflation rate, youth unemployment rate, foreign direct investment, production volume, total population, urban population rate, life expectancy at birth, business cycle, average temperature, and internet usage.

The comparison between Poland and Germany yields a compelling case study for this type of investigation. The growth patterns of neighboring economies with strong trade ties display both shared and diverging economic trajectories. Germany is one of the largest economies in the European Union (EU), with a mature, innovation-driven economy and a well-established industrial base. On the other hand, Poland is a key player in Eastern Europe's economy. Poland has experienced a rapid economic transformation since joining the EU in 2004, benefiting from structural funding, market integration, and institutional reforms (Kolodziejczyk, 2016). This contrast provides an ideal setting to investigate both conventional and emerging growth drivers across different stages of development.

We used annual data from 1991 to 2023 and over 20 variables across economic, demographic, environmental, and technological dimensions. The novelty of our study resides in the application of a range of predictive models, which contains four linear econometric models (linear, ridge, lasso, elastic net), a linear machine learning algorithm (support vector regression [SVR]) and three nonlinear machine learning algorithms (decision tree, random forest, XGBoost) through which we evaluated the accuracy and interpretability of different approaches in estimating annual GDP. In this context, the use of both linear and nonlinear models allowed us to examine whether complex relationships among variables required more advanced techniques for reliable prediction.

Empirical findings revealed that nonlinear machine learning models significantly outperformed linear econometric models in predicting GDP for Germany and Poland. Specifically, XGBoost achieved the highest accuracy for Germany, while the decision tree model performed best for Poland. We also found that the most important GDP predictors differed between the two countries; life expectancy, net migration, and foreign direct investment were the most influential factors for Germany. In the case of

Poland, the key indicators were production volume, life expectancy, urban population, internet usage, foreign direct investment, and the unemployment rate. Our results highlight the need for country-specific modeling strategies and demonstrate the added value of advanced machine learning techniques in economic estimation. This study addresses three central research questions:

1. Does internet usage serve as a reliable indicator of GDP in Poland and Germany?
2. What are the most important factors that determine GDP growth in Poland and Germany, as well as growth differences?
3. Can a linear model accurately estimate GDP in Poland and Germany, or are more advanced machine learning models needed to achieve a better fit?

The remainder of the article proceeds as follows. In Section 2, we review the relevant literature and highlight the contribution of our study relative to previous work. In Section 3, we describe the methodology and the dataset, and analyze the evaluation of our machine learning predictions. Section 4 presents the main results and describes certain robustness checks. The last section draws overall conclusions and addresses policy implications.

2. Literature review

The phenomenon of economic growth measured via the gross domestic product is influenced by various macroeconomic, demographic, technological, and environmental factors, as shown by recent studies (Klasen & Lawson, 2007; Peterson, 2017; Newell et al., 2021; Kreuter & Riccaboni, 2023; Lianos et al., 2023; Sijabat, 2023; Wondimu, 2023; Berg et al., 2024). In this sense, technological development, particularly digitalization, plays an important role in a country's economic growth, as internet use facilitates taxpayers' daily activities and business operations. The extant literature indicates that investments in technology increase labor productivity, which, in turn, raises economic growth as measured by the GDP indicator (Moroz, 2017; Boikova et al., 2021).

Because of a significant decline in birth rates and an accelerating aging rate worldwide, migration to countries in need of a labor force can positively contribute to national economies by addressing labor shortages. Studies conducted in Germany, the country with the oldest population in Europe, show that migration has a positive impact on the country's economy (Dorn & Zweimüller, 2021). Moreover, Poles are among the largest groups of foreign nationals in Germany and contribute substantially to the German economy (Cyrus & Vogel, 2006; Fihel & Okólski, 2016).

Studies with economic models include comparisons of various machine learning methods and classical econometric methods. Moreover, research on macroeconomic estimations has focused on testing the accuracy of different models and identifying the best methods. Zarkova et al. (2023) argued that there would be a change in the four groups of indebted EU countries in the period 2023–2024, with France taking Spain's place. Ghosh and Ranjan (2023) found that hybrid models were the most successful in GDP estimations.

In contrast to classical econometric methods, the literature suggests that machine learning and artificial neural networks have greater predictive power for GDP. Therefore, studies by Hsu et al. (2016), Martin (2019), Nosratabadi et al. (2020), and Magazzino and Mele (2025) supported this observation.

The efficiency of different models has been emphasized to preserve the distribution of machine learning methods in economic modeling (Feurer & Hutter, 2019). Kant et al. (2025) found that the random forest model produced the most accurate estimates, while the dynamic factor model performed best in backward-looking estimates. Similarly, Yoon (2021) reported that the gradient boosting model had an error capacity of 0.39, the random forest model had an error capacity of 0.57, and overlearning (overfitting) did not pose a significant problem. Bhardwaj et al. (2023) found that artificial neural networks (ANNs) performed best among other models. Robotko et al. (2023) found a 2.68% deviation between predicted and observed values with the random forest model. According to Sofianos et al. (2022), the DVD and elastic-net logit models provided better estimates than other models across nine different interest rates.

The impact of datasets on model performance is also analyzed by comparing estimations with different data. Heinisch and Scheufele (2019) reported different estimates using real-time and final data; however, they did not find any key differences in performance across indicators. Maccarrone et al. (2021) found that the K-nearest neighbors (KNN) method yielded the best predictive results. This suggests that machine learning techniques are extensively deployed in economic modeling. It proves that this modeling approach is more successful than others in specific scenarios.

Our analyses conducted on data from the neighboring countries of Poland and Germany, which have a high level of interaction, provide a significant contribution to the literature by emphasizing the importance of different GDP determinants and allowing a systematic comparison of machine learning and econometric approaches concerning their estimation of economic performance for the two developed nations in the EU. The phenomenon of economic growth measured via the gross domestic product is influenced by various macroeconomic, demographic, technological, and environmental factors, as shown by recent studies (Klasen & Lawson, 2007; Peterson, 2017; Newell et al., 2021; Kreuter & Riccaboni, 2023; Lianos et al., 2023; Sijabat, 2023; Wondimu, 2023; Berg et al., 2024). In this sense, technological development, particularly digitalization, plays an important role in a country's economic growth, as internet use facilitates taxpayers' daily activities and business operations. The extant literature indicates that investments in technology increase labor productivity, which, in turn, raises economic growth as measured by the GDP indicator (Moroz, 2017; Boikova et al., 2021).

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3. Methodology

3.1. Data

We conducted analyses over 33 years (1991–2023) and used variables representing macroeconomic, demographic, environmental, and technological factors. We applied extensive feature engineering and selected a final set of variables to run our econometric and machine learning analyses. These variables are critical in enabling a comparative analysis of GDP determinants for Poland and Germany. Because econometric models have limited capacity to handle multicollinearity, we used different sets of variables for linear econometric and machine learning models. The complete list of variables is presented in Table 1.

Table 1. Variable definitions and data sources.

Model use	Variable type	Variable name	Variable definition	Source
Econometric and machine learning modeling	Outcome variable	Log GDP	Quantifies a nation's economic performance. It was log-transformed for modeling stability.	OECD
Econometric and machine learning modeling	Explanatory variable	Internet usage	Represents digitalization and access to technology, key to modern innovation and economic growth.	Federal Reserve Economic Data (FRED)
Machine learning modeling	Control variable	Urban population	Measures total urban population, indicating urbanization trends that affect economy and infrastructure.	OECD

Continued on next page

Model use	Variable type	Variable name	Variable definition	Source
Econometric and machine learning modeling	Control variable	Net migration	Reflects migration flows, impacting labor markets and demographic shifts.	OECD
Machine learning modeling	Control variable	Production volume	Industrial production measure, key indicator for sectoral economic activity.	Federal Reserve Economic Data (FRED)
Machine learning modeling	Control variable	Population	Total population size	OECD
Machine learning modeling	Control variable	Life expectancy	Reflects overall health conditions and development level of the population.	OECD
Econometric and machine learning modeling	Control variable	Inflation rate	General price level change, crucial for macroeconomic stability and purchasing power.	OECD
Econometric and machine learning modeling	Control variable	Foreign direct investment	Net inflow of investments, indicating investor confidence and global integration.	OECD
Econometric and machine learning modeling	Control variable	Unemployment rate	Measures general unemployment, key indicator of economic health.	OECD
Machine learning modeling	Control variable	Youth unemployment rate	Unemployment among youth, reflects labor market entry difficulties.	OECD
Econometric and machine learning modeling	Control variable	Average temperature	Climate variable potentially affecting agricultural output and economic behavior.	World Bank
Econometric and machine learning modeling	Dummy variable	EU Membership (only for Poland)	Indicates EU membership status (0 = non-member, 1 = member).	Manual
Econometric and machine learning modeling	Categorical variable	Inflation period	Encodes different inflationary regimes for macroeconomic context.	Manual
Econometric and machine learning modeling	Categorical variable	Business cycle	Represents phases of economic cycles (e.g., recession, growth).	Manual
Machine learning modeling	Control variable	Urban population percentage	Urban share of total population; tracks urbanization intensity.	OECD

Continued on next page

Model use	Variable type	Variable name	Variable definition	Source
Machine learning modeling	Derived variable	GDP rollmean5	5-year rolling mean of GDP to smooth short-term fluctuations.	Calculated
Machine learning modeling	Derived variable	Unemployment Rate_rollmean3 and rollsd3	3-year rolling value of unemployment rate.	Calculated
Machine learning modeling	Derived variable	Internet usage rollmean3 and rollsd3	3-year rolling value of internet usage.	Calculated
Machine learning modeling	Derived variable	Production volume rollmean3 and rollsd3	3-year rolling value of production volume.	Calculated
Machine learning modeling	Derived variable	Inflation rate rollmean3 and rollsd3	3-year rolling value of inflation rate.	Calculated
Machine learning modeling	Derived variable	Foreign direct investment rollmean3 and rollsd3	3-year rolling value of foreign direct investment.	Calculated
Machine learning modeling	Derived variable	Net migration rollmean3 and rollsd3	3-year rolling value of net migration.	Calculated
Machine learning modeling	Derived variable	Population rollmean3 and rollsd3	3-year rolling value of population.	Calculated

Source: Authors' elaboration.

Table 2 shows how the data for Germany and Poland were split into a training period (1991–2018) and a testing period (2019–2023). It also compares the number of variables used in econometric and machine learning models. While econometric modeling uses fewer features (9 for Germany, 10 for Poland) due to multicollinearity issues, machine learning modeling includes more features (30 for Germany, 31 for Poland), emphasizing a more complex approach.

Table 2. Dataset configuration and variable selection for Germany and Poland.

Data	Train split	Test split	Number of features for econometric modeling	Number of features for machine learning modeling
Germany	1991–2018	2019–2023	9	30
Poland	1991–2018	2019–2023	10	31

Source: Authors' elaboration.

The dataset contains no missing values. Outliers can distort findings and affect the reliability of the analysis. We winsorized numeric columns to reduce their influence. This method reduces the impact of extreme outliers while preserving essential data. Winsorization targets the upper and lower tails, using the 1st and 99th percentiles as cutoffs. We carefully prepare data for accuracy and consistency. Each variable is set to the proper type, such as numeric for continuous variables. This process boosts computational performance and reduces errors by ensuring compatibility with statistical and machine learning models. The prepared dataset provides a strong basis for analysis and supports sound conclusions.

3.2. Exploratory data analysis

After preparing the data, we conducted EDA (Exploratory Data Analysis) to examine changes in GDP and other macroeconomic indicators.

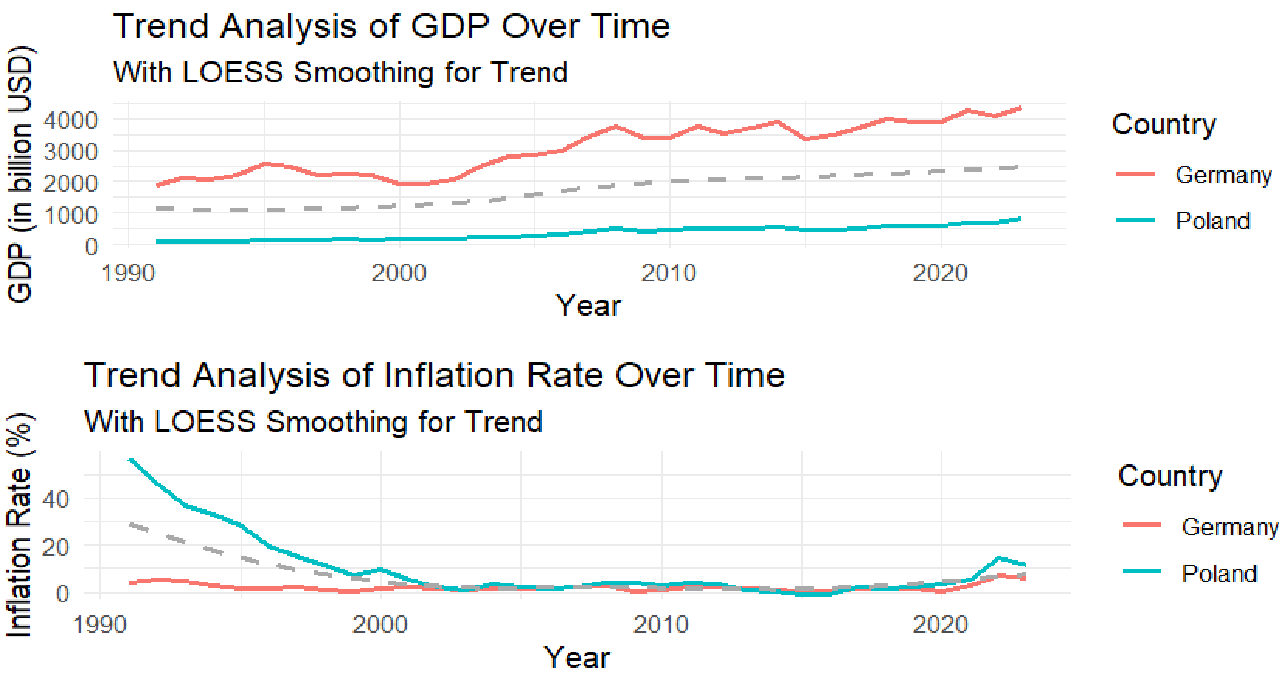

Figure 1. Trend analysis of GDP and inflation rate. Source: Authors' elaboration.

Figure 1 displays the trajectories of GDP and inflation in both Poland and Germany. Both countries achieved steady GDP growth over the years. Poland's GDP growth rate is notably more consistent than Germany's, reflecting rapid economic progress after its transition. LOESS smoothing clarifies the upward trend and year-to-year regularity in GDP. Inflation rates have generally declined, though intermittent spikes occur, especially in Poland, in recent years. Poland experienced much higher inflation in the 1990s due to instability during its transition to a market economy. Since joining the EU in 2004, Poland's economy has strengthened. Its GDP growth accelerated after the early 2000s, underlining the benefits of EU membership.

Following 2020, both countries experienced surges in inflation rates. This volatility may stem from the impact of COVID-19. The pandemic disrupted the global economy, triggering lockdowns, supply chain interruptions, and weakened consumer demand. These conditions caused pronounced swings in inflation rates.

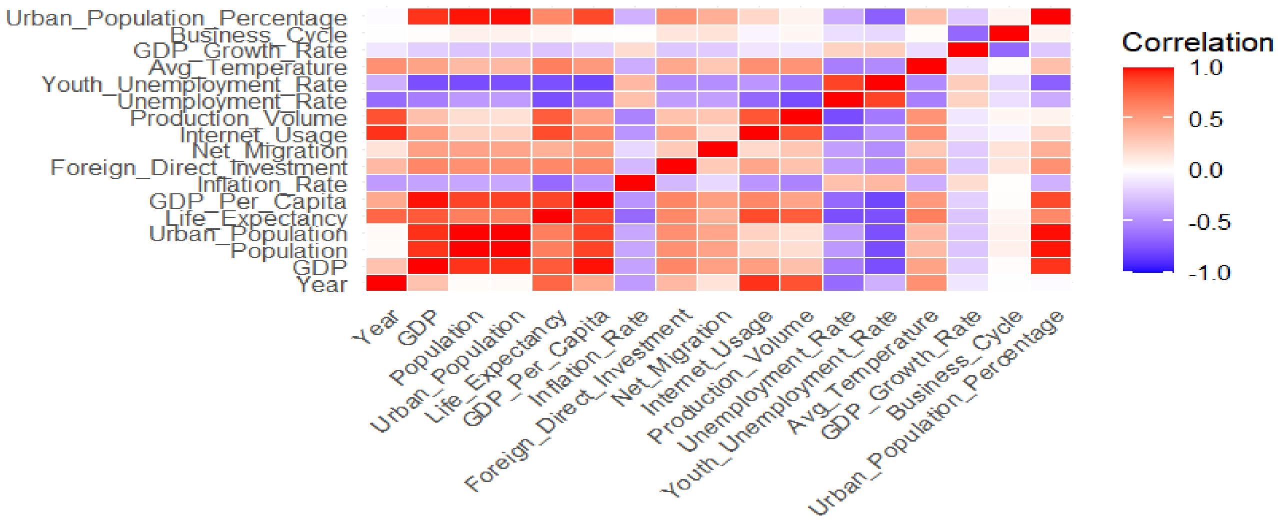

Figure 2. Correlation heatmap. Source: Authors' elaboration.

Figure 2 displays a heatmap that provides a comprehensive view of the pairwise correlations among key numeric variables. High positive correlations were observed among the variables GDP, urban population, life expectancy, and internet usage. This correlation can be explained through the lens of urban development. It is expected that GDP levels and variables related to population, life expectancy, and internet technology will exhibit similar trends, especially in today's digitalized economies. Strong negative correlations were observed between GDP and the unemployment rate, as expected and consistent with the labor market context. If GDP increases, unemployment rates could also decline because a larger share of potential workers would return to the labor force and find employment with companies producing more value added. Certain variables, such as the youth unemployment rate and the unemployment rate, were highly correlated. This correlation also suggests redundancy. Briefly, this heatmap highlights the justification for excluding some variables, such as the GDP growth rate (logical redundancy with GDP) and the urban population percentage (correlated with urban population).

Figure 3. Inflation rate over business cycles. Source: Authors' elaboration.

Figure 3 displays inflation rates for Poland and Germany over 33 years of business cycles. Across business cycles, the GDP of both nations varies. As described, Germany's economy is stable and developed, as evidenced by its lower cyclical volatility. At the same time, Poland's GDP fluctuates more across business cycles, which is typical of a transition economy (following the 1990s period). In both nations, inflation rates fluctuate across business cycles, as expected in such contexts (Kumar et al., 2021; Georgarakos et al., 2025). Specifically, Poland's inflation rate was above 40% in the early 1990s and, since 2000, has been stabilized below 5%, while Germany's inflation remained consistently low, generally between 0% and 3%. This reflects its strong monetary stability.

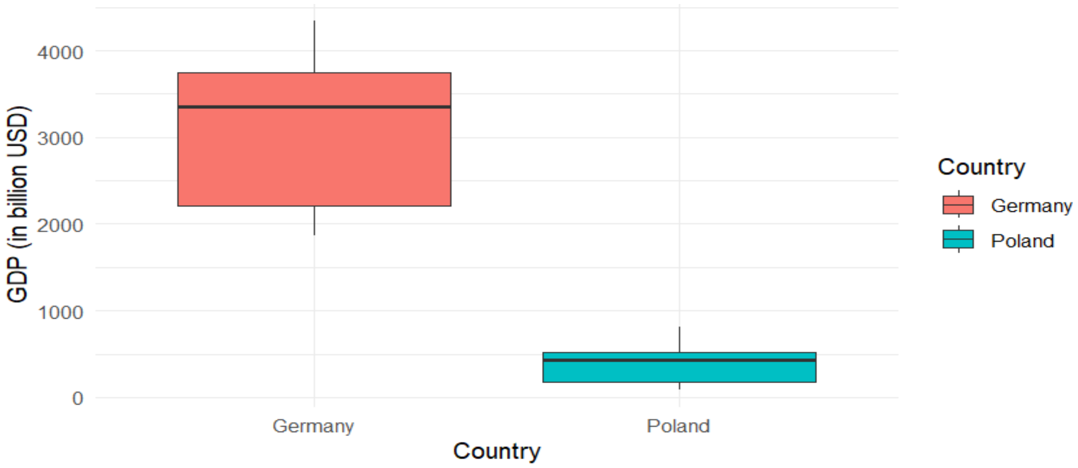

Figure 4. GDP distribution by country. Source: Authors' elaboration.

Figure 4 is a box plot comparing GDP values of Germany and Poland. Germany's GDP was significantly higher than Poland's, averaging around 3,000 to 3,500 billion USD, while Poland's GDP remained below 800 billion USD over the observed 33-year period. Germany's GDP also showed lower volatility. It suggests a more stable, mature economy. In contrast, Poland exhibited greater fluctuations, dynamic growth, and structural transformation over the years.

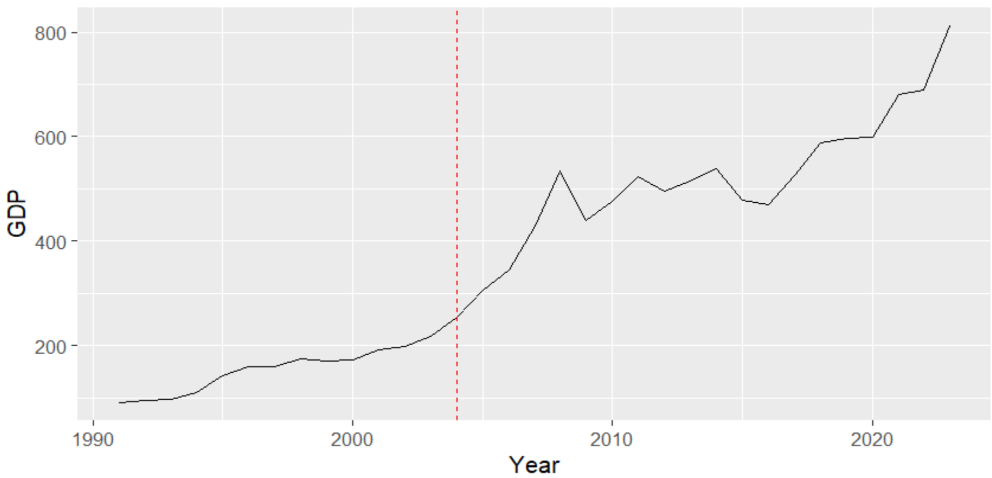

Figure 5. Poland GDP: pre and post EU accession. Source: Authors' elaboration.

Figure 5 is a line plot showing Poland's GDP trajectory by EU membership status. Poland's GDP rose after joining the EU in 2004 (marked by the vertical red line). Poland experienced steady growth after joining the EU. It is characterized by rising foreign investment, increased trade integration, and access to structural and cohesion funds. This transformation contributed significantly to industrial development, infrastructure modernization, and labor market growth. The significant rise in GDP after 2004 proves the positive and ongoing economic impact of EU membership on Poland's macroeconomic stability and long-term growth prospects (European Commission, 2019).

3.3. Feature engineering

In our research, two distinct predictive modeling strategies are implemented using econometric linear models and machine learning models. Nonlinear models are not sensitive to data preparation or multicollinearity, whereas linear models require careful feature engineering. This procedure has been carefully executed to optimize the linear model's predictive performance while addressing issues such as multicollinearity, redundancy, and variable relevance (Tables 3–4).

Although we removed specific predictors due to multicollinearity, we also calculated variance inflation factors (VIFs) as a robustness check. The standard benchmark value for VIFs is 10. According to the literature, variables with VIF values above this threshold are frequently eliminated or modified to address multicollinearity (Tay, 2017). In addition, VIFs should be recalculated after modifications to ensure multicollinearity has been adequately reduced.

During the feature engineering process, we compiled a set of technical variables designed explicitly for nonlinear machine learning models rather than traditional linear econometric models. These features are derived by using moving averages, rolling statistics, and window-based transformations to capture dynamic patterns, trends, and short-term fluctuations in our data. Using techniques such as rolling means, rolling maxima/minima, and momentum indicators, we aimed to enhance the model's ability to detect complex, nonlinear relationships and momentum effects in time-series stock data. Linear modeling approaches would likely miss these patterns.

Table 3. Multicollinearity check with variance inflation factors.

No	Variable name	VIFs Germany	VIFs Poland
1	Urban population	1074112.68	11518052.40
2	Population	155265.21	291086.47
3	Life expectancy	651.33	924.23
4	Inflation rate	5.45	29.44
5	Foreign direct investment	3.20	4.90
6	Net migration	52.96	3.35
7	Internet usage	328.01	154.37
8	Production volume	25.92	570.20
9	Unemployment rate	176.20	469.78
10	Youth unemployment rate	66.33	206.80
11	Average temperature	2.52	4.04

Source: Authors' elaboration.

In Table 3, we identified multicollinearity among certain independent variables. In the following stage, we excluded problematic variables from the dataset to reduce potential biases in our analyses.

Table 4. Multicollinearity check with variance inflation factors after modification.

No	Variable name	VIFs Germany	VIFs Poland
1	Unemployment rate	5.00	2.15
2	Net migration	4.74	1.21
3	Foreign direct investment	1.97	2.40
4	Internet usage	1.91	4.47
5	Inflation rate	1.78	2.63
6	Average temperature	1.31	1.65

Source: Authors' elaboration.

After variable reduction and refinement based on the initial multicollinearity analysis, Table 4 presents the updated VIF scores for our selected variables. All VIF scores now fall below the commonly accepted threshold of 10, reflecting a significant reduction in multicollinearity. The successful removal of highly correlated variables, such as urban population, population, and life expectancy, has resulted in a more stable and interpretable dataset for econometric modeling. This ensures statistical validity, maintains theoretical relevance, and captures essential macroeconomic, demographic, environmental, and technological dynamics. These modifications enhance the robustness and reliability of our analyses by ensuring that predictors contribute uniquely to the model's explanatory power.

3.4. Predictive modeling

In summary, we considered two predictive modeling approaches for the country datasets. These approaches were the econometric and machine learning approaches. Generally, eight predictive models are applied and compared using three evaluation metrics: R-squared, mean absolute error, and root mean squared error.

3.4.1. Econometric approach

We estimated four linear econometric models to investigate the relationship between GDP and selected macroeconomic predictors. These models included the standard linear regression model and three widely used, regularized linear models: lasso, ridge, and elastic net. Linear regression served as a baseline to assess the fit between the independent variables and the outcome variable, assuming no multicollinearity. However, due to multicollinearity among several explanatory variables, the inclusion of regularized models improved estimation stability and predictive performance.

Lasso regression, through its L1 penalty, performed variable selection by shrinking some coefficients to zero, while the ridge regression applied an L2 penalty to shrink coefficients without eliminating them. Elastic net combines L1 and L2 regularization, leveraging the strengths of both lasso and ridge, and is particularly useful for correlated predictors. The application of these econometric models aimed not only to produce reliable estimates but also to interpret the individual effect of each explanatory variable on GDP, offering valuable economic insights for both Germany and Poland over the 1991–2023 period.

3.4.2. Machine learning approach

In the machine learning modeling approach, both linear and nonlinear algorithms are applied to capture the data's underlying structure and improve GDP estimation accuracy. Among the linear models, SVR with a linear kernel is used to model linear relationships while maintaining robustness to outliers. For nonlinear modeling, several tree-based algorithms are implemented. A simple decision tree is used to identify basic nonlinear patterns and interactions in the data, although it is prone to overfitting. To enhance stability and accuracy, random forests are an ensemble bagging methods that combine multiple decision trees trained on bootstrapped samples. Additionally, XGBoost, a powerful gradient boosting technique, is applied to model complex nonlinear relationships through sequential learning and weighted error correction. These nonlinear models are particularly effective in capturing interactions and variability within the dataset. The study aims to develop a comprehensive, flexible predictive framework for analyzing GDP trends in Germany and Poland by combining linear and nonlinear machine learning methods.

4. Empirical results

Our models were trained on the training data and evaluated on the test data. We used mean absolute error (MAE), root mean square error (RMSE), and R-squared (R2) as evaluation metrics, and created a variable importance graph for bagging and boosting models to show how each attribute contributes to predictive performance. These criteria set the foundation for comparing results.

4.1. Modeling results

Table 5. Machine learning model results for Germany.

Model type	Models	Mae train	Mae test	Rmse train	Rmse test	R^2 Train	R^2 Test
Linear econometric model	Linear regression	0.49068673	0.3621566	1.2699722	0.4196548	0.09155278	0.1534028
Regularized linear econometric model	Lasso regression	0.12647821	0.3834212	0.1636139	0.3988466	0.68228985	0.5195497
	Ridge regression	0.11390835	0.3665200	0.1490834	0.3873796	0.58424292	0.7231839
	Elastic net regression	0.12005438	0.3822858	0.1517550	0.3935334	0.65543371	0.7013697
Linear machine learning model	SVR with linear kernel	0.13056911	0.3702164	0.1531386	0.4384310	0.61981894	0.1081599
Nonlinear machine learning model	Decision tree	0.07869056	0.3442708	0.1002212	0.3851944	0.83921189	0.8074471
	Random forest	0.36877155	0.3687715	0.3744472	0.3744472	0.62282448	0.6228245
	XGBoost	0.35492618	0.3549262	0.3604158	0.3604158	0.83212601	0.8321260

Source: Authors' elaboration.

Building on these criteria, Table 5 presents the predictive modeling performance results for Germany across eight models. The models were evaluated using the three key metrics (R^2, RMSE, and MAE). Results indicated that certain models had clear limitations. For instance, the linear econometric model performed poorly, with very low R^2 values of 0.09 (training) and 0.15 (testing), indicating that it explains little of the data's variance and is likely underfitting. Similarly, the SVR (linear) model, although showing an acceptable training R^2, performs poorly on the test set with an R^2 of 0.11 and the highest test RMSE among all models. This disparity suggests the model may be overfitting the training data or lacks the flexibility to capture data complexity. Lasso regression surprisingly achieved a high R^2 on the test set but still recorded higher error metrics, indicating that its predictions, while correlated, are less accurate overall. Among all models, XGBoost emerges as the best-performing, with consistent, strong results across all three metrics. It achieves the lowest test MAE and RMSE, and the highest test R^2 of 0.83, demonstrating both predictive accuracy and good generalization. Based on this comprehensive evaluation, we identified XGBoost as the most successful model for estimating GDP in the Germany dataset.

Table 6. Machine learning model results for Poland.

Model type	Models	Mae train	Mae test	Rmse train	Rmse test	R^2 Train	R^2 Test
Linear econometric model	Linear regression	0.5251139	0.7281290	1.3447395	0.7599699	0.02187604	0.6307406
Regularized linear econometric model	Lasso regression	0.1291352	0.7362687	0.1665207	0.7678608	0.91101975	0.6297594
	Ridge regression	0.2131920	0.7346231	0.2545399	0.7403066	0.85683807	0.6098931
	Elastic net regression	0.1551867	0.7445041	0.1979161	0.7616110	0.88699616	0.6192844
Linear machine learning model	SVR with linear kernel	0.1634348	0.7328416	0.2110643	0.7401375	0.88777029	0.5904810
Nonlinear machine learning model	Decision tree	0.1949218	0.7371305	0.2529873	0.8272547	0.83203160	0.7022315
	Random forest	0.7819269	0.7819269	0.8424970	0.8424970	0.76572993	0.7657299
	XGBoost	0.9321700	0.9321700	1.0426220	1.0426220	0.65956933	0.6595693

Source: Authors' elaboration.

Table 6 presents the results for eight models used to predict Poland's GDP, which were evaluated using three performance metrics. The linear regression model demonstrates clear underfitting, with a near-zero R^2 on the training set and high test-set prediction errors. Unlike the German dataset, XGBoost performs poorly across all metrics in Poland's data. It reached the highest test MAE and RMSE, and failed to learn effectively from the data. Although the random forest model achieved an acceptable R^2 value, their prediction errors remained high. So, it makes it less desirable. Among all models, the decision tree model delivers the most balanced and accurate results. It achieved the highest R^2 on the test set (0.70) and one of the lowest MAE and RMSE values. It indicated strong predictive power and generalization. Regularized linear models, such as ridge and lasso, also perform reasonably well but fall slightly behind in test performance. Based on these results, we identified the decision tree model as the best-performing approach for GDP estimation in the Poland dataset.

The overall comparison between econometric and machine learning models reveals a clear performance gap. This gap is particularly in predictive accuracy and the ability to capture complex data patterns. Econometric models such as linear regression and its regularized variants (ridge, lasso, elastic net) often struggle to handle multicollinearity and nonlinear relationships in the data. Linear econometric models' performance was particularly weak for Germany, where the standard linear regression model achieved a test R^2 of only 0.15. This showed poor explanatory power. In contrast, nonlinear machine learning models, such as decision trees, random forests, and XGBoost, demonstrated a stronger ability to model complex interactions and provided significantly better predictions. These models do not rely on strict statistical assumptions and can naturally handle nonlinearities and feature interactions, which resulted in improved performance. The best-performing model was the decision tree, achieving a test R^2 of 0.70, therefore reflecting strong predictive capability and generalization. While in Germany, the XGBoost model outperformed all others, achieving a test R^2 of 0.83. Hence, XGBoost and decision tree models were the most accurate and reliable models for GDP estimation.

4.2. Variable importance results

Variable importance plots for boosting (XGBoost) and bagging (random forest) models are used to identify the most important factors influencing GDP in Germany (Figure 6) and Poland (Figure 7). We used the degree to which a variable increases or reduces model accuracy, and split significance across all trees to determine variable relevance. These graphs are useful tools for understanding the relative influence of features in a model, as variables with higher significance scores are more important for predicting the desired outcome (Genuer et al., 2010).

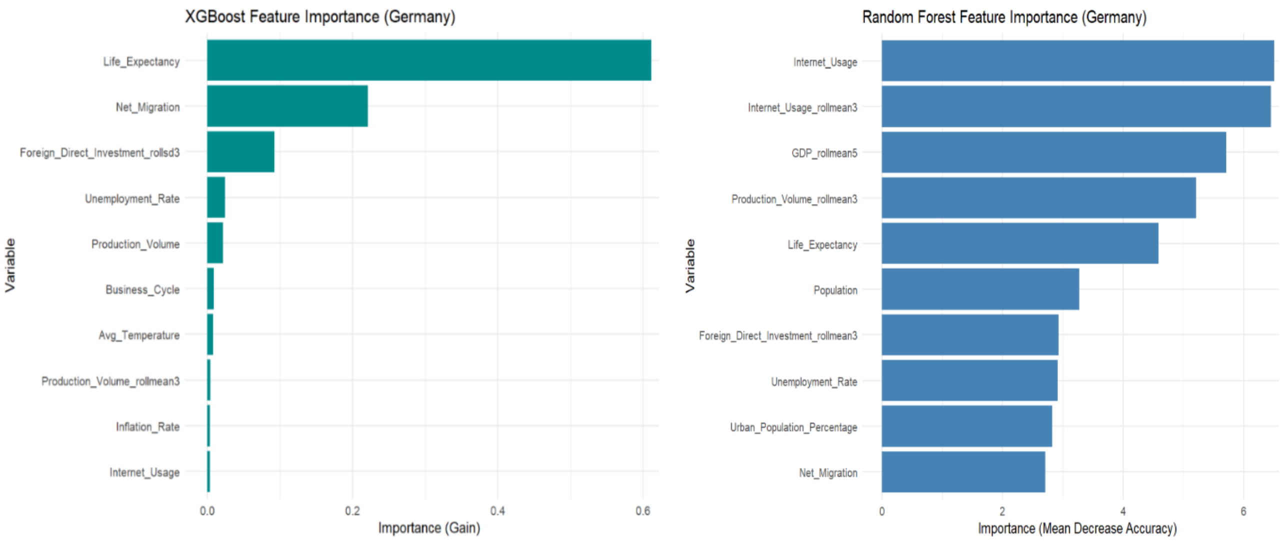

Figure 6. Variable importance plot for Germany. Source: Authors' elaboration.

Figure 6 shows feature importance for Germany using two nonlinear models: random forest and XGBoost. According to the random forest model, the most influential variables for predicting GDP were internet usage, internet usage (3-year rolling mean), and GDP (5-year rolling mean). This result suggests that digital connectivity and smoothed economic trends are critical predictors of economic growth. Other variables, such as production volume (3-year rolling mean), life expectancy, and population, also had significant importance. It describes the relevance of industrial activity and demographic factors.

In contrast, the XGBoost model highlights life expectancy and net migration as the most dominant predictors, followed by foreign direct investment (3-year rolling standard deviation). Interestingly, variables such as internet usage and production volume, which are top-ranked in random forest, have negligible importance in XGBoost. This result illustrates how distinct nonlinear models capture varying aspects of data complexity. Yet both agree on the importance of certain demographic and structural indicators in explaining Germany's economic performance.

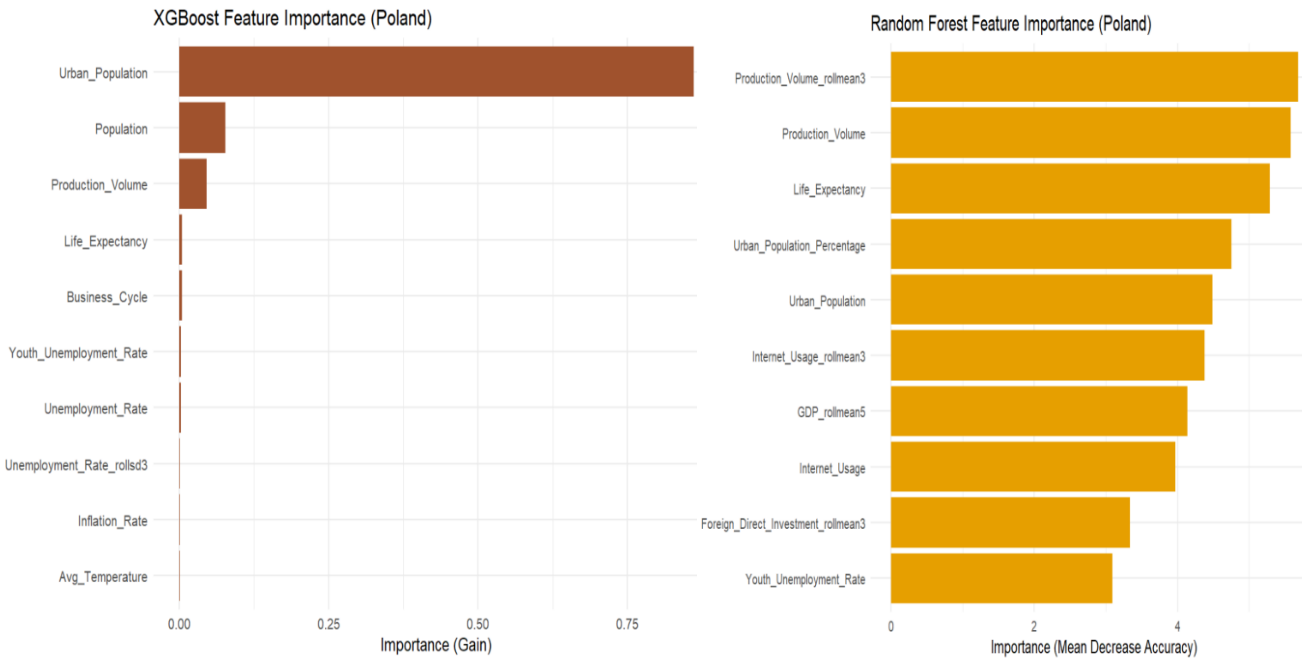

Figure 7. Variable importance plot for Poland. Source: Authors' elaboration.

Figure 7 illustrates feature importance for Poland using the same nonlinear models. The XGBoost model highlights the urban population as the most dominant predictor. This is followed distantly by population and production volume, while the remaining variables (e.g., life expectancy, business cycle, and unemployment rates) show minimal influence. In contrast, the random forest model distributes variable importance more evenly. It identifies production volume (3-year rolling mean), production volume, and life expectancy as the top three predictors, with urban population percentage and internet usage (3-year rolling mean) also playing significant roles. This difference in rankings highlights the models' differing strategies. XGBoost prioritizes a few strong predictors for decision paths, while the random forest model averages across multiple trees, which gives weight to a broader set of features. Despite these differences, both models emphasize the importance of demographic and industrial indicators in predicting Poland's GDP.

5. Conclusions and policy implications

In this study, we performed a comparative analysis of GDP predictions for Germany and Poland using a novel combination of linear econometric models and advanced linear and nonlinear machine learning methods, thereby contributing to the literature on GDP determinants. Overall, the empirical analyses we conducted were grounded in the following approaches: linear, ridge, lasso, and elastic net regressions (as linear methods); and SVR, decision trees, random forests, and XGBoost (as machine learning methods).

Models were trained and tested on time series data spanning 1991 to 2023, with numerous explanatory variables reflecting macroeconomic, demographic, technological, and environmental factors. The performance of each model was assessed using three standard metrics: MAE, RMSE, and R^2. We estimated separate models for each country and assessed their predictive performance using validation data from recent years.

Our study addressed three research questions:

1. To determine whether internet usage was a reliable determinant of national GDP,
2. To describe the set of important determinants influencing GDP in the two countries and notable differences between the countries, and
3. To determine whether linear models were sufficient for accurate GDP estimation or whether nonlinear machine learning models offered superior performance.

These research questions are relevant given the economic transformations underway across Europe. In 2024, Poland was the sixth contributor to the EU economy and a growth champion (Surwillo and Slakaityte, 2024). Meanwhile, Germany has consistently been ranked as the largest and strongest economy in Europe and the third-largest globally (KPMG, 2025).

Empirical results showed the dominance of nonlinear machine learning models in both their accuracy and explanatory power. For Germany, the best-performing model was XGBoost, with an R^2 of 0.83. Unlike the German dataset, the decision tree model performed best in Poland, with an R^2 of 0.70. This suggests that linear models are insufficient to capture the complexity of GDP determinants, particularly in datasets with multicollinearity and nonlinear relationships.

In Germany, GDP was mostly influenced by factors such as life expectancy, net migration, and foreign direct investment. These results emphasized the relevance of demographic structure, workforce mobility, and international capital flows for the country's economic growth. In light of these outcomes, German state authorities should promote sound migration policies and continue to attract highly skilled foreign workers to increase innovative human capital and the country's production capabilities. Moreover, authorities should continue to invest in high-quality living conditions, as these ultimately improve life expectancy. In this sense, people who enjoy better living conditions live healthier lives, are expected to live longer, and can educate themselves and develop into productive members of society, contributing to economic growth. Last but not least, German state authorities should also focus on attracting more foreign direct investment, which (in the case of a highly developed functioning economy) could be used to innovate and digitalize the national economy, change the industrial policy agenda, support green technology (i.e., electric mobility, green hydrogen production, modern power grids, wind energy) (Wettengel, 2024), and prioritize sustainable economic growth. Although such investments are substantial and require considerable involvement from public decision-makers, they would strengthen the country's competitiveness on the global market and relative to other leading economies (China and the United States of America).

In contrast, Poland's GDP was primarily driven by factors such as production volume, life expectancy, urban population, internet usage, foreign direct investment, and the unemployment rate, reflecting a combination of industrial output, demographic expansion, and growing digital infrastructure. In this case, Polish public authorities could increase the national production volume (beyond what they have achieved so far) by continuing to develop productivity-oriented industrial policies and adopting Industry 4.0 technologies (i.e., AI analytics, automation, big data, cloud computing) (International Trade Administration, 2024). Poland has been recognized as a regional manufacturing powerhouse in industries such as automotive, chemicals, electronics, food, and metal products. It is also the first country from the former Soviet bloc to be included in the developed countries category after being recognized by the FTSE Russel index in September 2018. In terms of life expectancy, authorities should make efforts to increase it, as it is currently slightly below the average of other developed countries and the OECD average. Other policies that could stimulate economic growth would be the following: (1) urban population increase by incentivizing young skilled labor to relocate to larger cities due to better living conditions, (2) massive investments in digital infrastructure (artificial intelligence technologies, 5G networks), and (3) incentivizing potential workers and unemployed individuals to reenter the labor market, which secured Poland one of the lowest unemployment rates in the region.

Our investigation is subject to certain limitations in this concept. First, the sample country included two developed nations, EU members, which contribute substantially to the regional GDP. Second, our analyses used traditional machine learning methods to examine the relationship between GDP and various macroeconomic, demographic, environmental, and technological factors. Hence, future research could contribute to a better understanding of global economic dynamics by extending our research to more countries from the EU and abroad, with different levels of economic development. Additionally, the use of deep learning-based models can help refine GDP estimates and provide more comprehensive information to public decision-makers.

Our findings underscore the importance of tailoring economic modeling to country-specific dynamics and support the view that nonlinear machine learning models are essential for understanding and estimating modern economic performance with greater precision than traditional econometric models.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Author contributions

All authors have contributed equally to the development of this study. All authors have read and approved the final version.

Conflict of interest

All authors declare no conflicts of interest in this paper.

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