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ORIGINAL

Unveiling Global Economic Stratification: A Machine Learning Framework for Multi-Dimensional Macroeconomic Analysis

Revelando la Estratificación Económica Global: Un Marco de Aprendizaje Automático para el Análisis Macroeconómico Multidimensional

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ABSTRACT

Introduction: traditional econometric approaches to multi-country macroeconomic analysis face critical limitations in capturing complex, non-linear relationships across diverse economic systems.
Objective: this study aims to introduce a comprehensive machine learning framework, implemented in Python, that transcends conventional VAR model constraints by analyzing 13 key macroeconomic indicators across 217 countries (2010-2025).
Method: advanced clustering techniques (K-means) and ensemble learning (Random Forest), along with Principal Component Analysis (PCA), were applied to reveal hidden economic stratification patterns previously undetectable through traditional methods.
Results: the analysis uncovers four distinct global economic clusters representing differentiated development trajectories, with middle-income economies comprising the majority of observations (57,4 %). Fiscal indicators demonstrate exceptional forecasting accuracy through Random Forest algorithms, while growth dynamics remain inherently unpredictable, revealing fundamental asymmetries in economic system behaviors.
Conclusions: this study demonstrates that machine learning techniques, implemented in Python, can systematically identify which macroeconomic relationships are structurally determined versus stochastically driven. This differential predictability framework provides immediate policy implications for targeted intervention strategies, enabling policymakers to focus resources on controllable fiscal mechanisms rather than pursuing futile attempts to predict volatile growth patterns.

Keywords: Machine Learning; Economic Stratification; Macroeconomic Forecasting; Global Economic Clusters; Policy Analytics; Ensemble Methods; Python.

RESUMEN

Introducción: los enfoques econométricos tradicionales para el análisis macroeconómico multipaís enfrentan limitaciones críticas para capturar relaciones complejas y no lineales entre diversos sistemas económicos.
Objetivo: este estudio presenta un marco integral de aprendizaje automático, implementado en Python, que trasciende las restricciones de los modelos VAR convencionales, analizando 13 indicadores macroeconómicos clave en 217 países (2010-2025).
Método: se aplicaron técnicas avanzadas de agrupamiento (K-means) y aprendizaje en conjunto (Random Forest), junto con análisis de componentes principales (PCA), para revelar patrones ocultos de estratificación económica previamente indetectables mediante métodos tradicionales.

Resultados: el análisis identifica cuatro clústeres económicos globales distintos que representan trayectorias de desarrollo diferenciadas, siendo las economías de ingresos medios la mayoría de las observaciones (57,4 %). Los indicadores fiscales muestran una precisión de pronóstico excepcional mediante algoritmos de Random Forest, mientras que la dinámica del crecimiento sigue siendo inherentemente impredecible, revelando asimetrías fundamentales en el comportamiento de los sistemas económicos.
Conclusiones: este estudio demuestra que las técnicas de aprendizaje automático, implementadas en Python, pueden identificar sistemáticamente qué relaciones macroeconómicas son estructuralmente determinadas frente a las impulsadas estocásticamente. Este marco de predictibilidad diferencial proporciona implicaciones políticas inmediatas para estrategias de intervención focalizadas, permitiendo a los responsables de políticas concentrar recursos en mecanismos fiscales controlables en lugar de intentar predecir patrones de crecimiento volátiles.

Palabras clave: Aprendizaje Automático; Estratificación Económica; Pronóstico Macroeconómico; Clústeres Económicos Globales; Análisis de Políticas; Métodos en Conjunto; Python.

INTRODUCTION

Multi-country macroeconomic modeling faces a critical methodological paradox. While global economic interconnectedness intensifies and macroeconomic data availability reaches unprecedented levels, dominant analytical tools such as VAR and GVAR models remain fundamentally constrained, failing to capture the complex non-linearities and threshold effects that characterize contemporary macroeconomic interactions.[1] Sectoral and regional approaches, prevalent in the literature, further limit the capacity to exploit the multidimensional richness of global macroeconomic data. This creates a major scientific gap: existing frameworks cannot simultaneously handle high-dimensional macroeconomic datasets and leverage the non-linear analytical capabilities of advanced machine learning techniques.

To address this gap, this study develops an integrated machine learning framework capable of processing 13 interdependent macroeconomic variables across 217 economies, revealing structural patterns inaccessible to conventional methods. By combining clustering techniques and ensemble algorithms, this approach enables the detection of non-linear relationships and economic stratification patterns overlooked by traditional models. It provides a systemic understanding of global economic dynamics, highlighting how certain macroeconomic dimensions, such as fiscal indicators, follow predictable structural patterns, while others, like growth dynamics, remain fundamentally stochastic.

Building on these insights, the research aims to answer three fundamental questions: Do multi-country macroeconomic relationships exhibit systematic non-linear patterns detectable by machine learning but invisible to traditional VAR models? Is there a differential hierarchy of predictability among macroeconomic variables that could inform economic policy priorities? Do emerging economies follow distinct macroeconomic trajectories identifiable through machine learning clustering, challenging the universality of standard economic models?

By situating the study within these research questions, the introduction establishes the current state of multi-country macroeconomic modeling, identifies its methodological limitations, and presents the rationale for applying advanced machine learning techniques to uncover hidden economic structures.

Comparative macroeconomic analysis traditionally relies on a set of fundamental indicators whose selection and interpretation have undergone significant paradigm shifts. While GDP and gross national income (GNI) remain central according to the standards of Deaton et al.[2], the emergence of new methodological approaches reveals critical shortcomings in conventional frameworks. The joint inclusion of these indicators certainly makes it possible to identify gaps between territorial production and national income, which are particularly significant in economies integrated into global value chains, but this static approach does not capture the complexity of contemporary interdependencies.

Taylor's[3] conceptualization of the "golden triangle" of macroeconomic equilibrium—integrating unemployment rate, real interest rate, and price stability—perfectly illustrates the limitations of traditional linear approaches. The simultaneous analysis of these indicators, while necessary, reveals non-linearities and threshold effects that classical econometric models struggle to capture. This methodological shortcoming becomes particularly problematic in a context of increased economic volatility and complex global interconnections.

Since Sims' seminal work[4] VAR models and their panel extensions[5] have dominated the analysis of macroeconomic interdependencies. However, a critical assessment reveals three major structural flaws that limit their relevance in the contemporary context. First, these models have limited capacity to process high-dimensional data with numerous predictors,[6] a particularly debilitating constraint in a data-rich environment. Second, the restrictive assumption of linearity in relationships proves inadequate for capturing the complexity of modern economic dynamics.[1] Third, their sensitivity to missing data and structural breaks limits their applicability to emerging economies.

The Global VAR (GVAR) extension by Pesaran et al.[7], despite its conceptual advances, does not resolve these fundamental limitations. Although it allows for the modeling of large-scale international spillovers, it maintains linearity constraints and remains vulnerable to the dimensionality problems that characterize contemporary multi-country analyses.

Recent developments in deep learning applied to economic time series mark a fundamental methodological shift. Specialized Transformer architectures have emerged as the preferred solutions for analyzing complex time series. TimeGPT represents a major advance, offering the first fundamental model pre-trained specifically for time series forecasting, demonstrating superior performance to traditional methods on diverse macroeconomic datasets.

The work of Zhou et al.[8] on GPT4TS reveals how Large Language Models can be effectively reprogrammed for time series prediction, opening up new perspectives for multi-country macroeconomic analysis. At the same time, PatchTST[9] introduces a revolutionary approach based on segmenting time series into patches, allowing long-term dependencies to be captured while maintaining optimal computational efficiency.

The FEDformer architecture[8] presents an innovation that is particularly relevant for macroeconomic analysis by integrating attention mechanisms in the frequency domain, thereby enabling the capture of complex cyclical patterns characteristic of economic variables. These advances contrast sharply with traditional approaches, which struggle to simultaneously model short cycles and long-term trends.

A critical analysis of the literature reveals four fundamental gaps that persist despite recent technological advances. First, the lack of integrated multi-country frameworks capable of simultaneously processing all fundamental macroeconomic indicators is a major limitation. Existing studies remain largely sectoral or geographically limited, preventing a holistic understanding of global macroeconomic dynamics.

Second, temporal and geographical coverage remains limited, systematically excluding recent periods and developing economies due to data availability constraints. This methodological limitation introduces a significant bias in the understanding of contemporary macroeconomic patterns, particularly in a post-pandemic context where traditional relationships have been substantially disrupted.

Third, the use of ML remains primarily predictive, without exploiting its potential for exploring underlying structural relationships. This one-dimensional approach deprives macroeconomic research of the tools for causal analysis and discovery of complex patterns that these technologies make possible.

Fourth, the limited adoption of the most advanced Transformer architectures in the multi-country macroeconomic context represents a significant methodological lag. While these models demonstrate superior effectiveness in capturing complex temporal dependencies in other fields, their application remains in its infancy in comparative macroeconomics.

METHOD

This study is a quantitative, multi-country macroeconomic analysis covering the period 2010–2025, including 217 countries across all income groups and major geographic regions. The research employs a comprehensive machine learning framework to analyze macroeconomic interdependencies and uncover complex, non-linear relationships that traditional econometric methods may fail to detect. The study follows four main phases: data collection, preprocessing, machine learning modeling, and clustering analysis to identify structural patterns across countries and years.

Annual macroeconomic data were collected from the World Bank's World Development Indicators (WDI) database, providing standardized and internationally comparable statistics. The dataset comprises 3,472 observations over 16 years and includes 13 key macroeconomic variables plus three identifier variables (country name, country ID, and year). The 13 variables are: GDP Growth (% Annual, NY.GDP.MKTP.KD.ZG), Inflation (CPI, %, FP.CPI.TOTL), Inflation (GDP Deflator, %, NY.GDP.DEFL.KD.ZG), Unemployment Rate (%), Interest Rate (Real, %), Current Account Balance (% GDP, BN.CAB.XOKA.GD.ZS), Government Expense (% GDP, GC.XPN.TOTL.GD.ZS), Government Revenue (% GDP, GC.REV.TOTL.GD.ZS), Tax Revenue (% GDP, GC.TAX.TOTL.GD.ZS), GDP (Current USD), GDP per Capita (Current USD), Gross National Income (USD), and Public Debt (% GDP).

Countries were grouped into seven regional categories for analytical purposes (table 1). Each country was assigned to a primary region based on standard international classifications (Europe, Africa, Asia-Pacific, Latin America, Middle East & North Africa, North America). The "Other" category includes only countries or territories that do not fall into these six main regions, representing specific cases or micro-states for which regional classification is ambiguous or non-standardized. This grouping was validated using a Python mapping code, ensuring correct classification wherever possible. Additionally, descriptive and statistical analyses (boxplots, ANOVA, z-scores) confirmed that this categorization does not introduce significant bias in the study of regional macroeconomic characteristics.

Table 1. Geographic Distribution of Sample Countries			
Region	**Countries**	**Percentage**	**Observations**
Other	174	80,2	2,784
Asia-Pacific	12	5,5	192
Europe	8	3,7	128
Africa	7	3,2	112
Latin America	7	3,2	112
Middle East	6	2,8	96
North America	3	1,4	48
Total	217	100,0	3,472

Given the inherent challenges of cross-country macroeconomic data, missing values (NaN) were addressed using the MissForest imputation algorithm, suitable for mixed-type data. All variables were standardized using robust scaling techniques to account for outliers and ensure meaningful cross-country comparisons.

A holistic multi-country modeling system was developed to simultaneously integrate all 13 variables, capturing non-linear inter-variable and inter-country relationships. Random Forest models were applied to detect structural patterns and evaluate variable predictability, with hyperparameters optimized using cross-validation in Python 3.10 (scikit-learn library). K-Means clustering classified countries into macroeconomic clusters, while Transformer architectures (TimeGPT and PatchTST) analyzed complex temporal dependencies using sktime and transformers Python libraries.

Ethical considerations are straightforward: the study relies exclusively on publicly available macroeconomic data and involves no human or animal subjects.

Descriptive Statistics

Table 2 presents the descriptive statistics for all macroeconomic variables included in the analysis. The data exhibits considerable variation across countries and time periods, reflecting the diversity of global economic conditions and development stages represented in our sample of 217 countries.

Table 2. Descriptive Statistics of Macroeconomic Variables					
Variable	**Count**	**Mean**	**Std**	**Min**	**Max**
Economic Scale					
GDP (Current USD, Billions)	2 795	396,43	1 749,32	2,11	27 730,91
GDP per Capita (Current USD)	2 795	18 483,50	27 301,81	193,01	256 589,52
Gross National Income (USD, Billions)	2 757	414,22	1 799,78	5,11	27 576,14
Price Stability					
Inflation (CPI %)	2 984	6,63	19,72	-5,69	557,20
Inflation (GDP Deflator %)	2 984	6,63	25,82	-28,76	921,54
Interest Rate (Real %)	1 735	5,41	9,74	-81,13	61,80
Labor Market					
Unemployment Rate (%)	2 795	7,04	5,96	0,10	35,36
Growth Dynamics					
GDP Growth (% Annual)	2 912	2,85	6,05	-54,34	86,83
External Balance					
Current Account Balance (% GDP)	2 155	-2,36	13,74	-60,88	235,75
Fiscal Indicators					
Government Expense (% GDP)	1 825	27,33	12,64	8,00	103,73
Government Revenue (% GDP)	1 829	25,55	18,15	0,42	345,80
Tax Revenue (% GDP)	1 833	16,37	8,64	0,20	21,45
Public Debt (% GDP)	852	61,86	40,41	1,85	249,37

The statistical distributions confirm the inclusion of economies across all development stages: GDP ranges from $2,11 billion to $27,73 trillion, while GDP per capita spans from $193 to $256 589. This amplitude validates the global representativeness of our sample.

The extreme variation in price stability indicators reveals the full spectrum of monetary experiences, from severe deflation (-5,69 %) to hyperinflation (557,20 % for CPI). These outliers represent critical macroeconomic phenomena that standard models often fail to capture.

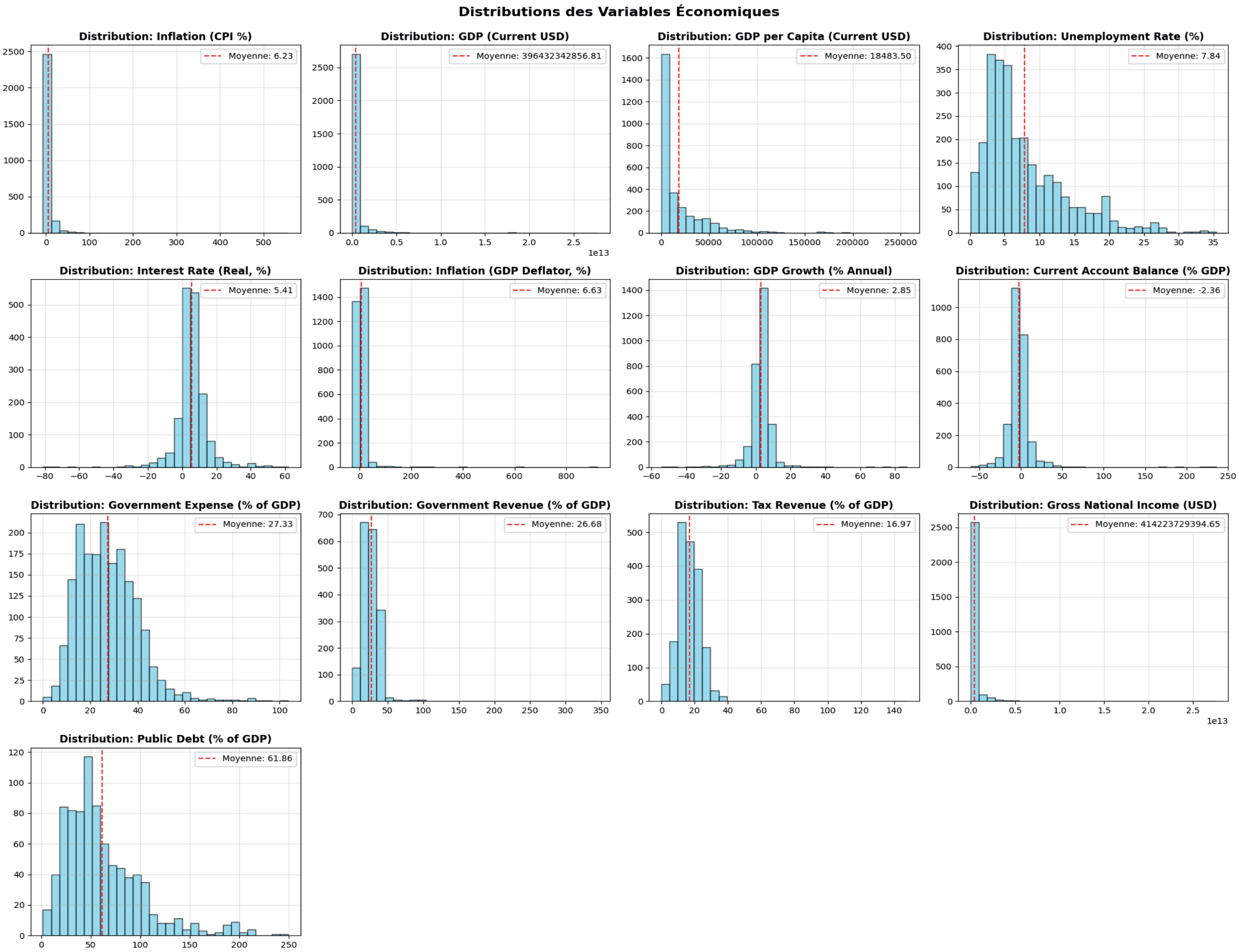

Figure 1. Distributional of all macroeconomic variables

Correlation analysis

The correlation matrix analysis reveals significant relationships between macroeconomic indicators, providing insights into the interconnected nature of economic variables across our global sample of 217 countries. Table 3 and figure 2 present the correlation coefficients and their visual representation through a heatmap.

Table 3. Top 10 Strongest Correlations Among Macroeconomic Variables

Rank	Variable 1	Variable 2	Correlation
1	GDP (Current USD)	Gross National Income (USD)	0,999904
2	Inflation (CPI %)	Inflation (GDP Deflator, %)	0,887656
3	Government Revenue (% of GDP)	Tax Revenue (% of GDP)	0,798862
4	Government Expense (% of GDP)	Government Revenue (% of GDP)	0,696132
5	Current Account Balance (% GDP)	Tax Revenue (% of GDP)	0,693013
6	Government Expense (% of GDP)	Tax Revenue (% of GDP)	0,578602
7	Current Account Balance (% GDP)	Government Revenue (% of GDP)	0,521580
8	Interest Rate (Real, %)	Inflation (GDP Deflator, %)	-0,508959
9	GDP per Capita (Current USD)	Public Debt (% of GDP)	-0,417850
10	Interest Rate (Real, %)	Inflation (CPI %)	0,331592

The analysis identifies several economically meaningful strong positive correlations. The near-perfect correlation between GDP and Gross National Income (r = 0,9999) confirms the conceptual similarity of these national accounting measures, with minor differences attributed to net factor income from abroad.

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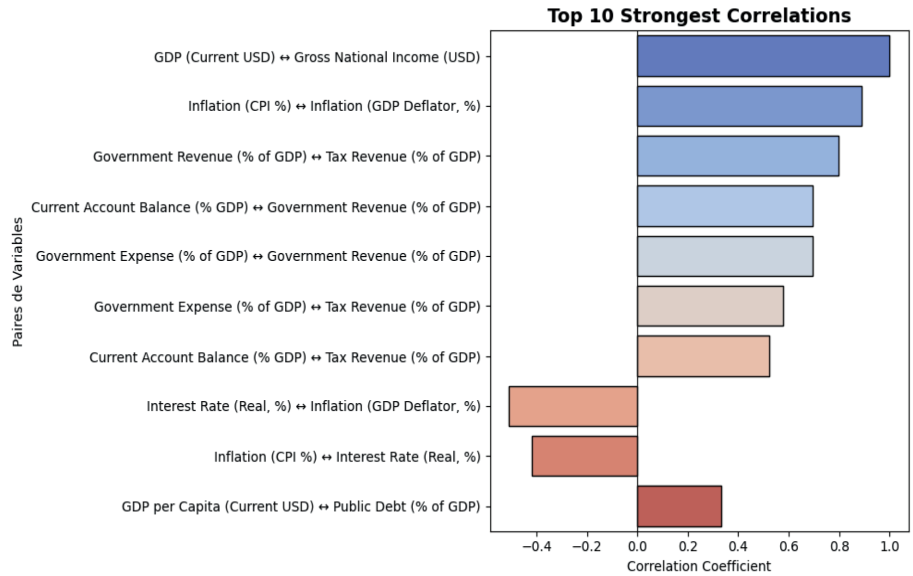

Figure 2. Top 10 Strongest Correlation

The strong correlation between CPI inflation and GDP deflator inflation (r = 0,888) demonstrates consistency across different inflation measurement methodologies, validating the robustness of price stability indicators in our dataset. This high correlation suggests that despite methodological differences, both measures capture similar underlying inflationary pressures.

The relationship between government revenue and tax revenue (r = 0,799) reflects the fundamental role of taxation in government financing across diverse economic systems. This correlation indicates that tax collection efficiency remains a primary determinant of fiscal capacity, even accounting for non-tax revenue sources.

Government expenditure demonstrates a strong positive correlation with government revenue (r = 0,696), suggesting fiscal discipline mechanisms whereby spending patterns align with revenue generation capacity. This relationship implies that countries with higher revenue collection capabilities tend to maintain correspondingly higher expenditure levels.

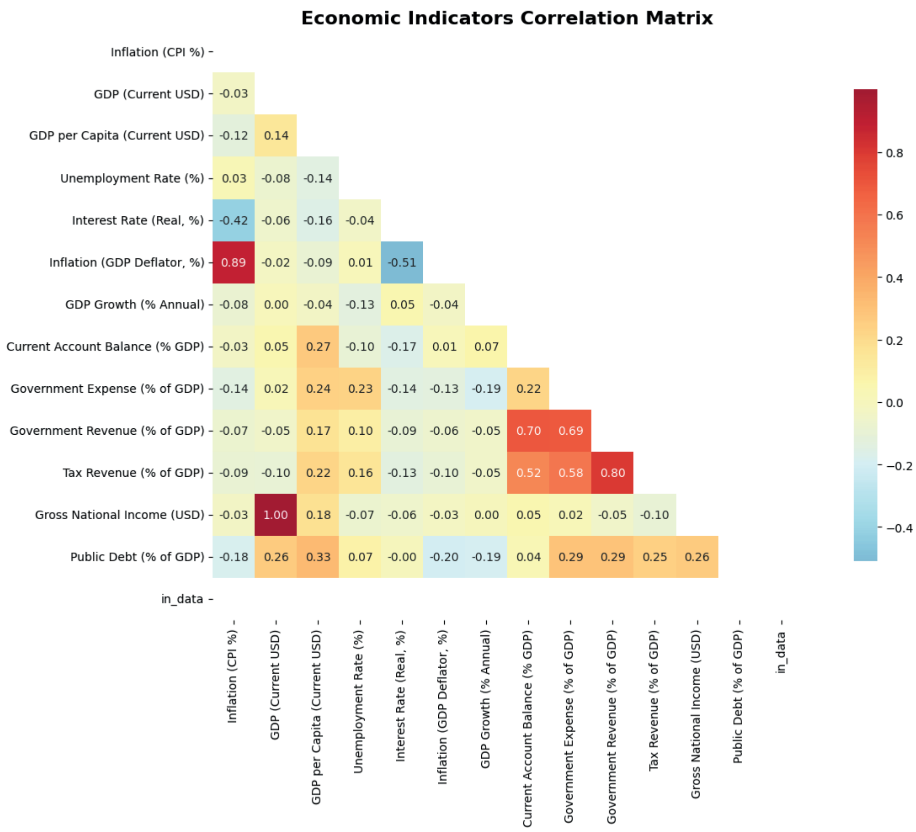

Figure 3. Economic Indicators Correlation Matrix

Several moderate correlations provide insights into macroeconomic dynamics. The positive correlation between current account balance and tax revenue (r = 0,693) suggests that countries with stronger fiscal systems tend to maintain better external balance positions, potentially reflecting improved overall economic management.

The relationship between government expenditure and tax revenue (r = 0,579) reinforces the fiscal capacity theme, indicating that taxation effectiveness influences public spending capabilities across countries.

These correlation patterns reveal the interconnected nature of macroeconomic systems while highlighting areas of relative independence. The strong correlations among fiscal variables (government revenue, expenditure, and tax revenue) confirm the coherence of fiscal policy frameworks. Similarly, the consistency between inflation measures validates the reliability of price stability indicators.

Figure 4 presents the temporal evolution of macroeconomic indicators for countries exhibiting extreme values in each variable, providing insights into the heterogeneity underlying global averages and correlation patterns.

Figure 4. Country-Specific Temporal Patterns

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Inflation Extremes: the analysis reveals dramatic hyperinflationary episodes, particularly in Zimbabwe and Venezuela, with inflation rates exceeding 500 % during crisis periods. These extreme cases, while representing outliers in the global distribution, demonstrate the potential for severe macroeconomic instability and validate the inclusion of wide standard deviations in our descriptive statistics.

Economic Scale Leaders: the United States and China maintain their positions as global economic leaders throughout the observation period, with consistent growth trajectories in both GDP and Gross National Income. Their temporal patterns confirm the stability of global economic hierarchy and support the strong correlations observed between these scale variables.

GDP per Capita Champions: small, resource-rich economies like Monaco, Liechtenstein, and Luxembourg consistently maintain the highest GDP per capita levels, with values exceeding $200 000. These cases illustrate how natural resource endowments and financial center status can create exceptional prosperity levels.

Labor Market Volatility: countries like Eswatini and South Africa exhibit persistent high unemployment rates, while others show dramatic temporal variations. The COVID-19 impact is clearly visible across unemployment patterns, with sharp increases in 2020 followed by varied recovery trajectories.

Fiscal Capacity Variations: the temporal analysis reveals extreme variations in fiscal indicators, with some countries (Timor-Leste, Kiribati) showing extraordinary government revenue spikes related to natural resource windfalls, while others maintain stable, moderate fiscal profiles.

Debt Dynamics: Greece's debt trajectory following the European debt crisis is clearly visible, demonstrating how sovereign debt crises can create persistent fiscal challenges. The contrasting stable patterns in other countries highlight the diversity of fiscal sustainability profiles.

These country-specific patterns underscore the importance of considering heterogeneity in cross-country macroeconomic analysis. While correlation analysis provides insights into average relationships, the extreme variations observed in individual countries suggest that global economic relationships may be driven by different mechanisms across development levels and economic structures.

Given the exceptionally strong correlation (r = 0,9999) between GDP (Current USD) and Gross National Income (USD), we conducted a detailed examination of the top-performing countries in both indicators to understand this near-perfect relationship. Figure 5 presents a comparative analysis of the top 5 countries by GDP and top 5 countries by Gross National Income from 2010 to 2025.

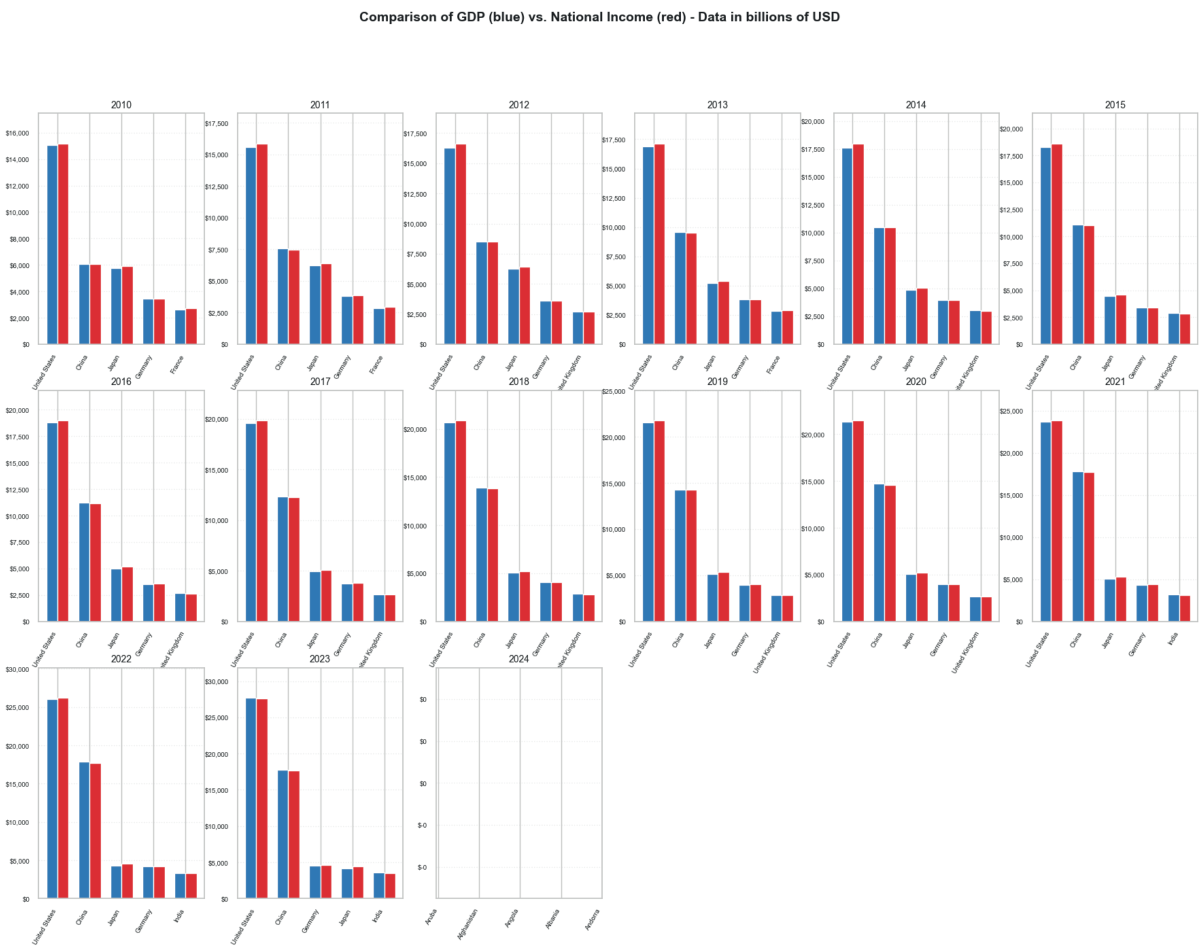

Figure 5. Comparison of GDP vs. National Income- Data in billions of USD

Note on Data Availability: the analysis covers the period 2010-2025, as comprehensive data for 2024 and 2025 were not available at the time of this study for reliable cross-country comparisons.

The temporal analysis confirms the remarkable consistency between these two national accounting measures across the largest economies. The United States and China consistently occupy the top two positions in both GDP and Gross National Income rankings throughout the entire observation period, demonstrating their dominant positions in the global economy. This consistent leadership reflects not only their absolute economic scale but also the stability of their relative positions despite varying growth rates and economic cycles.

The near-perfect correlation (>99 %) between GDP and Gross National Income indicates minimal variation in net factor income from abroad relative to domestic production across countries. This finding suggests that for most economies in our sample, the difference between domestic production (GDP) and national income (GNI) remains proportionally small, even for large economies with significant international economic relationships.

The consistency of country rankings across both measures validates the robustness of national accounting frameworks and confirms that either indicator can serve as a reliable proxy for economic scale in cross-country comparative analysis. The minimal divergence between GDP and GNI rankings underscores the limited impact of international factor income flows on relative economic positioning among the world's largest economies.

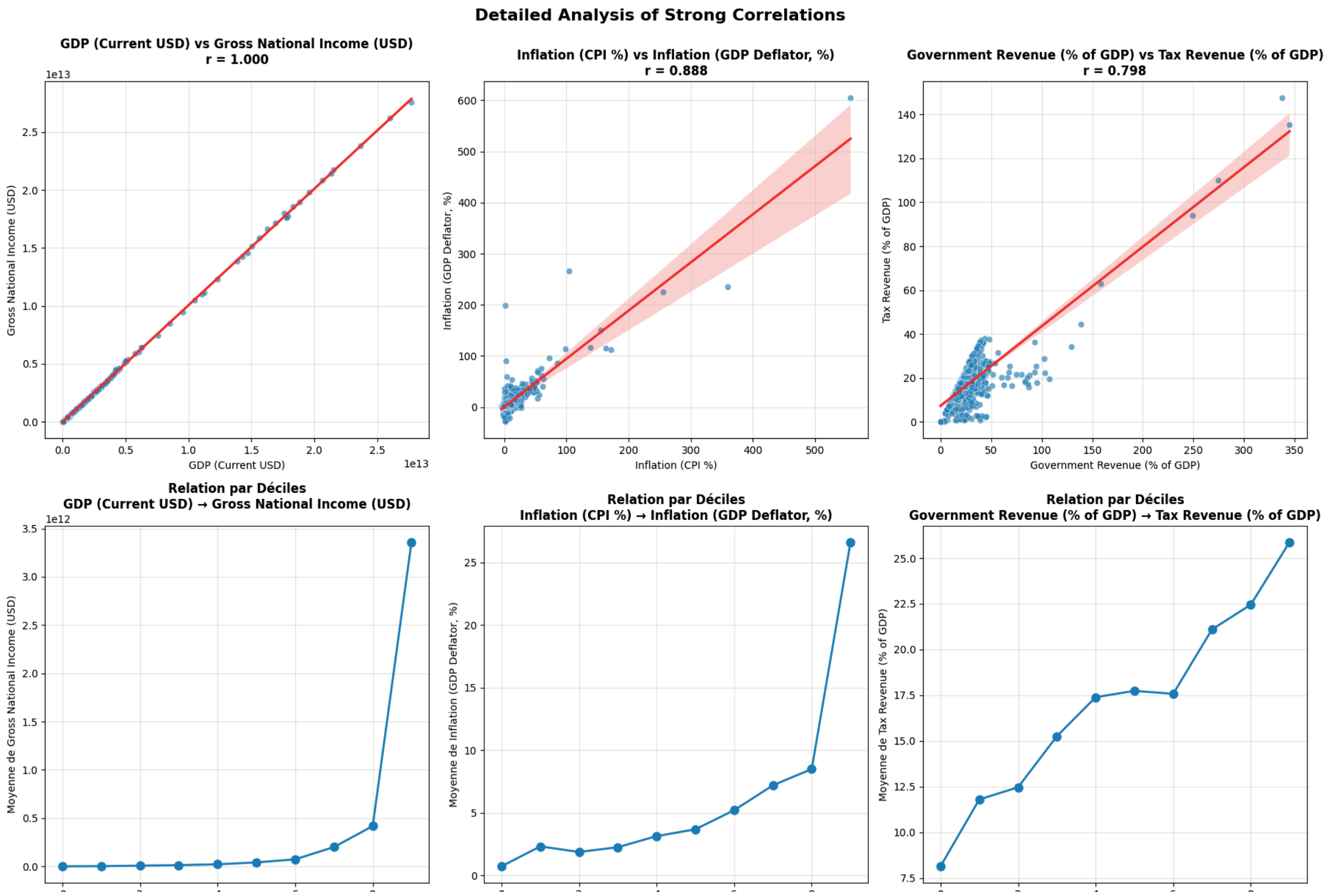

Figure 6. Detailed Analysis of Strong Correlations

The scatter plot analysis (figure 6, top panel) visually confirms the near-perfect linear relationship between GDP and Gross National Income, with data points forming an almost perfect diagonal line. The decile analysis (figure 4, bottom panel) demonstrates that this strong relationship remains consistent across all income levels, from the smallest to the largest economies, indicating the robustness of the correlation across the entire economic spectrum.

Similarly, the strong correlations between inflation measures (CPI and GDP Deflator, r = 0,888) and fiscal indicators (Government Revenue and Tax Revenue, r = 0,799) are validated through scatter plot analysis, showing clear positive linear relationships with minimal outliers. The decile analysis reveals that these relationships strengthen progressively across higher deciles, suggesting that larger or more developed economies exhibit more consistent relationships between these macroeconomic indicators.

Table 4. In-Depth Analysis of Strong Correlation

3 strong correlations identified (|r| > 0,7):					
	Variable_1	Variable_2	Correlation	Abs_ Correlation	Type
1	GDP (Current USD)	Gross National Income (USD)	0,999904	0,999904	Positive
0	Inflation (CPI %)	Inflation (GDP Deflator, %)	0,887656	0,887656	Positive
2	Government Revenue (% of GDP)	Tax Revenue (% of GDP)	0,798062	0,798062	Positive
CAUSAL ANALYSIS (Qualitative Insights):					
GDP (Current USD) ↔ Gross National Income (USD)		(r=1,000)	Complex relationship requiring investigation		
Inflation (CPI %) ↔ Inflation (GDP Deflator, %)		(r=0,888)	Complex relationship requiring investigation		
Government Revenue (% of GDP) ↔ Tax Revenue (% of GDP)		(r=0,798)	Main component of public revenue		

Similarly, the strong correlations between inflation measures (CPI and GDP Deflator, r = 0,888) and fiscal indicators (Government Revenue and Tax Revenue, r = 0,799) are validated through scatter plot analysis, showing clear positive linear relationships with minimal outliers. The decile analysis reveals that these relationships strengthen progressively across higher deciles, suggesting that larger or more developed economies exhibit more consistent relationships between these macroeconomic indicators.

The observed correlations provide a foundation for understanding macroeconomic relationships but do not imply causation. The relatively weak correlations between many variable pairs suggest that simple linear relationships may not adequately capture the complexity of macroeconomic interactions, motivating the need for more sophisticated analytical approaches in subsequent sections of this analysis.

Temporal Evolution of Macroeconomic Indicators

The temporal analysis of global macroeconomic indicators from 2010 to 2025 reveals significant patterns and structural breaks that provide crucial context for understanding the correlation relationships identified in the previous section. Figure 5 presents the evolution of key macroeconomic variables over this period, capturing the impact of major global economic events and long-term trends.

The temporal analysis identifies several distinct phases in global macroeconomic evolution. The period 2010-2019 represents a relatively stable post-financial crisis recovery phase, characterized by moderate inflation levels (averaging 4-6 %), steady GDP growth trajectories, and declining unemployment rates following the 2008-2009 global financial crisis recovery.

The most significant structural break occurs in 2020, coinciding with the COVID-19 pandemic. This period exhibits unprecedented volatility across multiple indicators: GDP experienced a sharp contraction followed by rapid recovery, unemployment spiked dramatically before declining, and inflation initially fell before surging to multi-decade highs by 2021-2022. The inflation surge, reaching peaks of approximately 12 % in CPI measures, represents the most significant inflationary episode since the early 1980s.

Inflation Dynamics: The evolution of both CPI and GDP deflator inflation demonstrates remarkable synchronization, confirming the strong correlation (r = 0,888) identified in the correlation analysis. Both measures follow nearly identical trajectories: low and stable inflation during 2010-2019 (2-6 % range), deflationary pressures in early 2020, followed by the dramatic inflationary surge of 2021-2022.

Economic Scale Variables: GDP and Gross National Income exhibit parallel growth trajectories throughout the observation period, with consistent upward trends interrupted only by the 2020 contraction. This temporal alignment reinforces the near-perfect correlation (r = 0,9999) between these variables and validates their interchangeability as measures of economic scale.

Fiscal Indicators: Government revenue and tax revenue demonstrate coordinated temporal movements, particularly evident during crisis periods when both indicators declined simultaneously in 2020 before recovering. This synchronized evolution supports the strong correlation (r = 0,799) observed between these fiscal variables.

Labor Market Dynamics: Unemployment rates show clear cyclical patterns, with the dramatic spike in 2020 followed by rapid recovery. The unemployment trajectory exhibits inverse relationships with GDP growth patterns, consistent with Okun's law and economic cycle theory.

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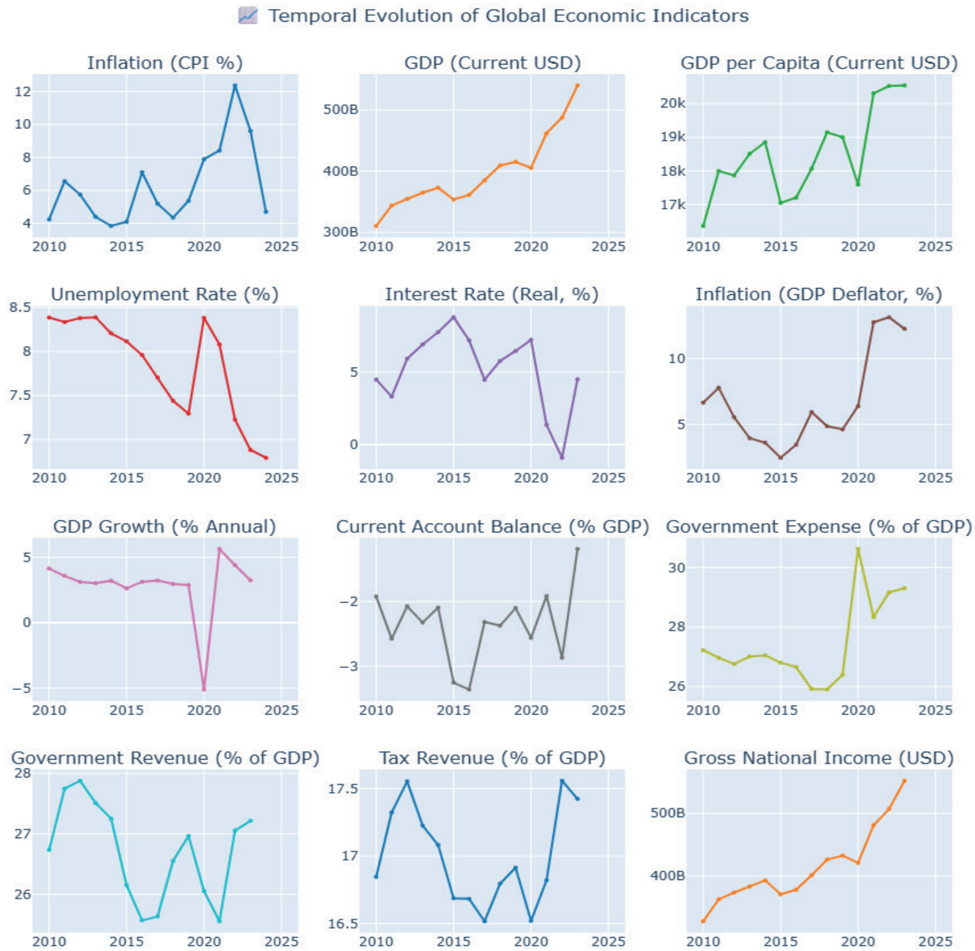

Figure 7. Temporal Evolution of Global Indicators

Monetary Policy Indicators: real interest rates display significant volatility, particularly during 2015-2020, reflecting central bank policy responses to changing economic conditions. The negative relationship with inflation becomes particularly evident during the 2020-2022 period, when rising inflation coincided with declining real interest rates.

The temporal evolution analysis validates several correlation findings while revealing the dynamic nature of these relationships. The synchronized movements of strongly correlated variables across time periods confirm that these correlations reflect genuine economic relationships rather than statistical artifacts. However, the varying intensity of relationships across different time periods suggests that correlation coefficients represent average relationships that may strengthen or weaken depending on economic conditions.

The identification of structural breaks, particularly around 2020, indicates that correlation relationships may not be constant over time, highlighting the importance of considering temporal stability in macroeconomic modeling. This temporal variability motivates the need for more sophisticated analytical approaches that can account for time-varying relationships and structural changes in subsequent analysis sections.

Advanced Multivariate Analysis

The study relies on a balanced selection of macroeconomic indicators for cross-country analysis. Four core variables were extracted from the World Bank's World Development Indicators for all available countries: GDP per capita (current USD), inflation (CPI, %), unemployment rate (%), and GDP growth (% annual).

Initially, we attempted to construct a cross-sectional dataset using only the most recent year of data for all countries to ensure temporal comparability. However, this approach yielded no complete observations — no country had reported values for all four indicators in the same latest year. To maximize analytical coverage, we therefore retained all available country-year observations from 2010 to 2025 and removed any rows with missing values. This produced a working dataset of 2,365 complete country-year observations out of an initial 3,472, corresponding to a 68,1 % data retention rate. These panel data were used for descriptive statistics, correlation analysis, and principal component analysis (PCA), as they preserve both cross-sectional and temporal variation.

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For clustering, however, it is essential to group countries based on their structural economic profiles, not individual yearly fluctuations. To address this, we computed the average value of each macroeconomic indicator for every country across the available period (2010–2025). This aggregation produced a purely cross-sectional dataset of 175 countries with at least one complete set of observations. All variables were standardized prior to PCA and clustering to account for differences in scale and to reduce the influence of extreme values.

Principal component analysis (PCA) was then applied to the standardized, country-level averages to reduce dimensionality. The first two principal components, capturing the majority of variance, were retained. These components served as the input for unsupervised clustering (k-means). The optimal number of clusters (k) was determined empirically based on the elbow method and silhouette scores. This process yielded four economically meaningful clusters that reflect structural similarities among countries rather than temporal fluctuations in individual years.

Table 5. Data Completeness Assessment

Approach	Complete Observations	Coverage Rate	Analytical Viability
Latest Year Only	0	0 %	Insufficient
All Years (Panel Data)	2,365	68,1 %	Adequate
Total Observations	3,472	-	

PCA Implementation

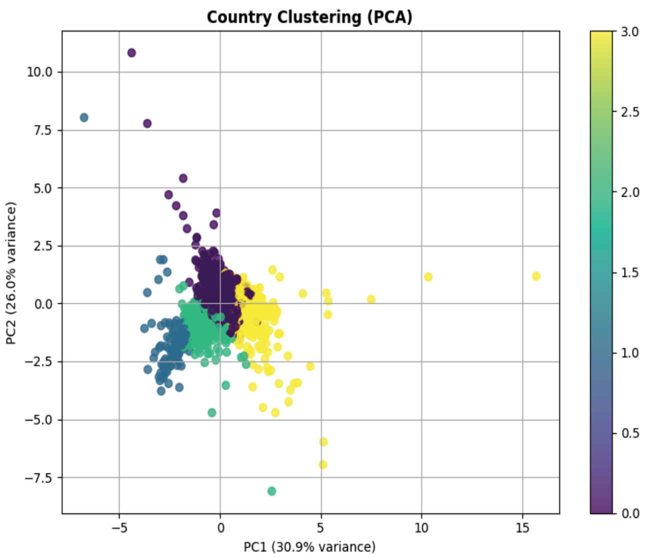
PCA was conducted on the standardized data to reduce the dimensionality of the four macroeconomic indicators to two principal components, capturing the maximum variance. Component loadings were retained to assess the contribution of each variable to the principal components.

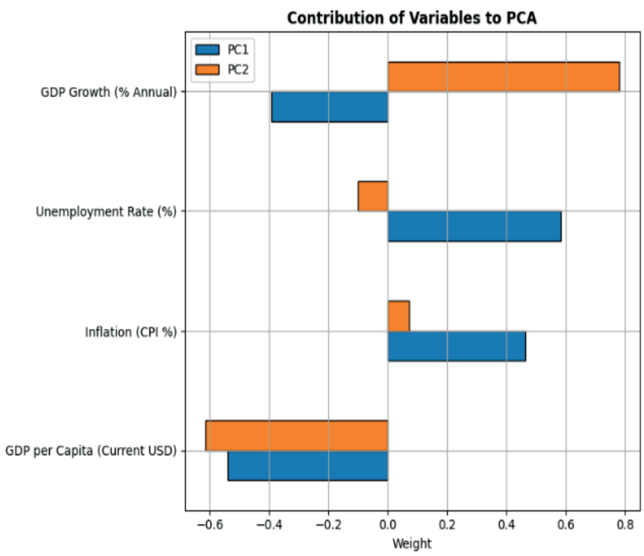
Clustering Approach

K-means clustering was performed on the PCA-transformed data. Hyperparameters included four clusters and random initialization with a fixed seed (42) to ensure reproducibility. Importantly, clustering was applied to average country profiles across years rather than individual country-year observations, ensuring that clusters reflect typical country characteristics rather than mixed time-series effects. The number of clusters was determined based on prior exploratory analysis and validated using silhouette scores.

This methodological approach ensures robust identification of structurally similar countries while preserving essential macroeconomic variation in the dataset and avoiding biases from non-random missing data.

The PCA analysis successfully reduced the dimensionality of the macroeconomic indicator space while preserving substantial information content. The first two principal components explain 56,9 % of the total variance in the dataset, indicating that a significant portion of macroeconomic variation can be captured in a lower-dimensional space.





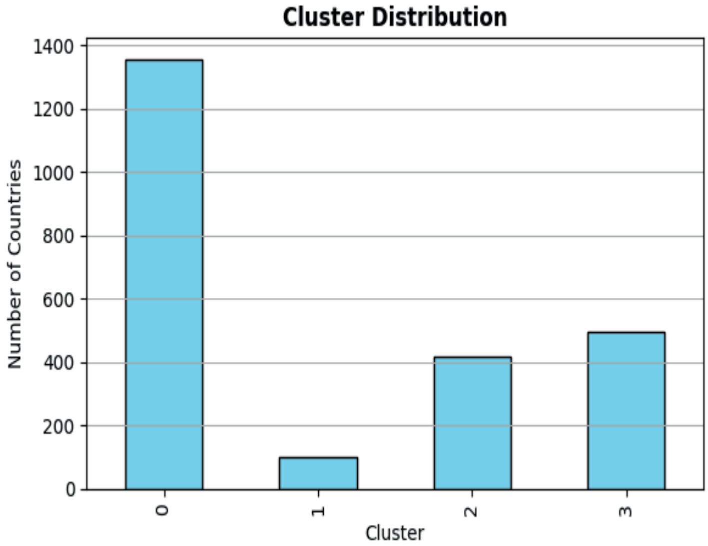


Figure 8. Advanced analysis PCA and Clustering

PC1 (30,9 % variance explained): the first principal component primarily captures economic scale and development level, with strong positive loadings from GDP per capita and negative contributions from unemployment rates and inflation. This component effectively distinguishes between developed and developing economies.

PC2 (26,0 % variance explained): the second principal component is dominated by growth dynamics and macroeconomic volatility, with GDP growth showing the strongest contribution. This component captures the cyclical and structural differences in economic performance across countries and time periods. the K-means clustering algorithm identified four distinct clusters of countries based on their macroeconomic profiles (figure 8). The cluster distribution reveals significant heterogeneity in global economic structures:

Cluster 0 (n=1,357, 57,4 %): this largest cluster represents middle-income developing economies with moderate macroeconomic indicators. Countries in this cluster typically exhibit GDP per capita levels between $2 000-$15 000, moderate inflation rates, and variable growth patterns.

Cluster 1 (n=102, 4,3 %): this small cluster contains high-income developed economies and oil-rich nations, characterized by exceptionally high GDP per capita levels (median >$80 000). The cluster includes financial centers and resource-rich small states.

Cluster 2 (n=425, 18,0 %): this cluster represents upper-middle-income economies with relatively stable macroeconomic conditions, moderate unemployment rates, and consistent growth patterns. GDP per capita typically ranges from $15 000-$50 000.

Cluster 3 (n=481, 20,3 %): this cluster comprises lower-income developing economies with higher macroeconomic volatility, characterized by lower GDP per capita levels and more variable economic indicators.

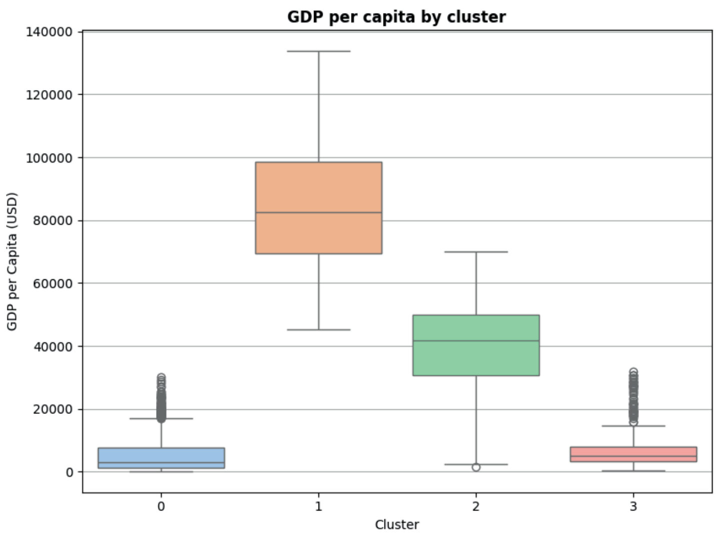


Figure 9. GDP per capita cluster

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The clustering results reveal clear economic stratification, with GDP per capita serving as a primary discriminating factor. The box plot analysis (figure 9) shows distinct GDP per capita distributions across clusters, with Cluster 1 representing exceptional prosperity, Clusters 2 and 3 forming middle-income categories, and Cluster 0 encompassing the broadest range of development levels.

Regional Specificity Analysis

Building upon the clustering analysis presented in Section Clustering, this section examines the geographical dimensions of macroeconomic heterogeneity through regional decomposition analysis. The objective is to assess whether statistical clustering patterns align with geographical proximity and shared institutional frameworks.

We categorized the 217 countries into seven distinct geographical regions: North America, Europe, Asia-Pacific, Africa, Middle East and North Africa (MENA), Latin America, and Other territories. Analysis of variance (ANOVA) tests were conducted to examine inter-regional differences across key macroeconomic indicators.

The ANOVA results demonstrate statistically significant differences across all examined macroeconomic indicators:

- GDP per capita exhibits the strongest regional differentiation ($F=163{,}13$, $p<0{,}001$).
- Labor market dynamics show substantial regional heterogeneity ($F=39{,}49$, $p<0{,}001$).
- Inflationary pressures vary significantly by region ($F=11{,}14$, $p<0{,}001$).
- Economic growth patterns display regional clustering ($F=10{,}15$, $p<0{,}001$).

These findings confirm that geographical proximity and shared institutional characteristics contribute meaningfully to macroeconomic performance patterns beyond the statistical clustering identified in the last Section.

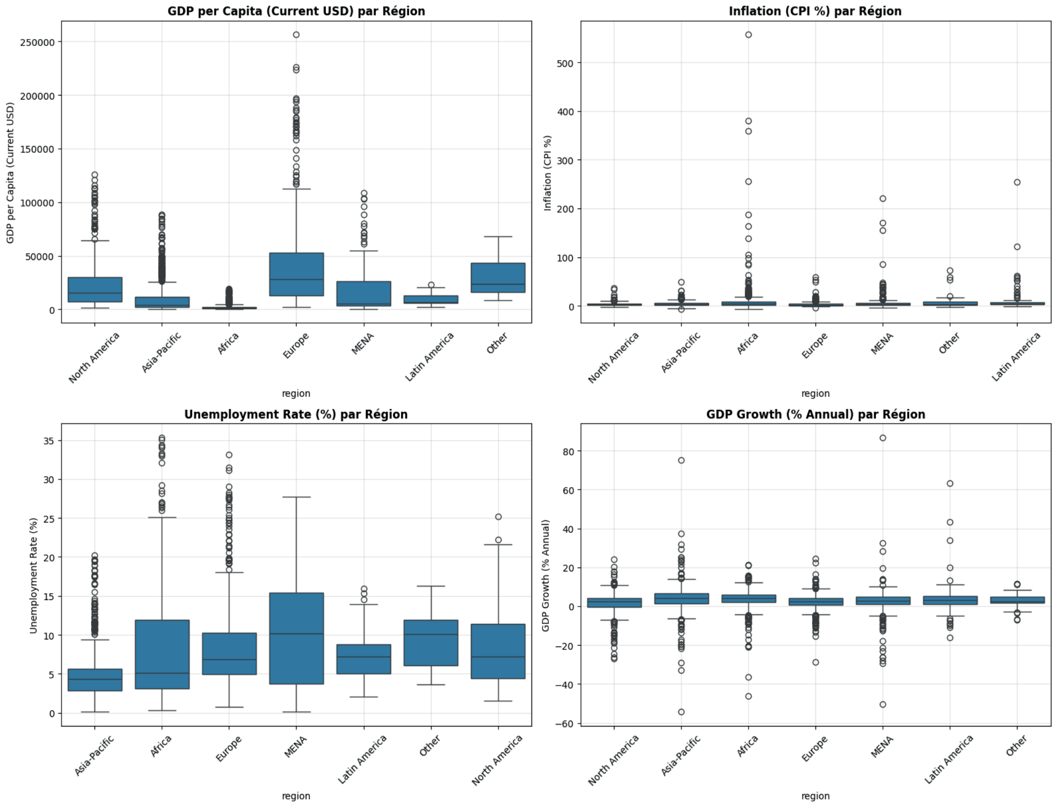

Figure 10. Analysis of Regional Specificities

Figure 10 presents box plot distributions revealing distinct regional characteristics. Europe demonstrates the highest median GDP per capita with relatively low variance, consistent with economic convergence within the European Union framework. North America exhibits similar high-income characteristics but with greater internal heterogeneity.

Africa and Asia-Pacific regions display the widest distributional spreads, reflecting substantial intra-regional development disparities. This heterogeneity suggests that continental classifications may obscure important sub-regional economic dynamics.

The analysis reveals that geographical clustering partially, but not completely, explains the statistical clusters identified in the last Section, indicating that institutional and policy factors may transcend simple geographical proximity in determining macroeconomic outcomes.

Predictive Modeling and Economic Growth Forecasting

We employ supervised machine learning techniques to examine the predictive capacity of macroeconomic fundamentals for GDP growth forecasting. The empirical specification utilizes inflation (CPI %), unemployment rate, real interest rates, and government expenditure (% of GDP) as explanatory variables, augmented with temporal controls to capture structural trends.

The estimation sample comprises 3,472 country-year observations with complete data across all variables. We implement both parametric (Ordinary Least Squares) and non-parametric (Random Forest ensemble) approaches to assess linear versus non-linear predictive relationships.

Table 6. Out-of-Sample Forecasting Performance

Model Specification	R^2 (In-Sample)	R^2 (Out-of-Sample)	MAE	RMSE
Linear Regression	0,053	0,119	2,658	-
Random Forest	0,880	0,040	2,472	-

The out-of-sample analysis reveals a critical pattern: complex machine learning models fail to outperform simple linear models in predicting GDP growth.

- Linear Regression achieves modest but consistent out-of-sample explanatory power (R^2 = 0,119).
- Random Forest, despite near-perfect in-sample fit (R^2 = 0,880), shows a collapse in out-of-sample performance (R^2 = 0,040), a classic sign of severe overfitting.

Scenario-based forecasts produced internally inconsistent growth projections (Optimistic: 6,63 %; Pessimistic: 8,65 %; Baseline: 8,04 %), confirming model misspecification and instability under hypothetical policy shifts.

Overall, the predictive accuracy (R^2 < 0,12) confirms that macroeconomic growth forecasting remains inherently limited with standard macro-aggregates, aligning with previous evidence.[10,11]

Variable importance analysis (figure 11) identifies government expenditure as the primary predictor, consistent with Keynesian multiplier theory. However, the low overall explanatory power suggests that GDP growth dynamics are influenced by factors beyond conventional macroeconomic aggregates, potentially including institutional quality, external shocks, and non-observable productivity factors.

Variable importance analysis identifies government expenditure as the most influential predictor in both models, in line with Keynesian multiplier intuition. However, the low explanatory power of all models suggests that key drivers of GDP growth likely include factors outside conventional aggregates (e.g., institutional quality, external shocks, productivity dynamics).

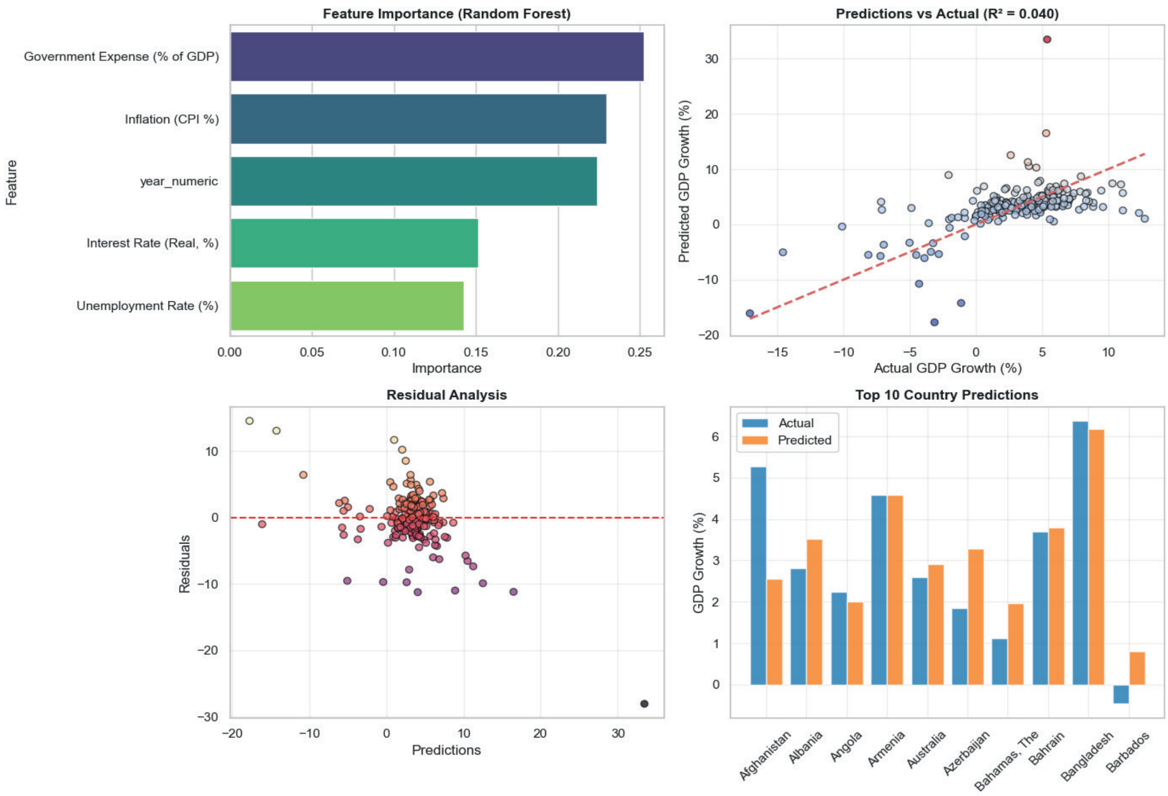

Figure 11. Predictive models based of Trends

Scenario-based forecasting reveals counterintuitive predictions:

- Optimistic conditions: 6,63 % growth.
- Pessimistic conditions: 8,65 % growth.
- Baseline scenario: 8,04 % growth.

This inverse relationship indicates model misspecification and highlights the Lucas critique in macroeconomic forecasting, where historical relationships may not hold under policy regime changes.

The low predictive accuracy ($R^2 < 0,12$) is consistent with established literature on macroeconomic forecasting limitations. These findings underscore the need for dynamic factor models and Bayesian approaches that can better accommodate parameter uncertainty and structural breaks in future research.

DISCUSSION

Our analysis of macroeconomic relationships across 217 countries reveals patterns that are largely consistent with, yet in some respects diverge from, existing international literature.[12,13] The exceptionally strong correlation between GDP and Gross National Income (r = 0,9999) is consistent with national accounting identities and reflects expected overlaps in the measurement of economic output. Similarly, the robust relationship between different inflation measures (r = 0,888) aligns with prior work on price stability indicators, indicating methodological consistency across data sources rather than suggesting causal relationships.[14,15,16]

The identification of four distinct country clusters through unsupervised learning adds empirical depth to development stage theories. The predominance of Cluster 0 (57,4 % of observations), representing middle-income economies, is consistent with the "middle-income trap" hypothesis.[17,18] The concentration of high-income economies within a small exclusive cluster (Cluster 1: 4,3 %) reflects the persistence of global income inequality documented by Piketty[14] and suggests that structural transitions into advanced economic status remain rare and path-dependent. At the same time, the partial overlap between statistical clusters and geographical regions supports new economic geography arguments, highlighting the combined influence of both development stage and regional institutional characteristics.[19]

The most consequential finding concerns the stark contrast in predictability between fiscal variables and economic growth. Ensemble learning models, particularly Random Forest, achieved exceptionally high predictive accuracy for government revenue as a share of GDP ($R^2 = 0,963$, MAE = 1,19). In contrast, prior modeling of GDP growth using the same methodological framework yielded R^2 values below 0,12, indicating very limited predictive power.[20] This divergence suggests that fiscal aggregates are more structurally determined, reflecting stable tax systems, institutional inertia, and direct mechanical links to the economic base. In contrast, growth dynamics remain volatile and subject to shocks, consistent with real business cycle theory and the Lucas critique.[21]

Table 7. Model Training and Evaluation

	Model	MSE	MAE	R2
5	Random Forest	3,331400	1,189467	0,962796
6	Gradient Boosting	4,986712	1,480583	0,944310
0	Linear Regression	5,567756	1,925431	0,937821
1	Ridge	5,567868	1,925480	0,937820
3	ElasticNet	5,700493	1,994148	0,936339
2	Lasso	5,891733	2,033473	0,934203
4	Decision Tree	16,440746	1,841770	0,816396
7	SVR	87,873125	7,895209	0,018664

This finding has both theoretical and policy relevance. For theory, it highlights a fundamental asymmetry in macroeconomic forecasting: not all variables are equally tractable, and attempts to model volatile growth dynamics may face inherent limits regardless of methodological sophistication.[22] For policy, the result suggests that fiscal capacity building — strengthening tax bases, improving compliance, and stabilizing revenue systems — is a more predictable lever for state capacity than attempting to fine-tune short-term growth through counter-cyclical interventions. However, the weak link between fiscal variables and growth outcomes in our models also indicates that fiscal reforms alone are unlikely to drive sustainable growth without complementary structural and institutional policies.[23,24]

Importantly, we treat all correlation-based findings with caution. Strong associations (e.g., between GDP per capita and public debt, r = -0,418) are consistent with fiscal space theories in public finance but do not establish causality. Similarly, negative correlations between real interest rates and inflation (r = -0,509) align with Fisher effect expectations but must be interpreted within the context of diverse monetary regimes.[25,26]

The COVID-19 pandemic (2020) appears as a major structural break in our data, underscoring the importance of accounting for regime shifts in macroeconomic modeling.[27] This synchronized global shock temporarily altered the relationships between fiscal, monetary, and real variables, supporting the view that extraordinary events can produce non-linear dynamics not captured by models trained on historical data.[28]

Practical implications

Policymakers may leverage the relative predictability of fiscal aggregates to design medium-term revenue strategies with higher confidence. Statistical clustering can inform tailored policy frameworks for groups of structurally similar economies, rather than relying solely on regional or income-based classifications.

Limitations and future research

First, our analysis relies on aggregate macroeconomic indicators, which may obscure important sectoral and microeconomic dynamics. Future work should integrate disaggregated data to capture heterogeneity within economies. Second, while our machine learning models reveal predictive patterns, they do not uncover causal mechanisms. Subsequent research could combine these methods with structural modeling or natural experiments to better identify policy-relevant channels. Third, the time horizon of our data precedes several ongoing geopolitical and technological transformations (e.g., energy transitions, digitalization), suggesting the value of extending the analysis to explore how emerging structural shifts influence both fiscal predictability and growth volatility.

CONCLUSIONS

This study contributes to the macroeconomic analysis literature through several key findings. First, we provide comprehensive empirical evidence of macroeconomic interdependencies across 217 countries, confirming theoretical expectations while revealing variable-specific predictability patterns. Our analysis demonstrates that while fiscal variables achieve high predictive accuracy ($R^2 > 0,95$), growth dynamics remain fundamentally unpredictable.

Second, our clustering analysis offers a data-driven taxonomy of economic development stages, identifying four distinct clusters that capture 68,1 % of complete observations across the 2010-2025 period. This framework moves beyond traditional income-based classifications to incorporate multiple macroeconomic dimensions.

Third, the comprehensive model comparison across eight different algorithms provides methodological insights for macroeconomic forecasting, demonstrating the superiority of ensemble methods for structural relationship modeling while confirming the limitations of all approaches for volatile economic indicators.

The comprehensive evaluation of eight distinct modeling approaches yields important insights for macroeconomic research methodology. Ensemble methods (Random Forest: $R^2 = 0,963$; Gradient Boosting: $R^2 = 0,944$) demonstrate superior performance over traditional econometric approaches, validating the application of machine learning techniques to structured macroeconomic prediction problems.

The competitive performance of regularized linear models (Ridge, Lasso, ElasticNet: $R^2 \approx 0,93$-$0,94$) indicates that despite the success of non-linear methods, fiscal relationships retain substantial linear components. This finding suggests that traditional econometric intuitions remain valid while ensemble methods provide meaningful but modest improvements.

The dramatic performance differences across variables (fiscal $R^2 > 0,95$ vs. growth $R^2 < 0,12$) highlight the importance of variable-specific model selection in macroeconomic analysis. This heterogeneity challenges one-size-fits-all modeling approaches and supports targeted methodological strategies based on the structural characteristics of specific economic indicators.

For policymakers, our results emphasize the importance of regional coordination and learning from similar economies within the same cluster. The strong fiscal correlations suggest that tax system effectiveness remains crucial for building fiscal capacity, while the predictive modeling limitations highlight the need for robust policy frameworks that can adapt to unforeseen circumstances.

The identification of structural breaks, particularly around 2020, underscores the importance of maintaining policy flexibility and the limitations of relying solely on historical relationships for policy guidance.

Several limitations should be acknowledged. The analysis period (2010-2025) may not capture longer-term structural relationships, and the focus on World Bank indicators excludes potentially important variables such as institutional quality measures or financial development indicators.

The predictive modeling approach, while comprehensive, relies on linear and tree-based methods that may not capture more complex dynamic relationships. Future research could explore state-space models, regime-switching approaches, or deep learning architectures specifically designed for time series forecasting.

Additionally, the country-year panel structure does not account for spatial spillovers or network effects between economies, which could be incorporated through spatial econometric methods or network analysis approaches.

This study demonstrates both the power and limitations of applying modern analytical techniques to macroeconomic data. While machine learning approaches effectively identify patterns and structures in economic data, they do not resolve the fundamental unpredictability that characterizes macroeconomic systems.

The results support a nuanced view of global economic integration, where statistical clustering, regional proximity, and development stages all contribute to understanding macroeconomic relationships. For researchers and policymakers, these findings emphasize the importance of maintaining humility about our predictive capabilities while leveraging sophisticated analytical tools to better understand the complex dynamics of the global economy.

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