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A Comparative Machine Learning, and Econometric Analysis of Macroeconomic Growth.

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Abstract

Globalization and macroeconomic integration have substantially transformed the economic structure of developing economies, yet accurately identifying and forecasting the determinants of economic growth remains challenging because macroeconomic relationships are often nonlinear, highly interdependent, and structurally unstable. This study investigates the major macroeconomic determinants of Pakistan's economic performance over the period 1960–2021 and develops a comparative framework between conventional Multiple Linear Regression (MLR) and Random Forest (RF) regression. Gross Domestic Product (GDP) is considered the principal measure of economic performance, while inflation, per capita income, foreign investment, military expenditure, and gross national expenditure are incorporated as explanatory variables. The analysis combines conventional regression estimation with extensive diagnostic assessment and nonlinear machine-learning techniques to evaluate both statistical validity and predictive robustness. The MLR model produces an exceptionally high in-sample explanatory power, with an R-Squared of approximately 0.9994; however, diagnostic analysis reveals substantial heteroscedasticity and severe multicollinearity among key economic predictors, with variance inflation factors exceeding 29 for several variables. These findings demonstrated that conventional goodness-of-fit measures can provide a misleading assessment of model reliability in the presence of structural deficiencies. In contrast, the random forest (RF) model provides a more robust framework for capturing complex and nonlinear relationships among macroeconomic variables and demonstrates stronger out-of-sample stability. Variable-importance analysis identifies foreign investment, military expenditure, and gross national expenditure as the dominant predictors of GDP, while partial dependence analysis indicates positive but nonlinear relationships characterized by diminishing marginal effects. Per capita income contributes comparatively less to predictive performance. Overall, the findings investegated that predictive accuracy should be evaluated alongside structural validity and diagnostic robustness rather than relying solely on conventional fit statistics. The study highlights the value of machine-learning approaches for macroeconomic forecasting in Pakistan and provides evidence that economic growth is driven by interconnected and nonlinear economic mechanisms, with important implications for evidence-based macroeconomic policy and forecasting.

Keywords: Globalization; Economic Growth; Pakistan; Gross Domestic Product (GDP); Macroeconomic Determinants; Multiple Linear Regression; Random Forest; Machine Learning; Multicollinearity; Heteroscedasticity; Variable Importance; Nonlinear Relationships; Macroeconomic Forecasting.

Introduction

Globalization has got various definitions and meanings. It is a complex phenomenon having strong social, political and economic implications. However, the term became common in the early eighties, even though it has never been defined properly, it is common today to discuss.

The Globalization of political economy that is being extremely rapidly integrated and interconnected due to the development of technology, communication and transportation by Lee [22]. International trade, liberalization of financial markets, expansion of foreign investment (FI) and intensified flow of people, ideas, information, and culture across borders all characterize this phenomenon. It also incorporates the cross border arrangement of production, where goods and services are created, distributed and sold using globally distributed supply chains [31]. It is also associated with a trend towards aligning and coordinating the economic and regulatory policies of nationalities to provide common standards and collaborative governance as well as more unified approach to global issues. The theory of globalization is also discussed by Virjan [26]. The period between 1870 and 1914 has seen the integration of the world into one global economy with one dominant power. Governments in this era were ones that had minimal roles and were highly constrained including the gold standard as well as lack of flexibility in monetary policies. Over the next few years, governments acquired broader roles such as the achievement of macroeconomic goals such as full employment, economic growth and price stability [3].

Although the greater use of macroeconomic instruments facilitated the greater integration of the economy of a country, Pakistan experienced a paradoxes effect whereby, with the greater international interdependence, there were periods of international economic fragmentation [19]. Having used over-valued exchange rates, import controls and export taxes, the Pakistan adopted an import substitution model after independence in 1947.The Pakistan and other developing nations were inspired by the Western industrialization and equated development to IS in the 1950 and 1960. Although, It was succeeded by the later method of preference as a result of financial difficulty and the success of exports promotion in certain countries in the East [32]. Past research has been conducted on the relationship between economic growth and other variables of globalization with major emphasis put on foreign direct investment (FDI).Forecasts of Economic Growth by Using Machine-Learning Algorithms (MLA) through Sentiment Index Analysis in Economy of Pakistan [25]. The variables of interest to be predicted by the fiscal authorities and the central banks to an economy are output growth, the rate of inflation and interest rates. Pakistan macroeconomic forecasting in data-rich setting [24]. Here, we combine the RF machine learning (non-linear regression) and the conventional econometric models (linear regression) to understand non-linear additions in investment analysis. What we find is that GDP growth has a positive effect on corporate investment but it differs widely across the regions .Comparison of two shrinkage and feature selection techniques to model GDP in Pakistan [3]. Comparative Analysis of RF and multilayer perceptron algorithms to predict GDP. Wheat in 2024 International Conference on Emerging Trends in Networks and Computer Communications .Wheat is the staple food of Punjab province of Pakistan, which produces over 75% of the national produce. Proper and in time prediction of the wheat output is one of the pillars to keep track of food security and agricultural market strategizing, yet the effectiveness of the existing system to predict near real-time should be enhanced Forecasting wheat yield from weather data and MODIS NDVI using Random Forests to Punjab province, Pakistan [20].

Research focused on the effects of globalization on poverty in the developing countries. They noted that over 50 percent of the developing countries which were experiencing globalization had subjected to significant growth in trade and huge decreases in tariff barriers [1]. Natural resource utilization has remained to be one of the most important elements of the world economy with a considerable amount of GDP per capita being based on extractive resources [23]. Vivarelli [28] examined the effect of globalization on the economy of Pakistan based on the available data covering the period between 1960 and 2006. Globalization has great potential of alleviating poverty in the world as many countries have a lot of integration and collaborations. It has the ability to influence low-income and developing nations in a positive way, not only directly, by providing more access to the international markets, the capital, and the investments, but also indirectly, by giving them a chance to exchange their cultural values, social practices, scientific knowledge, and technological inventions. This interaction will help in capacity building, productivity, increased access to modern tools and education and eventually sustainable economic growth and development because of increased trade and financial flows [10]. A thorough analysis to discuss how globalization relates to economic growth .Their analysis was specifically on the general globalization index together with its different components, such as the economic, social, and political dimensions of globalization. They sought to learn how different dimensions of globalization affect the economic performance of a country by studying each of these sub-indexes [7]. The current processes of globalization are viewed as a sort of modern colonialism [6].The role of natural resources in the globalization and growth of Pakistan has been explored. A comparison was done on economic growth in Africa [16]. Some of the large low-income countries like India and China have successfully used globalization to their advantage, recording a spectacular rate of economic growth and consequently contributing to the alleviation of some inequalities in the world [33]. Rahman [17] investigated the correlation between globalization and economic growth and came up with the same conclusion that globalization has a positive implication on the economic growth. The sustainability of the Pakistani environment based on the effects of various variables. According to it, globalization has opened numerous opportunities to some people and nations. Literacy levels, school attendance rates, infant mortality and life expectancy are key social indicators, which have significantly improved in recent decades. Asia in particular has benefited extensively through globalization and has aided in raising the global output with the contribution of the owners of the capital [9]. The effects of globalization on the economic growth of the 27 countries of the European Union (EU-27) have been explored, revealing that the growth of SMEs mediates this relationship [34]. The role of innovation in supporting the increase in the GDP of Pakistan has been studied and discovered that the growth of SMEs mediates this relationship [14]. The need to explore the effects of globalization on the economic growth of the Globalization is not just about economic exchange. It also involves cultural exchange and political interdependence hence redefining the place of nation state within the global system [31]. Zubair [36] explained that the different asymmetric effects of misalignment in the exchange rates on the economic growth of Turkey, with some significant insights discovered, using the analysis of threshold effects

This study aims to investigate the effects of globalization related to the economic performance of Pakistan between 1960 and 2021.In order to empirically examine these impacts. We first used the MLR model to be the major econometric tool to approximate the association among globalization-related variables (such as FII, trade openness, and external debt) and the main macroeconomic implications, which comprise the GDP growth, GNP and inflation. But during the analysis, intensive diagnostic testing, without which cannot be assured of sound findings, showed inherent structural defects in the MLR model such as extreme levels of multicollinearity, autocorrection in the residual, and non-Normal errors. As a result, the study was extended to an essential comparative study of the MLR model and the non-linear, ensemble RF regression model. Such a methodological expansion will enable us to quantify the predictive power and structural stability of both conventional econometric procedures and more sophisticated machine learning procedures, which ultimately will lead to the increased validity and accuracy of our results and policy advice.

Methodology

The next subsections contain a detailed description of the data, study variable, and sources of data. Also, the regression model employed as the analysis method is briefly introduced.

Data Description

Economic growth is generally determined by the real GDP, but it is a variable affected by a very broad spectrum of factors. These factors may have different significance and influence in different countries and may change in the course of time. In most developing countries, gross investment is a proxy of capital due to the inaccessibility of reliable data of capital stock, which is attributed to the challenges in measurement. This further be divided into public and private sector investments to determine the contribution that the economic growth makes by them. In order to assess the level of economic integration of Pakistan, two measures of openness are used. The first one is the ratio of imports sum (M) and exports sum (X) to GDP which is the trade openness and interdependence on the international level. The second is the ratio of the aggregate capital inflows and outflows to GDP that is the indicator of financial integration. The sum of official aid and foreign direct investment is a measure of capital inflows and the absence of a consistent time series lead to a measure of capital outflows which is a proxy of debt servicing. Health and education are critical areas of development and necessary factors in economic development. Health is key to productivity and school attainment of successful education is deeply rooted in having good health.

Study Variable

The main variable of this empirical research will be the GDP, expressed in current US dollars, as the main dependent variable in our regression analysis. GDP is a monetary total of all final goods and services that are produced in the geographical boundaries of a country during the period of the study and it is the ultimate indicator of the overall economic activity and well-being of a country. A high rate of GDP growth indicates economic growth hence the variable GDP will be the response variable, a low or negative rate will indicate economic difficulties or even recessions hence the variable GDP will be used to accurately model and measure the long-term effect of the various macroeconomic variables related to globalization in this instance, the rate of inflation, per capita income, foreign investment (FII), military expenditure (ME), and gross national expenditure (GNP).

Technique of Analysis

This study has used the dual model approach to guarantee the strong and structural validity of the results, starting with the traditional econometrics and further proceeding to the advanced machine learning MLR and Ordinary Least Square Estimates (OLS). The analysis has started with Multiple Linear Regression model which is a fundamental econometrics model used to estimate the linear relationship between the dependent variable and a series of independent variables. The overall structure of MLR equation is as $Y = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \varepsilon_i$, where Y is taken as response variable, α is intercept term, $\beta's$ are all slopes of corresponding k independent variables and ε_i is error term. The response and explanatory variables are: Y = Gross Domestics Product,(GDP) X_1= Inflation. Rate (consumer price index) ,X_2=per capita income (PCI), X_3= Foreign investment (FII), X_4=Military expenditure (ME), X_5=Gross national expenditure (GNP). The estimates of the parameters were done through OLS technique. It is a powerful estimator as it will reduce the total squared deviation between the values observed and the ones estimated by the model. Importantly, the OLS estimator is also deemed consistent when regressors are exogenous, and most efficient linear unbiased estimator (BLUE) only under several essential assumptions: namely, the lack of severe multicollinearity between predictors, the homoscedasticity of error terms, and serially independent nature [37]. RF model, Since data in macroeconomics are complex to process (notably non-linear relationship, high dimensionality), as well as the fact that the errors are not consistently connected with one another, it was necessary to use Random Forest is an ensemble learning algorithm that builds a large number of decision trees and averages their individual predictions to form a final, robust prediction [21]. The algorithm has two main mechanisms that help to reduce the threat of overfitting and contend with the high variance of complex data.(1)Bagging (bootstrap aggregation): each decision tree is trained on a random sample of the data, and (2)Random Subspace Method, in which only a random subsample of features is assumed at each split .This structure renders the Random Forest model particularly effective at stable prediction when non-linear interdependences and extreme multicollinearity that were subsequently identified in the MLR framework are present**.**

Results

A critical paradox exists in the first quantitative comparison of the MLR and RF models in Table 7 in its summary form. The MLR model seems to be the better predictor, which is reported to have an almost perfect in-sample R-squared and much smaller error magnitudes on the test set with a RMSE and MAE. This is supported by the model selection criterion, where the MLR model has lower complexity scores AIC and BIC than the RF model AIC and BIC, and the simpler and less complex model, the MLR, is highly favored under the principle of parsimony. But such a quantitative measure is very deceptive. The RF model has far greater errors RMSE, MAE and a lower R-squared, but it turns out that the MLR apparent accuracy is an illusion of failure in the structure which results in the only stable and reliable RF) models to be the sole solution when it comes to forecasting**.**

Regression Diagnostics

Table 1:Assessment of Heteroscedasticity Using Breusch-Pagan Test

	Model	df	p-values
Bp	11.896	5	0.036

Table 1 presents that Breusch-Pagan test is applied to test the heteroscedasticity, where the H0 (variances of errors are equal (homoscedasticity)). A p-value of less than the threshold (0.03624 < 0.05) indicates that the p-value is below the standard 5% (alpha = 0.05) level since the reported p-value is less than 0.05. Under statistical tradition, this outcome is sufficiently convincing that H0 is rejected. Hence, the right conclusion would be that the regression model has statistically significant heteroscedasticity,

Table 1 : Test for Serial Correlation Using Durbin-Watson Statistic

Lag	Autocorrelation	Durbin Watson Statistic
1	0.064	1.700

Table 2: The results of the Durbin-Watson test reveal that the residuals have no significant signs of the first-order autocorrelation. The Durbin-Watson is equal to 1.70023 which is close to 2, the desired value which indicates the absence of autocorrelation. The Autocorrelation value at Lag 1 is very low at 0.06402 and this is a strong indication that supports this conclusion. Lag 1 autocorrelation is small and the Durbin -Watson value is close to 2 indicating that the error terms are independent enough across observations. Thus, the conditions of independent residuals are satisfied and the estimates of standard errors as a method of hypothesis testing in the regression model can be regarded as effective with references to serial correlation.

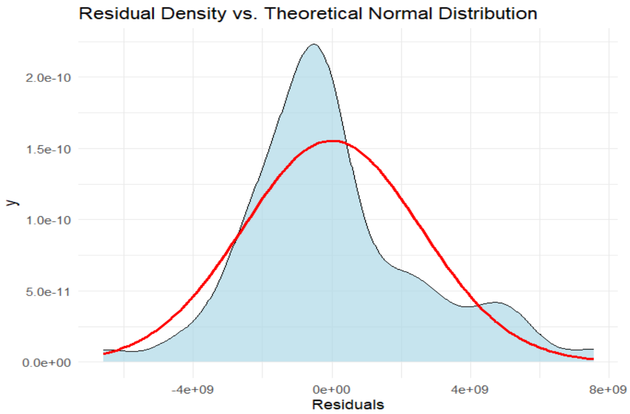

Figure 1 Diagnostic Plot: Distribution of Multiple Linear Regression (MLR) Residuals Compared to Theoretical Normality.

Figure 1 indicates that, the plot presents Residual Density (shaded in blue) in relation to a Theoretical normal distribution (smooth red curve), which is a visual verification of the normality assumption. The normality can be seen as the result of blue residual density being far off the red normal curve. In particular, the distribution of the residuals is skewed (or peaked) around the mean.

Table 3.Multicollinearity Diagnostics for in dependent Variables

Model Variables	**Collinearity Statistic**	
	Tolerance	VIF
$\mathbf{X_1}$	0.9286	1.0723
$\mathbf{X_2}$	0.9184	1.08806
$\mathbf{X_3}$	0.0335	29.82
$\mathbf{X_4}$	0.02553	39.15
$\mathbf{X_5}$	0.01415	70.64

Table 3 shows that, the multicollinearity test indicates that, the first two variables are free of any multicollinearity (VIFs of close to 1.0 and Tolerances of close to 0.9), whereas the final three variables have severe multicollinearity (VIF of 29.82, 39.15, and 70.64), and Tolerances are significantly lower than the usual set at 0.10.

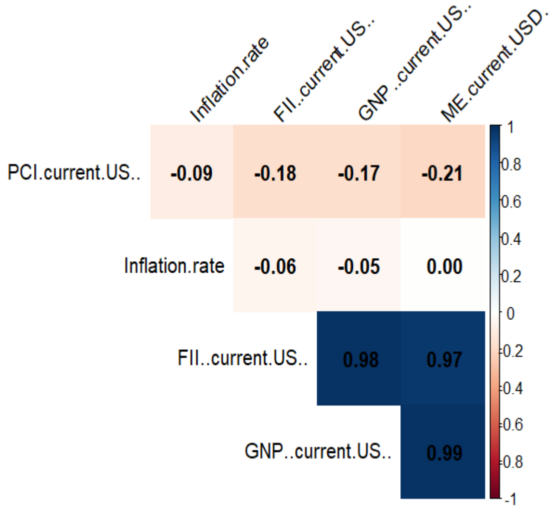

Figure 2: Correlation Matrix of Explanatory Variables (Inflation Rate, FII, GNP, ME) and Per Capita Income (PCI).

Multicollinearity among the predictor variables is also visually checked through Correlation Matrix Plot (Correlogram) displayed in figure 2.In particular, it is the case that there is an almost perfect correlation, GNP and FII is correlated at 0.98 and ME And GNP. Correlations of ME and FII are 0.97 and 0.99 respectively. Such close to 1.0 correlation will lead to very high values of VIF, and the model will not be able to reliably separate the specific effect of the highly correlated variables. On the other hand, the only weak negative correlations are observed between variables that include the (Inflation rate + Per Capita Income PCI) (e.g., -0.09 to -0.21). To eliminate the multicollinearity, the model involves the deletion of one or more of the highly correlated monetary variables GNP, FII and ME.

Table 4: Performance Evaluation of the Multiple Linear Regression Model for GDP Prediction

MLR Model	MSE	RMSE	MAE	R-squared	Adjusted-R-squared	AIC	BIC
	4×10^{18}	1.5×10^{9}	2.0×10^{9}	0.9994	0.9993	2326.1	2339

Table 4 shown that, the results of performance demonstrates that MLR model perfectly fits the data. The R-squared is 0.999 and this implies that the model accounts more than 99.9 percent of the variation in GDP indicating that the relationship between predictors and GDP is very strong. The fact that the Adjusted- R-squared is 0.9993 indicates that after the number of predictors is adjusted, the model has a very high explanatory power, that is, the predictors are significant and they have a positive contribution to the explanation of changes in GDP. The error measures indicate that the MSE = $4.06\text{x}10^{18}$, RMSE= $1.5\text{x}10^{9}$ and MAE = $2.0\text{x}10^{9}$ are very small compared to the actual GDP figures which are between 1011. This implies that the error in prediction is small as compared to the size of GDP, a good indicator of high model accuracy. The AIC = 2326.13 and the BIC = 2339.52 are used to measure the quality of the model and discourage the introduction of unnecessary complexity. The comparative low values indicate that the model is not only efficient but it is also statistically balanced in terms of fit and simplicity.

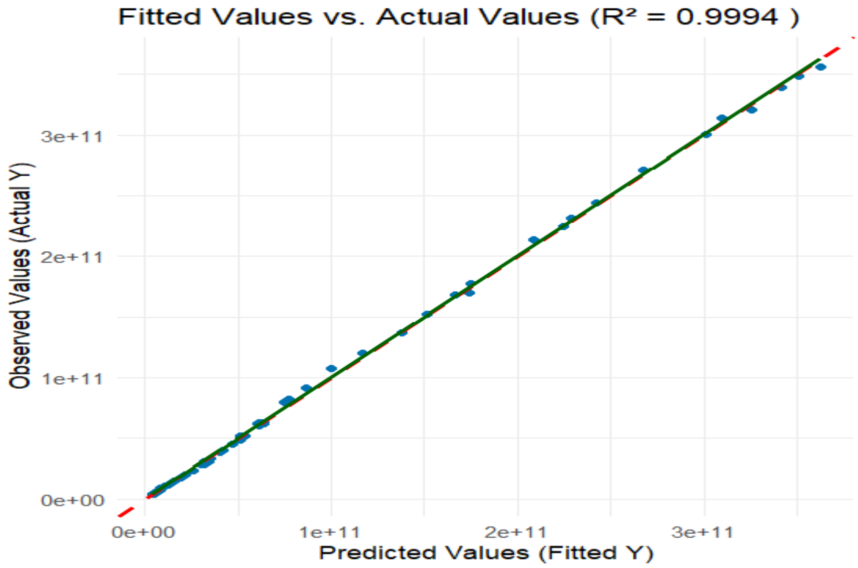

Figure 3: Fitted vs. Actual Values Plot: Multiple Linear Regression (MLR) Model In-Sample Goodness-of-Fit.

The Figure 3 demonstrates that, The Fitted Values vs. Actual Values plot represents the goodness-of-fit of the model by comparing the outcomes (x-axis) predicted by the model with the outcomes (y-axis) observed in reality. The very large value of R-Squared = 0.9994 is graphically verified when the data points plot nearly horizontally along the red dashed line indicating a situation where Predicted Y = actual Y. The trend line of the model, the green line, practically coincides with the perfect fit line, which means that the model can explain the variation of the outcome variable by 99.94. Although this is indicative of an extremely good fit, especially when used with log transformations, which tend to be most effective. When the highly correlated macroeconomic time series data are utilized, this almost perfect fit ought to be looked into with serious consideration as to the possibility of data leakage or overfitting.

Table 5: Performance Metrics of Random Forest Model

Rf_model	MSE	RMSE	MAE	AIC	BIC	R-squared
	4.39×10^{19}	6.63×10^{9}	5.414×10^{9}	2477.244	2668.447	0.9971

Table 5 demonstrated that, the RF model has an excellent predictive power as indicated by an excellent R-squared of 0.9971 implying that 99.71 percent of the variance in the outcome variable is effectively explained by the model. The large value indicates a very tight fit to the data. The error metrics that are linked to this, i.e. the RMSE=6.63×10^{9} and MSE=4.39$\times 10^{19}$, are massive in absolute terms, yet this high R -squared contextually shows the error is small in relation to the magnitude or scale of the dependent variable of the model comparison AIC=2477.244 and BIC=2668.4 ,Consequently, the model is very efficient and dependable and the error of prediction is quite low as compared to the magnitude of the values being forecasted.

Table 6: Variable Importance Metrics for the Random Forest Regression Model

Variables_ name	IncMSE	IncNodePurity
FII	23.520	1.63×10^{23}
ME	23.242	1.535×10^{23}
GNP	22.654	1.412×10^{23}
Inflation	11.943	5.098×10^{22}
PCI	5.383	4.207×10^{22}

The results of the analysis of the variable importance indicate that all the factors are significantly important to the performance of the RF model (Table 6). This table plots two major measures; Increase in MSE (IncMSE) and Increase in Node Purity (IncNodePurity).The findings always have the same three predictors as the most important ones to the accuracy of the model. The most important variables are FII, ME and GNP. The values of their (IncMSE) (23.52, 23.24 and 22.66 respectively) are very close and much higher than the rest. It means that when any of these variables are permuted, the model is the most affected with the greatest and almost equal predictive accuracy decline, which proves that the model is highly dependent on all three of them. Moreover, they (IncNodePurity) have their values in the (1023 range) which establishes their leading role in the data partitioning and variance decrease in individual decision trees. The rate of inflation is a somewhat significant predictor and has (IncMSE) of 11.94 nearly half of the significance of the first three. It plays a significant part in the reduction of prediction error but is not at the center of the core performance of the model. The least influential variable is PCI as it has the smallest value (IncMSE) of 5.38. This implies that its insertion does not help the overall fit and predictive power of the model. To sum up, it can be stated that the economic indicators that play the major role in driving the predictive power of the RF model are FII, ME current USD, and GNP, but Inflation rate and PCI current US are secondary and least important factors respectively

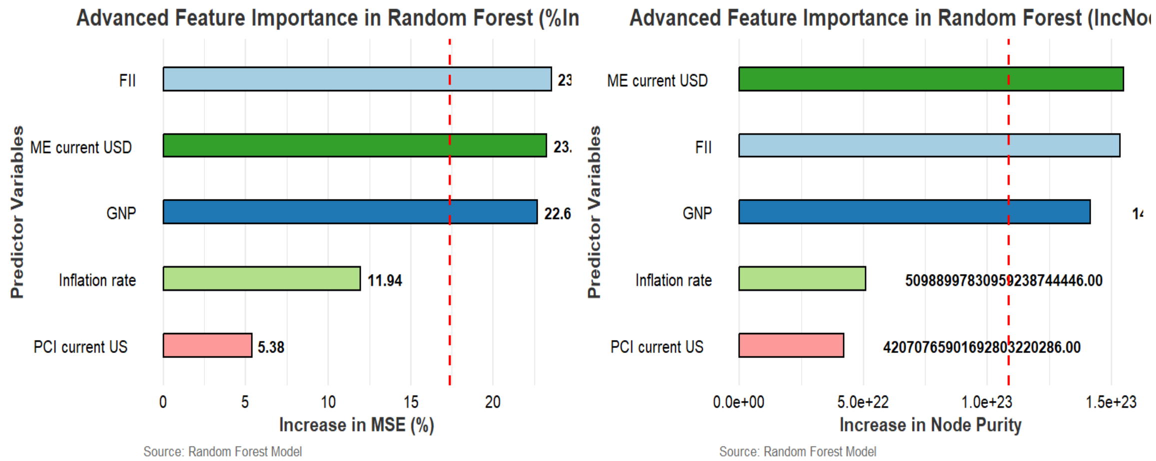

Figure 4: Advanced Feature Importance Diagnostics for Random Forest Model (Increase in MSE and Increase in Node Purity).

As Figure 4 indicates, the first bar chat demonstrates that, This horizontal bar chart, titled Advanced Feature Importance in RF (IncMSE) visually verifies the rank of predictor importance given by the percentage change in MSE (IncMSE) on permuting a variable. There is a clear indication in the graph that the top three variables, FII, ME current USD and GNP, have a greater influence on the model performance, since any shuffling of these three variables would cause a significant and almost equal decrease in the model accuracy where (IncMSE) values range between 22.6 percent to 23.5 percentage. Conversely, the Inflation rate is relatively less significant, with the (IncMSE) attribute being 11.94, and PCI current US, the least significant feature having a decrease of only 5.38% in the accuracy. This means that importance is heavily concentrated on the financial and the economic aggregate variables (FII, ME, and GNP) to influence correct predictions with the other two variables making a considerably less contribution. Second bar chart shows the importance of variables by the Increase in Node Purity (IncNodePurity), which validates the ranking formed between the (IncMSE) metric. It is clear that ME current USD, FII, and GNP are the most predictive variables, having generated the highest total reduction in the residual sum of squares in all splits in the Random Forest, with a range of values of 1.41×10^{23} to 1.51×10^{23}. On the other hand, Inflation rate and PCI current US played a much smaller role in the structural purity of the decision trees with an importance value of about a tenth the size of the top three. This is a major support of the idea that the high-level of magnitude of financial and economic aggregate variables are the basic driving force behind the structure and the predictive strength of the model.

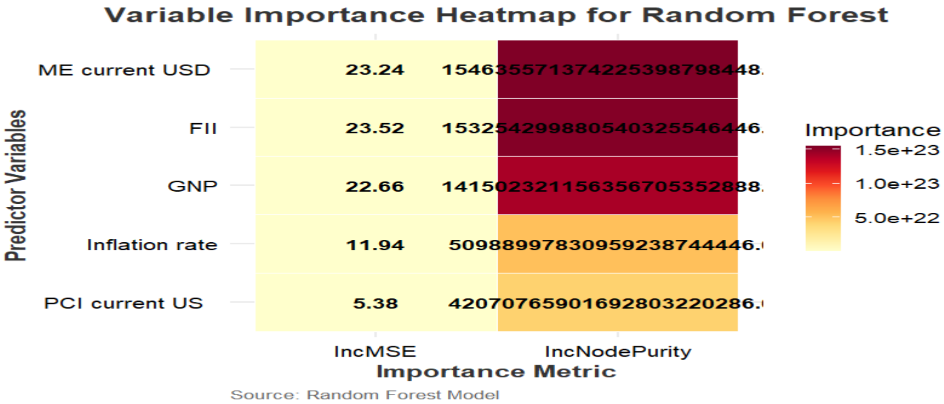

Figure 5**:** Variable Importance Heatmap for Random Forest Model (IncMSE and IncNodePurity Metrics).

Figure 5 demonstrates that, such heatmap gives a brief, visual, summary that is a strong validation of the variable importance results in both metrics; Increase in Mean Squared Error (IncMSE) and Increase in Node Purity (IncNodePurity). The three most significant economic variables ME current USD, FII, and GDP are all statistically insignificant (with the high almost identical (IncMSE) values (approximately 23)) and the darkest red shade in the (IncNodePurity) column (the values around 1.51×10^{23}).This is to show that these three variables are equally predictive of the model as well as the structural complexity of the decision trees. However, the Inflation rate, and PCI current US are represented by lighter colors (orange/yellow), which proves their insignificant contribution to the overall predictive process of the model..

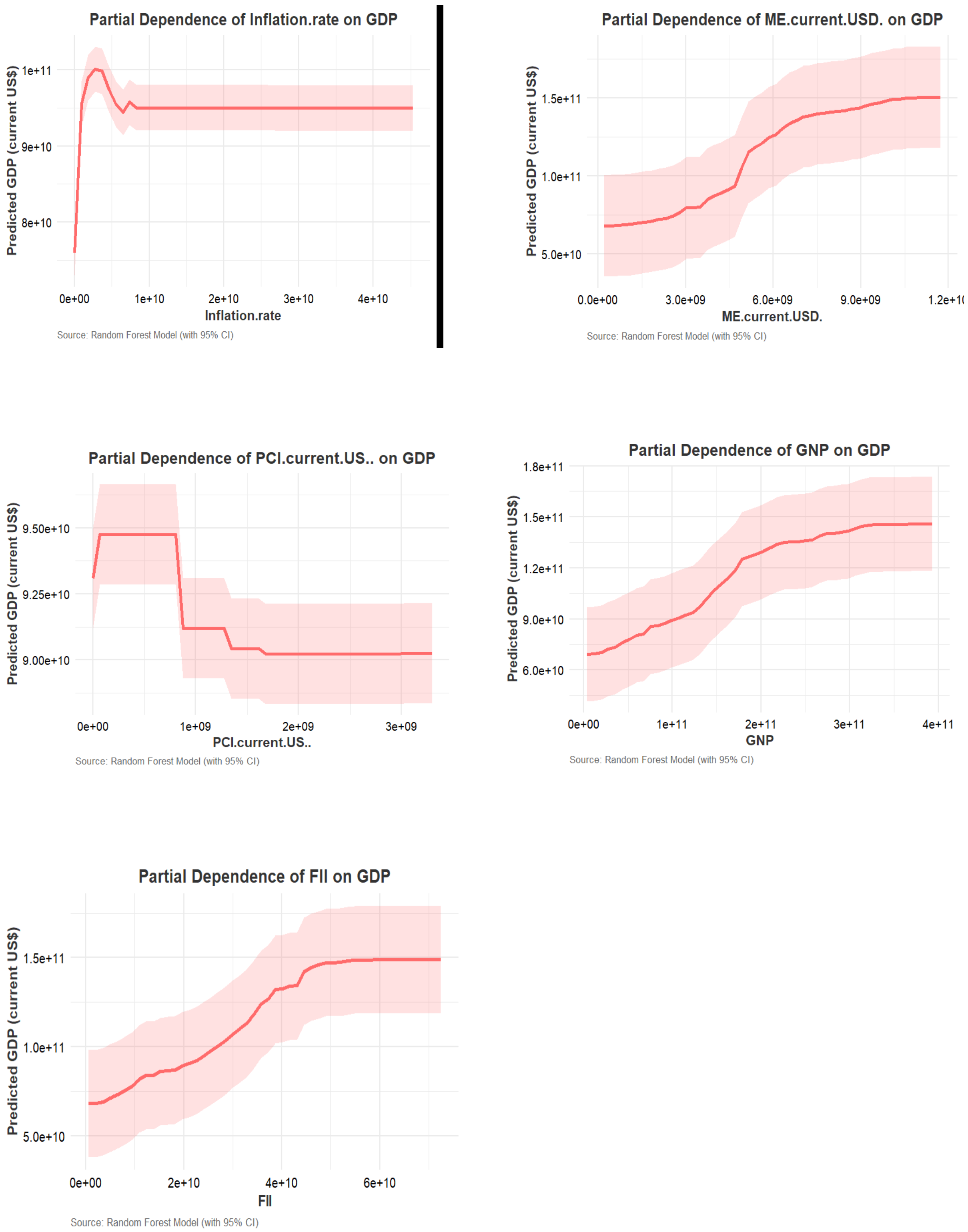

Figure 6: Partial Dependence Plots (PDPs) of Random Forest Model Predictors on Predicted GDP.

According to Figure 6,the set of Partial Dependence Plots (PDPs) demonstrates the marginal impact of every predictor on the forecasted GDP, including all the other variables identical, and to a big extent, the ranking of variable importance. All the three variables ME, FII and GNP are strongly, positively, and non-linearly related to the predicted GDP, low to medium values of these predictors relate to the predicted GDP strongly before leveling off and they appear to exhibit a diminishing return of these large-scale economic measures. Less important variables, by contrast, exhibit more complicated or weaker effects: the Inflation rate exhibits an initial steep increase in the forecasted GDP and then a steep decrease, indicating that it affects the result variable more indirectly or more diffracted, PCI exhibits an overall weak, non-monotonous relationship with the result variable, whereby it predicts GDP rise, which then decreases and then turns out to be an equilibrium.

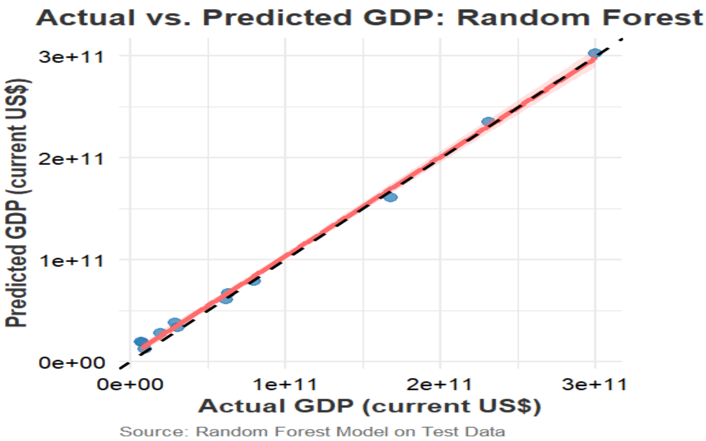

Figure 7: Predictive Calibration Plot: GDP vs. Predicted GDP of Random Forest Model (Test Data).

Figure 7 reveals that, the Actual vs. Predicted GDP scatterplot demonstrates that the Random Forest model is very predictive: the points fall very close to the 45 degree (y = x) line and the fitted regression line is very close to the 45degree line, implying that the model has high predictive fidelity (the predictions are very close to the observed values) and low levels of systematic bias (the regression line is almost parallel to the 45degree line). Further, the fact that the slope of the fitted line is almost a unit and the intercept is small, indicates that the model does not change the scale of GDP and does not need to be large-scale linearly corrected, and the fact that the vertical dispersion of the points around the diagonal is narrow, implies that RMSE and MAE will be small and (R-squared) will be large. The visual impression of not being curve-shaped or not being funnel-shaped indicates that there is not much homoscedasticity left (no evidence that the error of prediction increases with GDP), and the fact that there are not very distant points tells you there are no extreme cases or influential cases that are driving the performance, however, you do need to validate these visual impressions, e.g. by plotting residuals versus fitted values, by looking at standardized residuals and leverage, and by testing heteroscedasticity. To be model-valid and explainable, report cross-validated metrics RMSE, MAE, R-squared, the distribution of residuals (mean , variance) and a variable-importance ranking of the Random Forest to indicate which variables explain the greatest variation in GDP, at least give partial dependence plots of the most important variables to show the effect of variables individually. Lastly, talk about limitations, RF are sensitive to capturing non-linear trends but provide no causal estimates, performance may also be worse beyond the sampled range of GDP (limited external validity), correlated predictors can cause variable-importance measures to be unstable so complement this predictive evidence with sensitivity checks (different train or test splits, simpler baseline models such as OLS to compare), and, where possible, domain-grounded causal analysis is fully substantiating the argument that the model is a consistent predictor of GDP.

Table 7: Comparative Performance Diagnostics of Multiple Linear Regression (MLR) and Random Forest (RF) Models for GDP Forecasting.

Model	MSE	RMSE	MAE	R-squared	Adjusted-R-squared	AIC	BIC
MLR	4.06×10^{18}	2.01×10^{9}	1.56×10^{9}	0.9994	0.9995	2326.13	2339.5
(RF)	4.08×10^{19}	6.38×10^{9}	5.31×10^{9}	0.9973	0.9966	2375.69	2471.2

As shown in Table 7, MLR model, despite reportedly having numerically superior error measures RMSE = 2.01×10^{9}, and MAE $=1.56\times10^{9}$, and a visually supported near perfect in-sample (R-squared =0.9994) is simply a clearly unstable structural model incapable of making robust macroeconomic predictions, in contrast to the RF model, which is clearly the better one by virtue of its stability. This nominal quantitative success of the MLR is an illusion of gross overfitting ,which is fatalized by a combination of structural flaws, the model lies in extreme multicollinearity between key predictors, which destabilizes coefficients as well as which is invalidated by a convergence of structural flaws, and it is being overfitted by a small number of highly influential observations, meaning that the low error numbers are meaningless. Besides, the MLR has a smaller preference toward complexity density AIC =2326.13 and BIC =2339.5)than the RF model AIC =2375.69 and BIC= 2471.2, however, the preference toward parsimony does not matter given that the MLR does not pass the diagnostic tests, which proves that a simple, invalid structural model should not be selected instead of a complex, healthy model. In stark contrast, RF model with its higher error metrics and complexity penalties has a better generalization capability and structural integrity as it has been shown to have nearly perfect predictive calibration plot on the unseen test data, can accommodate highly correlated predictors and actually represents the real underlying non-linear dependencies, relationships that cannot be handled by a linear model and this ultimately attests the stability and reliability of the ensemble approach in making high stakes predictions.

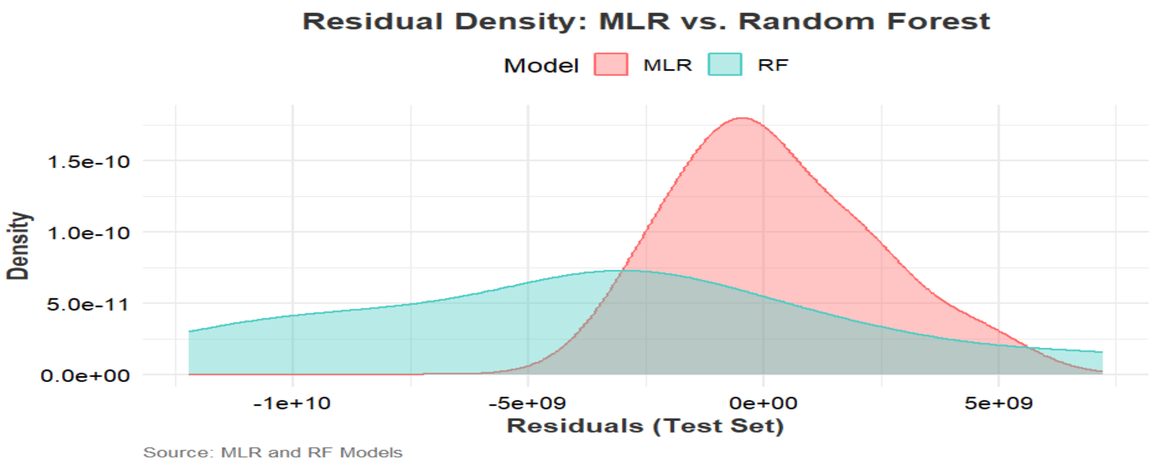

Figure 8: Comparative Residual Density Plot: Multiple Linear Regression (MLR) vs. Random Forest (RF) Model on Test Data.

The last and most important visual difference appears in the Comparative Residual Density plot (Figure 8) which validates that the MLR) model is structurally misleading, numerically superior. The residual distribution of the MLR (in red) is so peaked and narrowly centered on zero. This is also in line with the reported low MAE and visually perfect in-sample of the MLR. Nevertheless, this accumulation of small error is an illusion, obtained by excessive overfitting as well as misspecification of the model (as indicated by the extreme multicollinearity and the extreme autocorrelation of the residuals). In contrast, the RF model distribution (blue curve) is more clearly broader and flatter as they are more correct in terms of higher, but more straightforward, error measures RMSE, which is the actual, more robust, predictive uncertainty on the unobserved test set. This broader and more reliable distribution justifies the RF as the structurally reliable one, which can generalize with reliability and explain the non-linear dependencies that are complex and non-linear and which were not able to be considered by the structurally invalid linear model.

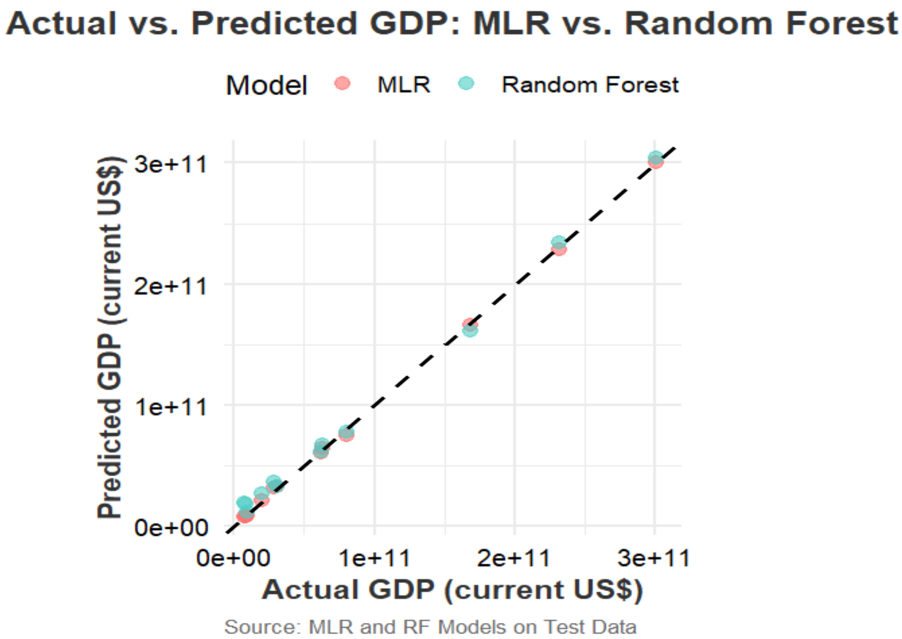

Figure 9: Predictive Calibration Plot, Actual vs. Predicted GDP of MLR and Random Forest Models (Test Data).

Final Comparative Predictive Calibration Plot (Figure 9) is a shocking summary of the overall predictive power of both models on the hidden test data, which graphically supports the findings of all the diagnostics. Both MLR, red dots and the RF, blue dots models exhibit a large amount of correlation, meaning that almost all of the points are concentrated closely around the dashed line of perfect agreement (the 45circ- line), indicating that both of the models are quite accurate in their predictions of the entire magnitude range of GDP, both at the low-end values of GDP and up to ($3x10^{11}$). Most importantly, though, the graph demonstrates that there are cases (especially on the lower side of the scale $0.5x10^{11}$).) where the predictions made by MLR (red dots) are even further off the (45circ line) than the predictions made by RF (blue dots). This moderate visual reason is in line with the prior-established stability of the RF model and its ability to handle complex, non-linear relationships in a better way than the structurally compromised MLR model to ensure that though both models are highly predictive, the RF model has the advantage of having the better, more stable out of sample generalization heart than the MLR model.

Conclusion

The results of this paper provide valuable and discriminated information on the main factors influencing the economic development of Pakistan, which highlights that the validity of the structure should overrule the goodness-of-fit in macroeconomic modeling. We found that the critical modeling paradox existed in our comparative diagnostic analysis, and MLR model obtained deceptively low test error and a high in-sample R-squared, a set of structural checks showed that its results are statistically unsound, with strong internal data dependencies, strong time-dependent residual correlation, and unstable coefficients brought by influential outliers. This shows that explanatory power of the MLR is actually an overfitting and inherent misspecification artifact making the conclusions based on coefficients unreliable even with such variables as ME, GDP, FII, and Inflation rate which would have been statistically significant in the early linear result. On the other hand, the non-linear model of the RF although it reported higher absolute errors and a higher penalty on its complexity was structurally robust. The analysis of the importance and marginal effect of variables in the RF model has yielded the valid determination of economic drivers, which are FII, GNP, and ME, and the variables play their role in the GDP in complex, non-linear ways that a simple linear model cannot explain. More importantly, PCI always proved to be the least effective predictor in both modeling strategies, which implies that its effects on the GDP are highly mediated by other structural or institutional. The findings reveal that economic growth is non-linear, multi-faceted and complex and therefore requires holistic policy approaches based on models of known predictive soundness.

Declarations

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Data Availability Statement: The source of data is provided in Section 3.3

References

Afzal, M. (2007). The impact of Globalization on economic growth of Pakistan. The Pakistan Development Review,46(4), 723-734. https://www.jstor.org/stable/41261192

Ahmed, Z., Ahmad, M., Murshed, M., Shah, M. I., Mahmood, H., & Abbas, S. (2022). How do green energy technology investments, technological innovation, and trade globalization enhance green energy supply and stimulate environmental sustainability in the G7 countries? https://doi.org/10.1016/j.gr.2022.09.014

Dar, I. S., Afzal, M., Khalil, S., & Shamim, M. (2022). Comparison of shrinkage and feature selection methods for modeling GDP of Pakistan. Journal of Statistics and Management,Systems, 25(4),957-969. https://doi.org/10.1080/09720510.2021.2021484 .

Dinant, G. J. G., Buntinx, F. F., & Butler, C. C. (2007). The necessary shift from diagnosticto,prognostic,research. BMC,Family,Practice, 8(1),53. https://link.springer.com/article/10.1186/1471-2296-8-53 .

Gani, A. (2022). Natural resource effect on child health outcomes in a multifactor health production model in developing countries. https://doi.org/10.1108/IJSE-06-2021-0332

Hassan, S. T., Xia, E., Huang, J., Khan, N. H., & Iqbal, K. (2019) Natural resources, globalization, and economic growth: evidence from Pakistan. https://doi.org/10.17687/JEB.0502.06

Jegede, E. (2018). From modernization to alternative paradigm: Development in history and ideological implications of unequal relations for the periphery. LWATI: A Journal of Contemporary Research, 15(1), 26-252. https://doi.org/10.4314/lwati.v15i1

Kihombo, S., Vaseer, A. I., Ahmed, Z., Chen, S., Kirikkaleli, D., & Adebayo, T. S. (2022). Is there a tradeoff between financial globalization, economic growth, and environmental sustainability?https://link.springer.com/article/10.1007/s11356-021-15878-z/metrics

Kihombo, S., Vaseer, A. I., Ahmed, Z., Chen, S., Kirikkaleli, D., & Adebayo, T. S. (2022). https://link.springer.com/article/10.1007/s11356-021-15878 .

Kılıçarslan, Z., & Dumrul, Y. (2018). The impact of globalization on economic growth: empirical evidence from the Turkey. International Journal of Economics and Financial Issues, 8(5), 115-123. http: www.econjournals.com

Kunda, D., & Chihana, S. (2017). Analysis of value added services on GDP Growth Rate using Data Mining Techniques. Database Systems Journal, 8(2). http://dbjournal.ro/

Landowska, A., Klo-potek, R. A., Filip, D. and Raczkowski, K. (2025). Comparison of panel regressions and random forests: GDP-GFCF Dynamics Across Global Economies. https:doi.org/10.48550/arXiv.2504.20993..

Linh, H. T. D., & Linh, T. N. (2023). Effects of globalization in the countries of the European Union on economic growth. Ho Chi Minh City Open University Journal of Science-Economics and Business administration, 13(1), 87-102. https:doi.org/10.46223/HCMCOUJS.econ.en.13.1.2206.2023.

Mubasher, S., Zakria, M., Shahzad, A., and Ali, N. (2024). Dynamic Ridge Regression vs. Lasso Regression Comparative Study of the Unemployment rate in Pakistan. The Global Journal of Mathematics and Statistics, 1(1), 21-45. https://doi.org/10.61424/gjme.v1i1.125. Mustafa, T., Nik Hassan, N. S., & Mohd Hassan, N. (2021). The effect of FDI towards GDP growth in Malaysia. https://ir.uitm.edu.my/id/eprint/44655

Mutize, M., & Nkhalamba, M. P. (2020). A comparative study of economic growth as a key determinant of sovereign credit ratings in Africa. International Journal of Emerging Markets, 16(4), 786-805. https://doi.org/10.1108/IJOEM-10-2019-0830

Rahman, M. M., Alam, K., & Khanam, R. (2022). Socio-economic factors affecting high infant and child mortality rates in selected African countries: does globalization play any role? Globalization and Health, 18(1): 69, . https://link.springer.com/article/10.1186/s12992-022-00855-

Rehman, A., Radulescu, M., Ma, H., Dagar, V., Hussain, I., & Khan, M. K. (2021). The impact of globalization, energy use, and trade on ecological footprint in Pakistan: does environmental sustainability exist?. Energies, 14(17), 5234, https://doi.org/10.3390/en14175234

Rimmer, M. (2024). The Regional Comprehensive Economic Partnership: the Asia-Pacific intellectual property and trade. Asia Pacific Law Review, 32(2), 392-435. doi: 10.1080/10192557.2024.2349387..

Saeed, U., Dempewolf, J., Becker-Reshef, I., Khan, A., Ahmad, A., and Wajid, S. A. (2017). Prediction of wheat production based on weather and MODIS NDVI in Punjab province, Pakistan, using the Random Forests. International journal of remote sensing, 38(17): 4831-4854. https://doi.org/10.1080/01431161.2017.1323282.

Sari, A., Saleha, M. A. S., Salsabilla, N. K. S., Azaria, N. A., & Agustina, R. A. (2024). The Dynamics And Impact Of Globalization In The Field Of Science And Technology. https://journal.cerdasnusantara.org/index.php/binary/article/view/23

Syed, A. A. S. G., & Shaikh, F. M (2013) Effects of macroeconomic variables on gross domestic product (GDP) in Pakistan. Procedia Economics and Finance, 5, 703-711. https://doi.org/10.1016/S2212-5671(13)00082-8

Syed, A. A. S., & Lee, K. H. (2021). Macroeconomic forecasting for Pakistan in a data-rich environment. Applied Economics, 53(9), 1077-1091. https://doi.org/10.1080/00036846.2020.1826399 .

Tanveer, A., Idrees Afzal, K. F., & Bano, S. (2024). Prediction of Economic Growth by Using Machine-Learning Algorithms through Sentiment Index Analysis in Economy of Pakistan. Journal of Social & Organizational Matters, 3(1), 165-175. https://doi.org/10.56976/jsom.v3i1.59.

Tran, l. t. east and southeast Asian perspectives on the internationalization of higher education. http://www.routledge.com/Internationalization-in-Higher-Education-Series/book-series/INTHE

Veenam, P. (2024). Cross-border e-commerce: Opportunities and challenges on the global market. International Journal of Multidisciplinary Research and Growth Evaluation, 5(5), 272-281. doi.org/10.54660/anfo..

Veltmeyer, H. (2013). The political economy of natural resource extraction: a new model or extractive imperialism? Canadian Journal of Development Studies, 34(1), 79-95. https://doi.org/10.1080/02255189.2013.764850

Virjan, D., Manole, A. M., Stanef-Puică, M. R., Chenic, A. S., Papuc, C. M., Huru, D., and Bancau, C. S. (2023). Competitiveness -the engine to enhance economic growth and revive the economy. https://doi.org/10.3389/fenvs.2023.1130173..

Vivarelli, M. (2018). Globalization, structural change and innovation in emerging economies: The impact on employment and skills (No. 11849). **https://hdl.handle.net/10419/185309**

Vlados, C., & Chatzinikolaou, D. (2025). The new globalization: the way of the evolutionary structural triptych. J Global Responsibility, 16(1), 139-161doi: 10.1108/JGR-04-2023-0063

Waseem, M. (2007). Politics and the State in Pakistan. (No Title). https://cir.nii.ac.jp/crid/1980023484817287197

Xu, X., Abbas, H. S. M., Sun, C., Gillani, S., Ullah, A., and Raza, M. A. A. (2021). Effects of globalization and governance determinants on the economic growth: an empirical study of Asian economies. Growth and Change, 52(2), 1137-1154. https://doi.org/10.1111/grow.12475

Xu, Y., & Zhao, F. (2023). Effect of energy depletion, human development and the distribution of income on the sustainability of natural resources. Resources Policy, 83, https://doi.org/10.1016/j.resourpol.2023.103531

Zhu, M. D., Iqbal, J., Nosheen, M., & Ahmed, S. (2025). Investigating the asymmetric effects of exchange rate misalignments on economic growth in Turkey: Insights from threshold effects. The Journal of International Trade & Economic Development, 1-35, https://doi.org/10.1080/09638199.2025.2449879

Zubair, M. A., & Adenomon, M. O. (2021). Comparison of estimators efficiency of linear regressions when autocorrelation and multicollinearity jointly occur. Science World Journal, 16(2), 103-109.https://www.ajol.info/index.php/swj .