International Journal of Advanced Statistics and Probability, 13 (1) (2026) 1-8

International Journal of Advanced Statistics and Probability

Website: www.sciencepubco.com/index.php/IJASP
https://doi.org/10.14419/85ej6036
Research paper

Predictive Modeling of Ghana's Economic Growth: a Comparative Analysis of Support Vector Regression and Ordinary Least Squares Regression Using Foreign Direct Investment Data

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Received: November 24, 2025, Accepted: January 9, 2026, Published: January 12, 2026

Abstract

The contribution of Foreign Direct Investment (FDI) to economic growth remains a central issue in development economics, particularly for emerging economies that are undergoing macroeconomic adjustment. This study examines the relationship between FDI and Ghana's Gross Domestic Product (GDP) growth by conducting a comparative assessment of Ordinary Least Squares Regression (OLSR) and Support Vector Regression (SVR). Annual data spanning 1996–2023 were obtained from the World Bank and OECD national accounts databases. Model performance was evaluated using out-of-sample Root Mean Square Error (RMSE) and coefficient of determination (R^2) to distinguish predictive accuracy from explanatory power. The results indicate that FDI exerts a statistically significant and positive effect on GDP growth under the OLSR framework, with an R^2 value of 0.47, suggesting moderate explanatory strength. In contrast, the SVR model , implemented with a radial basis function kernel and tuned via cross-validation, achieved a marginally lower prediction error (RMSE = 0.754) , but lower explanatory power (R^2 = 0.32). These findings highlight a clear trade-off between predictive accuracy and interpretability. The study emphasizes that the single-predictor specification serves a methodological purpose rather than a comprehensive economic representation, and that results should be interpreted within this constrained framework. Generally, the analysis shows the complementary roles of machine learning and econometric approaches in applied economic modeling and provides evidence-based guidance for model selection in macroeconomic forecasting and policy analysis in Ghana.

Keywords: *Foreign Direct Investment; Economic Growth; Predictive Modeling; Ordinary Least Squares Regression; Support Vector Machine.*

1. Introduction

Ghana's economic trajectory over the past few years has been dramatic, marked by a deep crisis, an intensive stabilization program, and now a cautious recovery driven in no small part by renewed foreign direct investment (FDI). This paper seeks to assess the predictive power of FDI for Ghana's economic growth by comparing Support Vector Regression (SVR), a flexible nonlinear machine-learning method, with the classical Ordinary Least Squares (OLS) regression. We argue that selecting the right model is critical at a time when Ghana's investment climate is rebounding, international capital flows remain volatile, and policymakers need reliable forecasting tools to guide growth and development strategy. After years of macroeconomic stress, Ghana recorded a notable rebound in real economic output in 2024: full-year GDP growth reached 5.70 percent, up from just 2.90 percent in 2023, according to the Ghana Statistical Service as reported by Trading Economics [1]. This surge is consistent with broader assessments: the World Bank, in its mid-2024 update, notes that Ghana has made steady progress in restoring fiscal stability, reducing inflation, and putting growth on a more sustainable footing [2].

Indeed, quarterly GDP figures released by Ghana's Ministry of Finance underscore the strength of the 2024 recovery. The non-oil sectors, especially services, construction, and mining, drove an average quarterly growth of 6.3 percent through the first three quarters, with the third quarter alone expanding by 7.2 percent, its fastest in years [3]. However, the rebound was uneven: in the fourth quarter of 2024, growth cooled sharply, with GDP expanding by just 3.6 percent (on a year-on-year basis), dragging the annual average to a more moderate pace [4]. In government planning circles, this stabilization represents more than just headline GDP strength. According to the National

Development Planning Commission's 2024 Annual Progress Report, construction grew by 9.6 percent, mining and quarrying by 9.4 percent, and the manufacturing sector recovered from contraction to a 3.9 percent growth rate [5]. These sectoral dynamics reflect both pent-up domestic demand and the initial payoff from structural reforms and investor-friendly policies. Foreign direct investment has resumed as a strategic lever in this recovery narrative. In the first quarter of 2024 alone, the Ghana Investment Promotion Centre (GIPC) recorded FDI inflows of US$123.06 million across 32 projects, a 16 percent increase over the same period in 2023 [6]. These early-year inflows were not simply token investments: they are expected to generate over 3,600 jobs once fully operational, spanning key sectors such as manufacturing, services, construction, agriculture, and tourism [6].

By the end of 2024, investment momentum remained resilient even in challenging global conditions. The GIPC reports that Ghana attracted US$651.7 million in total new investment in 2024, of which US$617.6 million was FDI, across 140 registered projects, 107 of which were wholly foreign-owned [7]. That the number of projects rose by over 11 percent compared to 2023 signals that investor sentiment remains strong, even if dollar-value inflows declined slightly against a backdrop of slowing global FDI flows [7]. This resurgence matters deeply for Ghana's economy: historically, private investment, including FDI, has accounted for a significant percentage of GDP. According to macroeconomic data compiled by the African Development Bank, private investment constituted approximately 14.4 percent of GDP in projections around 2024 [8]. Given this scale, even modest shifts in FDI can ripple through the economy, influencing credit, capacity utilization, employment, and ultimately GDP growth.

Yet, the relationship between FDI and economic output in Ghana is neither static nor linear. The country's IMF-supported reforms, including debt restructuring and monetary tightening, have changed the way capital inflows are transmitted into real growth. The IMF's baseline macroeconomic projections assume real GDP growth of 2.8 percent in 2024 under its program [9, 10], but actual data have outperformed that, suggesting that standard linear models may understate the impact of capital flows under dynamic reform regimes. This is precisely why we believe it is timely and academically valuable to compare Support Vector Regression to OLS regression in the Ghanaian context. OLS has the virtue of simplicity, interpretability, and widespread use in macroeconomic forecasting. But SVR, a machine-learning method, is powerful in capturing nonlinear patterns, interactions, and structural breaks that may characterize FDI-growth dynamics in transitional economies. For Ghana, where macro policies have transformed dramatically since 2022, SVR may better account for the "new normal" transmission channels of FDI.

In this study, we build a quarterly panel dataset using Ghana's annual foreign direct investment (FDI) and Gross Domestic Product (GDP) data spanning over 26 years from 1996-2023 extracted from the World Bank national accounts data and OECD National Accounts data files. We subject both OLS and SVR models to rigorous out-of-sample testing, evaluating predictive performance over rolling intervals. Beyond forecast accuracy, we undertake policy-relevant interpretation: which model better captures the economic meaning of FDI inflows under reform, and how should policymakers and analysts weigh its implications for future growth strategies? Generally, this paper offers both methodological innovation and applied economic insight. By comparing SVR and OLS, we provide guidance to economists and decision-makers in Ghana and similar emerging markets on how to forecast growth in an era of volatility and structural change. Our findings carry direct implications for investment promotion, fiscal planning, and macro-prudential policy: if FDI is a meaningful driver of growth, modeling it accurately and translating that into credible forecasts is essential for forging a stable, inclusive recovery.

2. Literature Review

2.1. Foreign direct investment and economic growth in Ghana

In recent years, Ghana's foreign direct investment (FDI) inflows have displayed significant fluctuations, shaping the nation's economic performance. In 2023, Ghana recorded FDI inflows of USD 649.58 million, representing a decline of more than 50% from the previous year's USD 1.35 billion. This figure marked one of the lowest annual inflows in over a decade, signalling continued challenges in attracting large-scale foreign investment during a period characterized by global economic uncertainty [11][12]. This downward trend persisted into 2024. Data from the Ghana Investment Promotion Centre (GIPC) shows that total FDI declined further by 5%, from USD 649.58 million in 2023 to USD 617.61 million in 2024. Interestingly, despite the fall in investment value, the number of registered projects rose from 126 in 2023 to 140 projects in 2024, demonstrating sustained investor interest even amid reduced capital inflows. The services sector accounted for the largest share of investment value, while manufacturing led in the number of projects [13]. By contrast, the first half of 2025 witnessed a significant resurgence in foreign investment. GIPC data indicate that Ghana attracted USD 862.96 million in FDI between January and June 2025, representing a dramatic 381.9% increase compared to the USD 179.07 million recorded during the same period in 2024 [14]. A total of 76 new projects were registered, with expected direct job creation of approximately 4,707 positions [15]. Manufacturing accounted for 32 of these projects, while general trading captured the highest investment value at USD 622.92 million [14]. This renewed investor confidence in 2025 coincides with more favourable macroeconomic conditions. Growth projections from the African Development Bank estimate Ghana's real GDP growth at 4.5% in 2025, driven by improvements in mining and ongoing fiscal consolidation [16]. Similarly, GIPC's July 2025 economic outlook projects 4.0% GDP growth for the year, suggesting an environment more conducive to FDI attraction compared to the previous two years [17]. Generally, while Ghana experienced notable declines in FDI inflows during 2023 and 2024, the strong rebound observed in early 2025 highlights improving economic stability and renewed foreign investor interest. These trends underscore the dynamic nature of Ghana's investment climate and the potential for FDI to play a strengthened role in supporting economic growth should current conditions persist.

2.2. Application of machine learning in economic modelling

The integration of machine learning (ML) techniques into economic modelling has gained significant attention in recent years due to their advanced capabilities in forecasting, pattern recognition, and nonlinear modelling. A study by [18] explored the role of ML in managing inflation in Ghana, employing time-series forecasting models to predict future inflation trends. Their findings underscored the strength of ML algorithms in producing accurate and reliable macroeconomic forecasts, thereby offering policymakers valuable insights for monetary and fiscal decision-making. In a related investigation, [19] examined the predictive efficiency of Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) architectures, in forecasting Gross Domestic Product (GDP). The study reported that ML-based models consistently outperformed traditional econometric models such as ARIMA and VAR, largely due to their flexibility in capturing complex, nonlinear, and dynamic economic relationships. Machine learning applications extend beyond macroeconomic forecasting to microeconomic and sector-specific modelling. For instance, [20] applied several ML algorithms, including CatBoost, XGBoost, and Random Forest, to predict house rental prices in Ghana. Their results revealed that CatBoost achieved the highest predictive performance, demonstrating the capability of ML to model intricate and multidimensional relationships within housing and real-estate markets. Beyond Ghana-specific applications, global literature also demonstrates the growing relevance of ML in economic modelling. A study by [21] evaluated the use of Support Vector Regression (SVR) and Artificial Neural Networks (ANNs) for inflation forecasting in emerging markets, concluding that ML approaches provide substantially lower forecast errors than conventional models. Similarly, [22] explored the use of ensemble learning techniques such as Gradient Boosting Machines and Random Forests in predicting foreign exchange rates, where ensemble models captured volatility patterns more effectively than linear models. In the domain of economic growth modelling, [23] applied hybrid ML frameworks combining LSTM networks with wavelet decomposition to forecast GDP growth in Asian economies. Their findings demonstrated that hybrid ML models excelled in environments characterized by structural breaks and high-frequency shocks. Additionally, [24] investigated the application of ML for unemployment forecasting in European economies, revealing that algorithms like Elastic Net and Support Vector Machines outperform classical regression techniques, especially under conditions of economic uncertainty. Furthermore, [25] examined the capability of deep learning models to predict stock market behaviour in African financial markets, highlighting their potential in capturing nonlinear dependencies and improving investment decision-making. Collectively, these studies demonstrate that machine learning has become a transformative tool in economic modelling. Its ability to uncover complex relationships, adapt to rapidly changing data environments, and outperform traditional statistical models makes ML an indispensable component of modern economic analysis. Building on this growing body of evidence, the present study contributes to the literature by applying ML, specifically Support Vector Regression, to forecast Ghana's economic growth based on FDI, and comparing its performance with the well-established Ordinary Least Squares (OLS) technique.

2.3. Synthesis and research Gap

Existing studies on Ghana's economic growth have largely relied on traditional econometric frameworks to assess the impact of FDI, emphasizing causal interpretation and statistical significance. More recent literature demonstrates that machine learning methods often outperform classical models in predictive accuracy, particularly in nonlinear and structurally unstable environments. However, few studies explicitly compare the predictive–explanatory trade-offs between machine learning and econometric models within a unified empirical framework. Moreover, while alternative machine learning techniques such as Random Forests, Gradient Boosting, and LSTM networks have shown strong forecasting performance, Support Vector Regression offers distinct advantages in small-sample contexts due to its margin-based optimization and robustness to overfitting. This study addresses the identified gap by directly comparing SVR and OLSR using the same dataset, evaluation metrics, and forecasting horizon, thereby providing clearer evidence on the complementary roles of machine learning and econometrics in applied economic modeling.

3. Methodology

3.1. Data source

The data employed for the study were Ghana's annual foreign direct investment (FDI) and Gross Domestic Product (GDP) data spanning over 26 years from 1996-2023, extracted from the World Bank national accounts data and OECD National Accounts data files. This study intentionally employs a single explanatory variable, Foreign Direct Investment (FDI), to enable a clean and transparent comparison between Ordinary Least Squares Regression (OLSR) and Support Vector Regression (SVR). While this specification facilitates methodological comparison, it represents a modeling constraint rather than a comprehensive economic representation. Additionally, economic growth is inherently multidimensional and influenced by factors such as inflation, trade openness, human capital, fiscal policy, and institutional quality. Therefore, the estimated models capture only the partial effect of FDI on GDP growth. The results should therefore be interpreted as conditional relationships within a parsimonious framework, not as exhaustive determinants of economic growth.

3.2. Data processing

The data obtained was arranged in two columns in a CSV file, with the first column being annual FDI (independent variable) and the second column being GDP (dependent variable). The first column was named (X) and the second named (Y) and imported into R. The Data was then diagnosed in terms of normality. However, after the normality check, the data appeared not to be normal, hence it was transformed by taking the natural logarithm of the data points to ensure normality before further analysis was done. The normality checks were done because it is one of the main assumptions to ensure the implementation of Linear regression. However, the e1071 package was loaded and used for the modeling.

3.3. Data splitting

The data set was split into two for model training and testing. In this study, 70% of the data was used for the model training, and the other 30% kept for model testing and prediction. The data selection was all done at random to avoid bias in prediction. The model framework is shown in Figure 1 below.

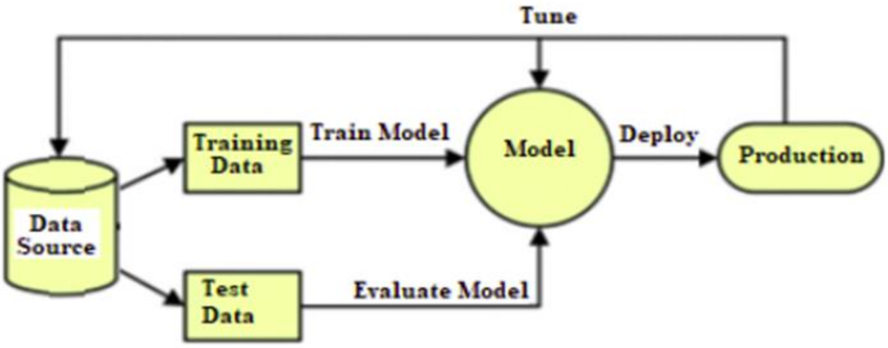

Fig. 1: Flow Chart of A Supervised Learning Process.

3.4. Support vector regression

Support Vector Regression (SVR) is derived from the Support Vector Machine framework and aims to estimate a function that deviates from observed responses by no more than a predefined margin ε while maintaining maximal flatness [26]. Given a training dataset $\{(x_i, y_i)\}_{i=1}^{n}$, SVR seeks to estimate a function of the form;

$$f(x) = w^T x + b \tag{1}$$

Where w is a vector of weights and b This is the bias term. The optimization problem is defined as;

$$\min_{w,b,\xi_i,\xi_i^*} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{2}$$

Subject to

$$\begin{aligned} y_i - (w^T x_i + b) &\le \varepsilon + \xi_i \\ (w^T x_i + b) - y_i &\le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* &\ge 0 \end{aligned}$$

Where ε defines the width of the insensitive tube, ξ_i and ξ_i^* Are slack variables capturing deviations outside the ε-tube, and C It is a regularization parameter controlling the trade-off between model complexity and prediction error. To capture nonlinear relationships, the input space is transformed into a higher-dimensional feature space using a kernel function. This study employs the Radial Basis Function (RBF) kernel, defined as;

$$K(x_i, x_j) = \exp\left(-\gamma\|x_i - x_j\|^2\right) \tag{3}$$

Where γ Controls the kernel width. SVR is particularly suitable for small samples and nonlinear economic relationships, making it appropriate for modeling FDI–GDP dynamics in Ghana.

3.5. Ordinary least squares regression

The ordinary least squares regression algorithm is a supervised learning algorithm that predicts the value of a response variable (y) based on a linearly related independent variable (x), also known as the covariates [27]. The general form of the ordinary least squares regression (OLSR) is obtained as;

$$y = \varphi_0 + \varphi_1 x_i + \varepsilon \tag{4}$$

where;
$y = $ *dependent* variable
$\varphi_0 = $ *Intercept*
$\varphi_1 = $ *slope*
$x_i = $ *independent* variable
$\varepsilon = $ unexplained *error*

We take the natural logarithm of the data to estimate the degree of responsiveness of GDP to changes in FDI. Here, the value of φ_1 It is interpreted as the elasticity, which estimates that changes in y due to a unit change in x [28]. Therefore, the model now becomes;

$$\ln(GDP) = \varphi_0 + \varphi_1(\ln FDI) + \varepsilon \tag{5}$$

Where ln (GDP) is the natural logarithm of GDP, ln (FDI) is the natural logarithm of FDI, φ_0 Is the intercept and φ_1 Is the elasticity.

3.6. Model performance evaluation measures

The root mean square errors (RMSE) for each model are used as the benchmark for selecting the best model with minimal errors of prediction. Here, the model with the least RMSE is selected as the best model. The RMSE formula is obtained as;

$$RMSE = \sqrt{\frac{\sum_{1}^{n}(y - \hat{y})^2}{n}} \tag{6}$$

$$R - Squared = 1 - \frac{\sum_{i=1}^{n}(y - \hat{y})^2}{\sum_{i=1}^{n}(y - \bar{y})^2} \tag{7}$$

4. Empirical Results

4.1. Descriptive statistics

The descriptive statistics for both FDI and GDP for the study period (1996-2023) are presented in Table 1.

Table 1: Descriptive Statistics of FDI and GDP

Variable	N	Min	Max	Mean	SD	Skewness	Kurtosis
GDP	26	22.33	25.100	23.82	1.004	-0.186	-1.712
FDI	26	-0.045	2.248	1.238	0.691	-0.159	-1.385

From Table 1, between the period of 1996-2023, the average GDP is approximately 23.82 with a standard deviation of 1.004, providing a measure of the typical economic output in the dataset. Also, the value of (-0.186) for skewness suggests that the data for GDP is slightly left skewed, whilst the value of (-1.712) for kurtosis indicates that the distribution of GDP values has thinner tails compared to a normal distribution. Furthermore, for FDI, the average is approximately 1.238 with a standard deviation of 0.691, providing a measure of the typical level of foreign direct investment in the dataset. The value (-0.159) for skewness also the data points for FDI are slightly left skewed. Also, the negative kurtosis (-1.385) suggests that the distribution of FDI values has thinner tails compared to a normal distribution, similar to that of GDP.

4.1.1. Time plots of study variables

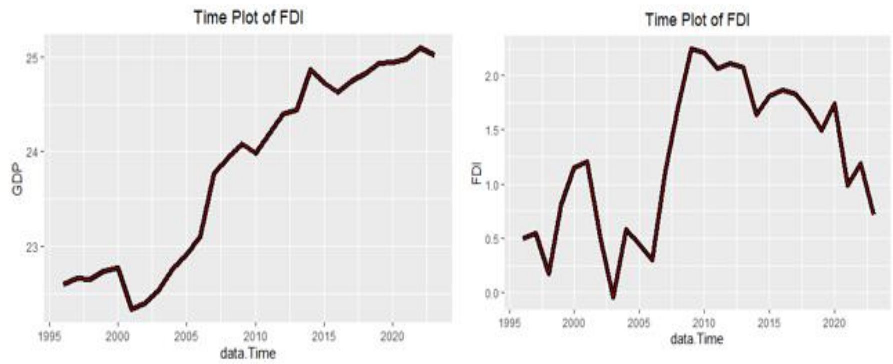

Fig. 2: Time Plot of Study Variables.

From Figure 2, we observed a fluctuating trend for FDI from 1996 until 2005, where there was a sharp rise, which reached its peak in 2010 and then began to fall steadily till 2023. This explicitly suggests a continuous decline in FDI observed for Ghana from 2010-2023. Furthermore, GDP growth for Ghana remained low from 1995-2000, where it began to rise steadily until 2023. Also, the time plots in Figure 2 reveal trending behavior in both GDP and FDI, which suggests potential non-stationarity, but due to the study's limited sample size, formal unit root tests such as the Augmented Dickey–Fuller (ADF) test were not emphasized to avoid power distortions. Instead, a logarithmic transformation was applied to stabilize variance and mitigate scale effects. While this approach improves model robustness, non-stationarity may still affect coefficient consistency in OLS estimation. Consequently, the results should be interpreted cautiously, with emphasis on comparative predictive performance rather than long-run equilibrium inference.

4.2. OLSR model

Table 2 below shows the parameter estimates of the trained OLSR model using 30% of the data sets, consisting of 18 observations.

Table 2: Parameter Estimates of OLSR

Variable	Estimate	St. Error	T-value	p-value
Intercept	22.530	0.345	65.267	<2e-16 ***
lnFDI	0.989	0.256	3.864	0.00125 **
R-Squared	0.47			
F-Statistic	14.93			
P-value	0.001			

From Table 2, we observed that the value of the log-transformed FDI is significant (p-value<0.05) and positive (0.989), implying that FDI has a significant positive impact on GDP. The value of (0.989) for the log-transformed FDI suggests that holding all other variables constant, a 1% increase in the log-transformed FDI will increase the value of the log-transformed GDP by a value of 0.989%. The R-square value (0.47) also shows that the model can explain 47% of the changes that occur in GDP as a result of a unit increase in FDI. Nevertheless, the p-value (0.001) for the F-statistic shows that the overall trained Ordinary Least Squares Regression (OLSR) model is significant and ready for prediction.

4.3. SVR model

Table 3 shows the parameter values for the support vector regression (SVR), which was tuned using 10-fold cross-validation. The essence of the tuning was to make the support vector regression (SVR) model better to avoid overfitting and underfitting after testing different models.

Table 3: Cross-Validation Results for SVR Model with RBF Kernel (σ = 0.1)

Cost Parameter (C)	RMSE	R-squared	MAE
0.25	1.0167	0.4747	0.8799
0.50	0.9197	0.4808	0.7802
1.00	0.8511	0.4839	0.7010

The Support Vector Regression (SVR) model using a Radial Basis Function (RBF) kernel was evaluated across three different values of the regularization parameter C, while holding the kernel parameter σ constant at 0.1. The model was trained on 19 samples with one predictor (FDI), and performance was assessed using bootstrapped resampling (25 repetitions) with preprocessing steps that included centering and scaling. Model evaluation was based on Root Mean Squared Error (RMSE), R-squared (R^2), and Mean Absolute Error (MAE). The results indicated that increasing the value of (C) led to consistent improvements in model performance as observed in Figure 3. The optimal model, selected based on the lowest RMSE (0.8511), was achieved at $C = 1.00$, which also corresponded to the highest R^2 value (0.4839) and the lowest MAE (0.7010). These results suggest that the SVR model with $C = 1.00$ Provides the best generalization performance for this dataset.

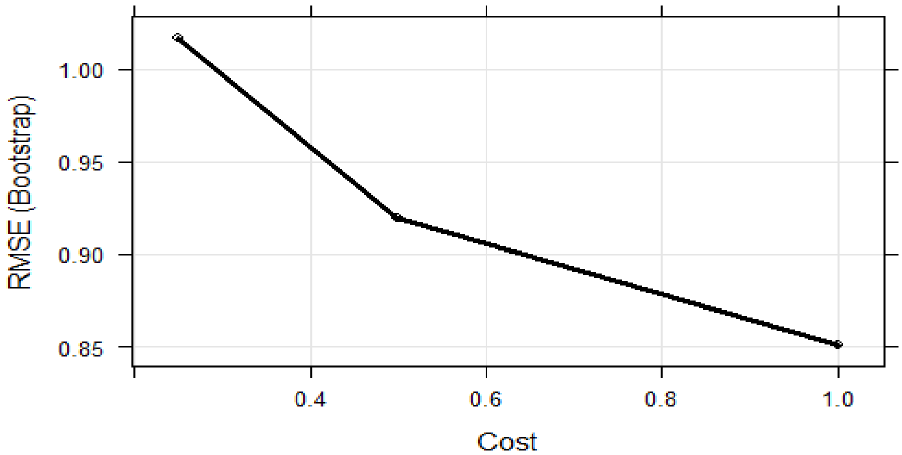

Figure. 3: 10-Folds Cross-Validation Results for SVR Model.

4.4. Model prediction (OLSR, SVR)

The remaining 30% of the data points, consisting of 9 observations, were used for prediction using the developed models (OLSR, SVR). The observations were the randomly selected observations that formed 30% of the test set. Table 4 shows the prediction of each model with its root mean square errors and R-squared values.

Table 4: Prediction of Models

S/N	OLSR		SVR	
	Actual (lnGDP)	Predicted (lnGDP)	Actual (lnGDP)	Predicted (lnGDP)
1	22.58957	23.02425	22.58957	23.05691
2	22.65956	23.07308	22.65956	23.10351
13	23.93521	24.22952	23.93521	24.20701
16	24.19516	24.56867	24.19516	24.53064
17	24.39542	24.61861	24.39542	24.57829
21	24.62334	24.37616	24.62334	24.34694
23	24.82435	24.19654	24.82435	24.17554
24	24.93241	24.00532	24.93241	23.99307
28	25.02416	23.23961	25.02416	23.26242
	RMSE = 0.7553		RMSE = 0.7541	
	R2=0.4676		R2= 0.3188	

From Table 4, we compared the predictions of both the SVR and OLSR models. From the Table, we observed that the OLSR model and the SVR model both provide relatively closer predictions of GDP; however, the support vector regression model predicted slightly better with the least mean square error, suggesting better predictions of unseen GDP values.

4.5. Model selection

The best model is selected based on their root mean square error (RMSE). Table 5 shows the mean square errors (MSE) and the root mean square errors of each model.

Table 5: Model Goodness of Fit

Model	R-squared	MSE	RMSE
SVR	0.3188	0.5688	0.7541
OLSR	0.4676	0.5706	0.7553

Model selection is based on Root Mean Square Error (RMSE) and R-squared statistics. As shown in Table 5, the SVR model exhibits a marginally lower RMSE than OLSR, while OLSR records a higher R^2 value. These metrics indicate that SVR performs slightly better in terms of predictive accuracy, whereas OLSR explains a larger proportion of GDP variability.

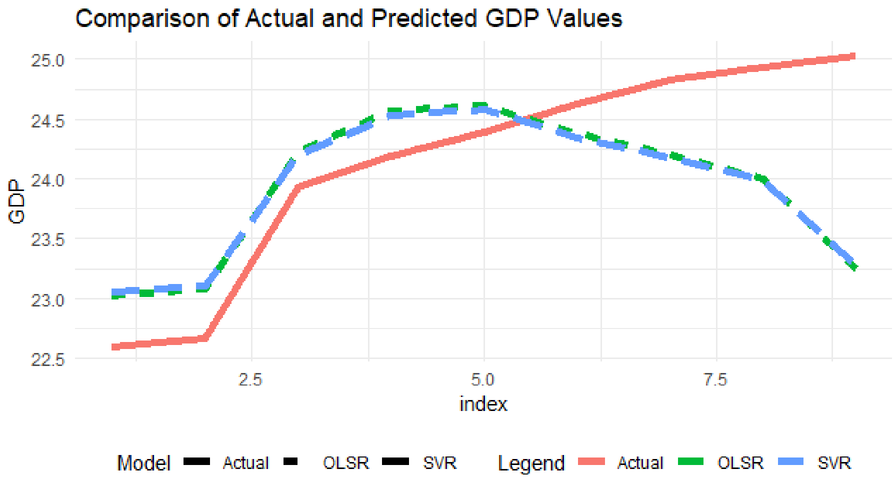

Figure. 4: Plot of Goodness of Fit.

5. Discussion of Findings

The study revealed that Foreign Direct Investment (FDI) has a significant and positive impact on Ghana's Gross Domestic Product (GDP) growth, as indicated by the OLSR model, which recorded an R^2 value of 0.47meaning approximately 47% of GDP variation is explained by changes in FDI. In contrast with this, the SVR model achieved an R^2 value of 0.32, capturing about 32% of the variation, but registered a slightly lower Root Mean Squared Error (RMSE) than OLSR, indicating marginally better predictive accuracy on the test data. This contrast underscores an important distinction: while machine learning models such as SVR can outperform in short-term predictive performance, traditional econometric models like OLSR offer superior interpretability and deeper insights into underlying economic relationships. Essentially, the results reaffirm FDI’s role as a key driver of Ghana’s economic growth, while also suggesting that a considerable portion of GDP variation is attributable to other macroeconomic and structural factors not accounted for in the present model. Additionally, the relatively small sample size constitutes an important limitation of the study, as small samples may increase sensitivity to training–testing splits, particularly for machine learning models such as SVR that rely on data-driven pattern extraction. To mitigate this risk, cross-validation and bootstrapped resampling were employed. Nevertheless, model performance metrics should be interpreted as indicative rather than definitive, and future studies using higher-frequency data or longer time spans may yield more stable estimates.

6. Conclusion

In conclusion, our study demonstrates that while both Ordinary Least Squares Regression (OLSR) and Support Vector Regression (SVR) can be employed to model the relationship between Foreign Direct Investment (FDI) and Ghana’s Gross Domestic Product (GDP), the OLSR model offers stronger explanatory power, whereas the SVR model exhibits marginally better predictive accuracy on test data. Our findings confirm that FDI is a significant driver of Ghana’s economic growth, though other macroeconomic, structural, and institutional factors also play a substantial role. From a policy perspective, these results establish the need for government and policymakers to continue to ensure an investment-friendly environment through stable macroeconomic policies, efficient regulatory frameworks, and targeted incentives to attract quality FDI that stimulates long-term growth in Ghana. Moreover, the evidence suggests that predictive modelling approaches should be integrated with traditional econometric analyses to enhance both forecasting accuracy and interpretability in economic planning. Future research should consider expanding the model to include additional variables such as inflation, trade openness, infrastructure development, and human capital, as well as exploring hybrid modelling approaches that combine the strengths of econometrics and machine learning for more robust economic forecasting in Ghana.

Funding

This research did not receive any specific grant or financial support from funding agencies in the public, commercial, or not-for-profit sectors.

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