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Developing mathematical models to analyze economic growth patterns in emerging market dynamics

Swati Jain [‡]
Department of Commerce
Manipal University Jaipur
Jaipur 303007
Rajasthan
India

Swami Nisha Bhagirath [†]
Department of Computer Applications
Manipal University Jaipur
Jaipur 303007
Rajasthan
India

Bhoomika Batra [§]
Department of Business and Management
CHRIST (Deemed to be University)
Bengaluru 560029
Karnataka
India

Vaibhav Bhatnagar *
Department of Computer Applications
Manipal University Jaipur
Jaipur 303007
Rajasthan
India

‡ *E-mail:* swati.jain@jaipur.manipal.edu
† *E-mail:* swami.bhagirath@jaipur.manipal.edu
§ *E-mail:* bhoomika.batra@christuniversity.in
* *E-mail:* vaibhav.bhatnagar@jaipur.manipal.edu (Corresponding Author)

Abstract

A key factor in determining national development and directing successful market strategies is economic growth. Making better judgements in developing countries is facilitated for investors and policymakers by having a better understanding of the main drivers of growth. The purpose of this paper is to use mathematical models to explain how economic growth patterns vary among the major growing nations. It examines the effects of inflation, foreign investment, trade, and current account balances on the GDP growth of five major economies India, China, Russia, Brazil, and South Africa between the year 2005 to 2025. The study presents how these variables connect to growth and vary among nations using techniques like logistic regression, linear regression, and ANOVA.

Subject Classification: *62G08, 62J02.*

Keywords: *Economic growth, Inflation, GDP, ANOVA.*

1. Introduction

Economic growth plays a central role in improving the quality of life, creating jobs, and reducing poverty. This paper focuses on the use of mathematical models to understand the growth patterns and market behavior in five major emerging economies: India, China, Russia, Brazil, and South Africa. These nations' large populations, abundant resources, expanding middle classes, and expanding trade roles draw attention from all around the world [1]. China's economy changed rapidly since the 1980s, moving from government control to a market-driven model. Its growth relies on manufacturing, exports, infrastructure, and technology [2]. Russia's economy is primarily dependent on gas and oil. Russia's market is heavily influenced by political developments and global energy trends. Brazil boasts abundant natural resources, a sizable local market, and agriculture [3]. The economy of South Africa is diversified and has a solid foundation in manufacturing and finance [4]. Reforms improved economic relations, and an emphasis on education can all help it prosper in the future [5]. economic growth (gdp) supports SGD goal 8 (Decent Work and Economic Growth) [6], while Economic growth in china supports SGD goal 17

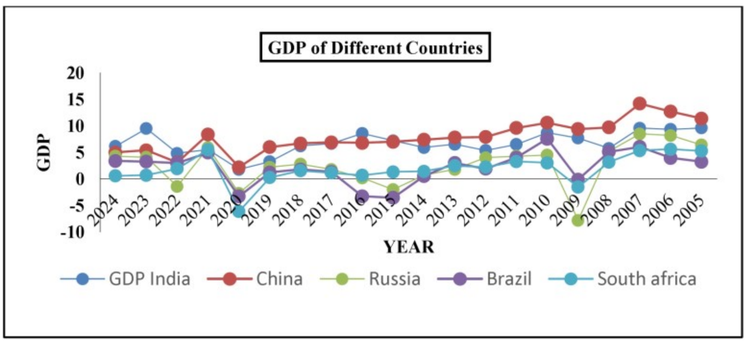

Figure 1
GDP of different countries

(Partnerships for the Goals) [7]. The policies, citizens, and resources of each nation determine its rate of development. Figure 1 shows the Gross Domestic Product (GDP) growth trends of India [8], China, Russia, Brazil, and South Africa from 2005 to 2024.

Over the years, China's economy has grown at the fastest rate and steadiest. India's growth is moderate, with notable declines in the year 2009 and 2021. Russia and Brazil experience fluctuations, particularly in times of international crisis [9]. South Africa grows more steadily but more slowly. The GDP of most nations declined during the year 2009 financial crisis and the COVID-19 pandemic in the year 2021 [10].

2. Methodology

The dataset has been downloaded directly from the Bloomberg terminal for 20 years (2005 to 2024) for the study.

2.1. *Forecasting Market Economic Dynamics*

Table 1 shows the statistics for linear regression predictions in India's GDP.

Table 1

Model Fit Statistics for Linear Regression Predicting India's GDP Growth

Model Fit Measures			
Model	R	R^2	RMSE
1	0.455	0.207	1.84

Table 2

Model Coefficients for India's GDP Growth

Model Coefficients - GDP India				
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept	6.55001	1.4518	4.512	<.001
India Imports (yoy %)	-0.01522	0.0452	-0.337	0.741
India Exports (yoy %)	0.05681	0.0478	1.189	0.254
India FDI (yoy %)	-0.00963	0.0128	-0.752	0.464
CA (% of GDP)	-0.12542	0.4562	-0.275	0.787
Inflation India	-0.04528	0.2476	-0.183	0.858

Table 2 shows the Model Coefficients for India's GDP Growth. The fitted model represents the mathematical relationship between GDP growth and selected economic indicators. It combines an intercept with weighted contributions from predictors such as imports, exports, FDI, current account balance, and inflation. The general multiple linear regression model is equation 1 [11].

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \dots + \beta_k X_k + \epsilon \tag{1}$$

Where:

- Y= Dependent variable (India's GDP growth)
- β_0 = Intercept
- β_i= Coefficient for predictor X_i
- ϵ= Error term
- X_1 = Imports (YoY %)
- X_2 = Exports (YoY %)
- X_3= FDI (YoY %)
- X_4= Current Account (% of GDP)
- X_5= Inflation Rate

$$\mathrm{Y} = 6.55001 - 0.01522\mathrm{X}_1 + 0.05681\mathrm{X}_2 - 0.00963\mathrm{X}_3 - 0.12542\mathrm{X}_4 - 0.04528\mathrm{X}_5$$

Residuals help assess the model's accuracy smaller residuals indicate better predictive performance. The residual $e_i$for each year (observation) is given in equation 2.

$$e_i = Y_i - \hat{Y}_i \tag{2}$$

Where Y_i is actual GDP for year i and $\hat{Y}_i$ is Predicted GDP from the model. This test evaluates whether each independent variable significantly influences the dependent variable. It compares the estimated coefficient to its standard error. For each coefficient β, the t-value is calculated as equation 3:

$$t = \frac{\hat{\beta}}{SE\hat{\beta}} \tag{3}$$

Where $\hat{\beta}$ is estimated coefficient and $SE\hat{\beta}$ is standard error of the coefficient. The percentage of the dependent variable's variation that the model can account for is measured by the coefficient of determination (R^2). A better fit is shown by a greater R^2, which means the model explains more of the behaviour of the data. The p-value is then derived from this t-value to determine significance as shown in equation 4.

$$R^2 = \frac{SS_{res}}{SS_{tot}} \tag{4}$$

Where, SS_{res} is sum of squared residuals and SS_{tot} is total sum of squares.

Root Mean Squared Error (RMSE) reflects the average magnitude of prediction error. It summarizes how far the model's predictions deviate from the actual values. A lower RMSE implies greater model accuracy. This shows how much of the variability in GDP is explained by the model given in equation 5.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5}$$

Table 3 shows the overall fit of the linear regression model used to predict China's GDP growth.

Table 3

Model Fit Statistics for Linear Regression Predicting China's GDP Growth

Model Fit Measures			
Model	**R**	**R^2**	**RMSE**
1	0.893	0.798	1.31

Table 4 presents the estimated effects of different economic indicators on China's GDP growth.

Table 4

Model Coefficients for China's GDP Growth

Model Coefficients - China GDP				
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept	3.52789	0.7271	4.852	<.001
Inflation China	0.63342	0.2499	2.535	0.024
CA (% of GDP) China	0.51756	0.1569	3.299	0.005
China FDI (yoy %)	0.19015	0.1144	1.662	0.119
China Export	0.00746	0.0569	0.131	0.898
China Import	-0.01508	0.0367	-0.411	0.688

Table 5 shows that the model predicting Russia's GDP growth has moderate accuracy. Table 6 shows that among all predictors, only imports have a statistically significant positive effect on Russia's GDP ($p = 0.015$).

Table 5

Model Fit Statistics for Linear Regression Predicting Russia's GDP Growth

Model Fit Measures			
Model	**R**	**R^2**	**RMSE**
1	0.736	0.541	2.61

Table 6

Model Coefficients for Russia's GDP Growth

Model Coefficients – GDP Russia				
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept	-0.2098	2.1491	-0.0976	0.924
Inflation Russia	-0.0298	0.2210	-0.1350	0.895
CA (Russia)	0.2732	0.3139	0.8702	0.399
FDI Russia	0.4779	0.5103	0.9365	0.365
Export Russia	-0.0409	0.0463	-0.8843	0.391
Import Russia	0.1645	0.0592	2.7801	0.015

Table 7

Model Fit Statistics for Linear Regression Predicting Brazil's GDP Growth

Model Fit Measures			
Model	**R**	**R^2**	**RMSE**
1	0.829	0.687	1.65

Table 7 presents the model fit statistics for predicting Brazil's GDP growth, while Table 8 shows the regression coefficients and significance of each economic predictor.

Table 8

Model Coefficients for Brazil's GDP Growth

Model Coefficients – GDP Brazil				
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept	0.5316	2.9816	0.178	0.861
Inflation Brazil	-1.2571	1.7073	-0.736	0.474
CA Brazil	0.0775	0.5216	0.149	0.884
FDI Brazil	0.4048	1.0888	0.372	0.716
Export Brazil	0.0753	0.0748	1.007	0.331
Import Brazil	0.2205	0.0487	4.526	<.001

Table 9 presents the model fit statistics for predicting South Africa's GDP growth, while Table 10 displays the regression coefficients and the significance of each economic factor.

Table 9

Model Fit Statistics for Linear Regression Predicting South Africa's GDP Growth

Model Fit Measures			
Model	**R**	**R^2**	**RMSE**
1	0.830	0.689	1.48

Table 10

Model Coefficients for South Africa's GDP Growth

Model Coefficients - GDP South Africa				
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept	-1.4799	3.8500	-0.384	0.706
Inflation South Africa	-0.3719	0.3372	-1.103	0.289
CA South Africa	-0.8846	0.2477	-3.572	0.003
FDI South Africa	0.9026	0.2651	3.405	0.004
Export South Africa	0.0952	0.0331	2.877	0.012
Import South Africa	0.0188	0.1478	0.127	0.901

2.2. *Prediction Model*

Logistic binomial regression helps explain how different factors affect a result with two possible outcomes, like high or low GDP. It calculates the chance of each outcome using a curve that keeps predictions between 0 and 1, as shown in Equation 6.

$$P(Y = 1) = \frac{1}{1+e^{-\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\beta_4X_4+\ldots+\beta_kX_k}} \tag{6}$$

The model can also be written in log-odds form as equation 7.

$$log\left(\frac{1}{1-p}\right) = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \ldots + \beta_kX_k \tag{7}$$

India's GDP growth (High/Low) depends on inflation, current account, FDI, exports, and imports. The model shows moderate fit with $R^2 = 0.163$ and AIC = 34.5.

Table 11

Model Fit Statistics for India

Model Fit Measures			
Model	Deviance	AIC	R^2_{McF}
1	22.5	34.5	0.163

Table 11 shows the model fit measures for India's GDP growth and table 12 shows the coefficients for logistic regression on India's GDP growth.

Table 12

Model Coefficients for Logistic Regression on India's GDP Growth

Model Coefficients - GDP_India				
Predictor	**Estimate**	**SE**	**Z**	**p**
Intercept	-1.02985	1.4980	-0.688	0.492
Inflation india	0.20757	0.2565	0.809	0.418
CA (% of GDP)	0.67456	0.5350	1.261	0.207
India FDI (yoy %)	-0.00525	0.0130	-0.404	0.686
India Exports (yoy %)	0.04684	0.0503	0.930	0.352
India Imports (yoy %)	-0.00900	0.0449	-0.200	0.841

Table 13 shows a perfect model fit ($R^2 = 1.000$, AIC = 12.0). Table 14 shows no predictor significantly affects China's GDP (all p = 1.000).

Table 13

Model Fit Statistics for China

Model Fit Measures			
Model	**Deviance**	**AIC**	**R^2_{McF}**
1	1.18e-9	12.0	1.000

Table 14

Model Coefficients for Logistic Regression on China's GDP Growth

Model Coefficients - GDP_China				
Predictor	**Estimate**	**SE**	**Z**	**p**
Intercept	-159.361	222577	-7.16e−4	0.999
Inflation China	20.460	35755	5.72e-4	1.000
CA (% of GDP) China	23.769	51385	4.63e-4	1.000
China FDI (yoy %)	-2.274	53199	-4.27e−5	1.000
China Export	6.565	17549	3.74e-4	1.000
China Import	-0.832	6911	-1.20e−4	1.000

Table 15

Model Fit Statistics for Russia

Model Fit Measures			
Model	**Deviance**	**AIC**	**R^2McF**
1	17.5	29.5	0.364

Table 16

Model Coefficients for Logistic Regression on Russia's GDP Growth

Model Coefficients - GDP_Russia				
Predictor	**Estimate**	**SE**	**Z**	**p**
Intercept	2.5535	1.9024	1.342	0.180
Inflation Russia	0.0492	0.1879	0.262	0.793
CA (Russia)	-0.4921	0.3324	-1.480	0.139
FDI Russia	-0.3944	0.4728	-0.834	0.404
Export Russia	0.0407	0.0462	0.882	0.378
Import Russia	-0.1281	0.0773	-1.657	0.097

Table 15 shows a moderate model fit for Russia's GDP ($R^2 = 0.364$, AIC = 29.5). Table 16 shows that none of the predictors significantly influence Russia's GDP, though imports show a borderline effect ($p = 0.097$).

Table 17

Model Fit Statistics for Russia

Model Fit Measures			
Model	**Deviance**	**AIC**	**R^2_{McF}**
1	9.87	21.9	0.644

Table 18

Model Coefficients for Logistic Regression on Brazil's GDP Growth

Model Coefficients - GDP_Brazil				
Predictor	**Estimate**	**SE**	**Z**	**p**
Intercept	8.417	7.037	1.1961	0.232
Inflation Brazil	-9.833	6.593	-1.4914	0.136
CA Brazil	-1.343	1.642	-0.8179	0.413
FDI Brazil	0.128	1.838	0.0694	0.945
Export Brazil	-0.289	0.227	-1.2771	0.202
Import Brazil	-1.256	0.690	-1.8201	0.069

Table 17 shows a good model fit for Brazil's GDP with $R^2 = 0.644$ and AIC = 21.9. Table 18 shows that none of the predictors are statistically significant, though imports have a near-significant effect on GDP ($p = 0.069$).

Table 19

Model Fit Statistics for South Africa

Model Fit Measures			
Model	**Deviance**	**AIC**	R^2_{McF}
1	7.29	19.3	0.737

Table 20

Model Coefficients for Logistic Regression on Soth Africa's GDP Growth

Model Coefficients - GDP_South Africa				
Predictor	**Estimate**	**SE**	**Z**	**p**
Intercept	7.604	31.53	0.241	0.809
Inflation South Africa	2.194	2.54	0.864	0.387
CA South Africa	-2.193	3.74	-0.586	0.558
FDI South Africa	4.075	5.34	0.763	0.445
Export South Africa	0.766	1.18	0.652	0.514
Import South Africa	-1.344	1.66	-0.812	0.417

Table 19 shows a strong model fit for South Africa's GDP ($R^2 = 0.737$, AIC = 19.3). Table 20 indicates that none of the predictors significantly impact GDP, as all p-values are above 0.05.

2.3. *Analysis of GDP Growth Pattern*

Analysis of Variance, or ANOVA, is a tool used to determine whether average values of a variable, such as GDP, vary substantially throughout several groups, such as nations or years [12]. ANOVA breaks total variation in the data into two components as given in equation 8.

$$\text{Total Sum of Squares (SST)} = \text{Sum of Squares Between (SSB)} + \text{Sum of Squares Within (SSW)} \tag{8}$$

Where, SST shows total data variation, split into SSB (difference between group means) and SSW (variation within each group).

Table 21

Analysis of Variance

ANOVA-B					
	Sum of Squares	**Df**	**Mean Square**	**F**	**p**
Overall Model	644	4	160.96	17.7	< .001
Residuals	865	95	9.11		

Table 21 presents the ANOVA results used to compare GDPs of different countries. The null hypothesis assumes no significant difference among the GDPs of these countries, while the alternative suggests a meaningful difference exists. Since the p-value is less than 0.05, the analysis rejects the null hypothesis [13]. This indicates that GDP levels vary significantly across the five countries during the studied period. Table 22 shows the post Hoc comparisons of GDP between different countries.

Table 22

Post Hoc Tukey HSD Comparisons of GDP Between Different Countries

Post Hoc Comparisons – A						
Comparison						
A	**A**	**Mean Difference**	**SE**	**df**	**T**	**p_{tukey}**
GDP India	GDP China	-1.171	0.954	95.0	-1.227	0.736
	GDP Russia	4.189	0.954	95.0	4.390	< .001
	GDP Brazil	4.530	0.954	95.0	4.748	< .001
	GDP SA	4.844	0.954	95.0	5.076	< .001
GDP China	GDP Russia	5.360	0.954	95.0	5.617	< .001
	GDP Brazil	5.701	0.954	95.0	5.974	< .001
	GDP SA	6.014	0.954	95.0	6.303	< .001
GDP Russia	GDP Brazil	0.341	0.954	95.0	0.357	0.996
	GDP SA	0.654	0.954	95.0	0.686	0.959
GDP Brazil	GDP SA	0.313	0.954	95.0	0.329	0.997

3. Conclusion

Trends in GDP growth in Brazil, Russia, China, India, and South Africa were studied in this paper. Strong relationships between GDP and variables including inflation, foreign investment, and current account balance were presented by China and South Africa. Changes in imports also had a noticeable impact on Brazil's GDP. On the other hand, GDP and the other economic indicators showed weaker relationships in Russia and India. ANOVA presented variations in GDP between these countries, particularly between Brazil, South Africa, Russia, and China and India.

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References

[1] S. Wu and Q. Pan, "Economic growth in emerging market countries," *Global Journal of Emerging Market Economies*, vol. 13, no. 2, pp. 192–215 (2021).

[2] W. Zhang, S. Zhao, X. Wan, and Y. Yao, "Study on the effect of digital economy on high-quality economic development in China," *PloS One*, vol. 16, no. 9, pp. e0257365 (2021).

[3] Y. Gruzina, I. Firsova, and W. Strielkowski, "Dynamics of human capital development in economic development cycles," *Economies,* vol. 9, no. 2, pp. 67 (2021).

[4] E. Bantis, M. P. Clements, and A. Urquhart, "Forecasting GDP growth rates in the United States and Brazil using Google Trends," *International Journal of Forecasting*, vol. 39, no. 4, pp. 1909–1924 (2023).

[5] A. B. Beyene, "Governance quality and economic growth in Sub-Saharan Africa: the dynamic panel model," *Journal of Economic and Administrative Sciences*, vol. 40, no. 2, pp. 404–418 (2024).

[6] United Nations, "SDG 17: Partnerships for the Goals," *United Nations Sustainable Development Goals* (2015). [Online]. Available: https://sdgs.un.org/goals/goal8. [Accessed: Jul. 14, 2025].

[7] United Nations, "Goal 17: Partnerships for the goals," *United Nations Sustainable Development Goals* (2015). [Online]. Available: https://sdgs.un.org/goals/goal17. [Accessed: Jul. 14, 2025].

[8] R. Pandey, D. B. Chand, and H. Tolani, "Bayesian multiple linear regression model for GDP in India," *International Journal of System Assurance Engineering and Management*, vol. 15, no. 6, pp. 2170–2187 (2024).

[9] U. Kayani, M. K. Hassan, A. Dejan, M. Khan, and F. Nawaz, "Assessment of Economic Policy Uncertainty spillovers: A cross-border analysis of global and BRIC economies," *International Economics*, vol. 179, pp. 100530 (2024).

[10] P. R. Jena, R. Majhi, R. Kalli, S. Managi, and B. Majhi, "Impact of COVID-19 on GDP of major economies: Application of the artificial neural network forecaster," *Economic Analysis and Policy*, vol. 69, pp. 324–339 (2021).

[11] D. C. Montgomery, E. A. Peck, and G. G. Vining, Introduction to Linear Regression Analysis. Hoboken, NJ: John Wiley & Sons (2021).

[12] G. Mahajan, S. Tiwari, R. Sharma, R. K. Gupta, and P. Dadheech, "Discrete mathematics for strengthening multivariate polynomial cryptography by addressing vulnerabilities," *Journal of Discrete Mathematical Sciences & Cryptography*, vol. 27, no. 7, pp. 2123–2132 (2024).

[13] W. Mertens and J. Recker, "New guidelines for null hypothesis significance testing in hypothetico-deductive IS research," *Journal of the Association for Information Systems*, vol. 21, no. 4, pp. 1 (2020).

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