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## Forecasting of state domestic product in different regions of India using autoregressive integrated moving average model

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### Abstract

State Domestic Product (SDP) is an important indicator of regional economic performance and plays a significant role in understanding economic disparities across different parts of India. This study examines the growth and forecasting of per capita State Domestic Product (SDP) for five major regions of India: Northern, Southern, Eastern, Western, and Central along with the per capita Gross Domestic Product (GDP) of India using annual data from 1961 to 2019. The Box-Jenkins methodology was employed to develop appropriate Autoregressive Integrated Moving Average (ARIMA) models, while Holt's Exponential Smoothing model was used for comparative forecasting. Stationarity of the series was examined using the Augmented Dickey-Fuller (ADF) test, model selection was based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), and diagnostic adequacy was evaluated using the Box-Ljung test. Forecast accuracy and bias were assessed through Mean Absolute Percentage Error (MAPE) and Mean Algebraic Percentage Error (MALPE). The results indicate that ARIMA (0,2,1) is the most suitable model for India and the Southern region, ARIMA (0,2,2) for the Northern, Eastern, and Central regions, and ARIMA (0,2,4) for the Western region. Forecasts for 2020-2030 reveal a steady increase in per capita GDP and SDP across all regions, with the Southern and Western regions exhibiting the strongest economic growth. The ARIMA model generally outperforms Holt's Exponential Smoothing model by providing lower forecast errors and reduced bias in most regions. The findings demonstrate that ARIMA is a reliable and effective approach for regional economic forecasting and can provide valuable support for policy formulation, regional planning, and balanced economic development in India.

**Keywords:** Per capita State Domestic Product, Gross Domestic Product, ARIMA, Box-Jenkins methodology, Holt's exponential smoothing, Regional economic growth, India

### 1. Introduction

The State Domestic Product (SDP) serves as a vital indicator of the economic performance of individual states within a country. It reflects the total value of goods and services produced within a state's geographical boundaries over a specific period. Time series analysis provides a powerful set of tools to understand and forecast economic data. Among the various forecasting methods available, the Auto Regressive Integrated Moving Average (ARIMA) model stands out due to its flexibility and effectiveness in capturing temporal dependencies in univariate time series data. Developed by Box and Jenkins, the ARIMA model is widely used in economic forecasting, particularly when dealing with non-stationary data that can be made stationary through differencing. According to the International Monetary Fund's World Economic Outlook (October 2021) [5], Gross Domestic Product (GDP) represents the total monetary value of all final goods and services produced within a country over a specific period. Between 1981 and 2011, the global economy expanded more than fivefold, reaching a value of \$71 trillion. By 2022, the total world GDP had risen to \$91.98 trillion. The United States, China, and Japan ranked as the top three global economies in terms of nominal GDP, with respective values of \$20.94 trillion, \$14.72 trillion, and \$5.06 trillion. Notably, the United States has held the position of the world's largest economy since 1871.

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Asia's contribution to global GDP has shown significant growth, increasing from 24% in 2001 to 34% in 2011 surpassing all other regions. This rise is primarily attributed to the expansion of industrial and service sectors across many Asian countries. Asia now stands as the world's largest continental economy, both in terms of nominal GDP and purchasing power parity (PPP). Collectively, Asia, North America, and Europe account for approximately 92% of global nominal GDP and about 89% of global PPP-based GDP. As of 2022, nominal GDP by region (in millions of U.S. dollars) is as follows Europe and Central Asia: \$21.96 trillion, Latin America and the Caribbean: \$4.84 trillion, Middle East and North Africa: \$3.10 trillion, North America: \$22.59 trillion, South Asia: \$3.35 trillion and Sub-Saharan Africa: \$1.69 trillion.

Ingale, K. Y., & Senan, R. (2023) <sup>[7]</sup> analysed reinforces the effectiveness of the ARIMA model as a forecasting tool for estimating India's GDP per capita. Drawing upon annual data from 1960 to 2020, the study evaluated various ARIMA model structures using the Box-Jenkins methodology and standard model selection metrics such as MAPE and RMSE. Among the tested models, ARIMA (0,2,1) emerged as the most suitable for forecasting, demonstrating both accuracy and consistency in capturing the underlying trend. Forecasts suggest that by 2039, GDP per capita may range between ₹2,621.65 and ₹5,369.51. The analysis also found a statistically significant positive impact of population growth on GDP. Overall, ARIMA offers a reliable method for economic forecasting and planning. Pijush Kanti Dev's (2018) analysis demonstrates that ARIMA modelling is effective for forecasting India's GDP. Utilizing annual GDP data from 1960 to 2017, the study applied the Box-Jenkins methodology and identified the ARIMA (12, 1, 7) model as the best fit after thorough diagnostic testing. According to the model's projections, India's GDP is estimated to reach approximately \$2,760.90 billion in 2018 and \$2,793.27 billion by 2020. These results underscore the ARIMA model's suitability for reliable short-term economic forecasting and provide valuable insights for policymakers and economic planners.

The study by Arneja, Kaur, and Saihjpal (2020) <sup>[10]</sup> validates the proficiency of the ARIMA model in forecasting India's GDP. Based on quarterly GDP data from 1980 to 2017, the researchers applied the Box-Jenkins methodology and determined that the ARIMA (1, 1, 7) configuration offered the best predictive performance. The model demonstrated strong fit diagnostics, accuracy, and reliability. While regional underdevelopment in India is often associated with the undivided BIMAROU states (Bihar, Madhya Pradesh, Rajasthan, Odisha, and Uttar Pradesh), several districts in otherwise economically advanced states also remain among the most underdeveloped. For instance, districts such as Dohad and Dang in Gujarat; Mahbubnagar, Srikakulam, and Vizianagaram in Andhra Pradesh; Mewat in Haryana; and Yadgir, Raichur, and Chamarajanagar in Karnataka fall within the bottom quartile in terms of development indicators (Bakshi, Chawla, & Shah, 2015) <sup>[11]</sup>. In a related study, Kumar and Rani (2019) <sup>[8]</sup> utilized a Social Development Index (SDI) to analyse regional disparities in social progress across India. Their findings highlight Kerala as the most socially advanced state, emphasizing that social development, alongside economic growth, is essential for holistic socio-economic progress. The relationship between urbanization and economic development has also been empirically validated. An analysis of 22 Indian states using co-integration

methods over the 1961-2011 period reveals a long-term association between urban growth and economic variables (Megeri & Kengnal, 2016). Additionally, evidence shows a statistically significant positive correlation between rising income levels and vehicular ownership, particularly in the case of personal vehicles (Krishna Raj, 2019).

This paper focuses on examining the State Domestic Product (SDP) of India across various regions. The classification of India into different regions often varies depending on the nature and scope of individual studies, with no universally fixed division. However, as per the regional framework proposed by Mitra, Mukherji, and Bose (1980), India is categorized into five broad regions: Northern, Southern, Eastern, Western, and Central. The Northern region comprises Chandigarh, Delhi, Haryana, Himachal Pradesh, Jammu and Kashmir, Punjab, and Rajasthan. The Southern region includes Andhra Pradesh, Karnataka, Kerala, the Laccadive and Minicoy Islands, Puducherry, and Tamil Nadu. The Eastern region encompasses states such as Assam, Arunachal Pradesh, Bihar, Manipur, Meghalaya, Mizoram, Nagaland, Odisha, Sikkim, Tripura, and West Bengal. The Western region consists of Gujarat, Goa, Maharashtra, and Dadra and Nagar Haveli, while the Central region includes Madhya Pradesh and Uttar Pradesh. This study aims to apply the ARIMA modelling approach to analyse and forecast the State Domestic Product of different regions of India, using historical data spanning from 1961 to 2019. By identifying suitable ARIMA parameters and validating the model through diagnostic checks and forecast accuracy measures, this research contributes to a better understanding of the economic trajectory of the state and provides valuable insights for planners and policymakers.

## 2. Methods and Materials

Autoregressive models were employed to analyse the sample and predict per capita GDP of India and per capita SDP for five different regions of India, aiming to study the forecasting of these variables. The Autoregressive (AR) and Moving Average (MA) models are statistical tools used for time series analysis. Additionally, the Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) models integrate the features of AR and MA for enhanced forecasting capabilities.

The Box-Jenkins method has gained widespread popularity. It relies on models like Autoregressive (AR), Integrated (I), and Moving Average (MA). Non-stationary datasets must be differenced until they achieve stationarity. Once stationarity is achieved, the Augmented Dickey-Fuller (ADF) tests are used to confirm the stationarity of the data, allowing the application of the Box-Jenkins method. Model selection is guided by criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). After estimating the model's parameters using Maximum Likelihood Estimation, diagnostic tests is conducted using R programming and the Box-Ljung test. If the model is deemed adequate, forecasts can be generated; otherwise, alternative models should be considered. The Holt-Winters model is commonly used for forecasting, while accuracy and bias are evaluated using Mean Absolute Percentage Error (MAPE) and Mean Algebraic Percentage Error (MALPE).

## Theoretical background

Granger and Newbold (1986) <sup>[2]</sup> demonstrated that time series analysis can deliver reasonably accurate short-term forecasts when a sufficiently large dataset is available. In univariate

time series analysis, the ARIMA model is both versatile and widely used. The ARIMA model integrates three key components: (i) the Autoregressive (AR) process, (ii) the Differencing process, and (iii) the Moving Average (MA) process.

The Autoregressive (AR) model of order  $p$  denoted as  $AR(p)$  can be expressed as:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \dots + \beta_p Y_{t-p} + \epsilon_t$$

Where:

$\beta_0$  is a constant,

$\beta_1, \beta_2, \dots, \beta_p$  are the coefficients, and

$\epsilon_t$  is a random error term.

In this model, all previous values  $Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$  contribute additively to the current value  $Y_t$ . The error term  $\epsilon_t$  is assumed to follow an independent and identically distributed (iid) random process, with  $E(\epsilon_t) = 0$  and  $V(\epsilon_t) = \sigma^2$  his means  $\epsilon_t \sim N(0, \sigma^2)$ , where it follows a normal distribution with a mean of 0 and variance  $\sigma^2$ .

### 2.1 Moving Average (MA) model

The Moving Average (MA) model of order  $q$ , denoted as  $MA(q)$ , can be expressed as:

$$Y_t = \beta_0 + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q}$$

Where:

$\beta_0$  is a constant,

$\theta_1, \theta_2, \dots, \theta_q$  are the coefficients, and

$\epsilon_t$  is a random error term.

In this model, the independent variables are the past error terms ( $\epsilon_{t-1}, \epsilon_{t-2}, \dots, \epsilon_{t-q}$ ) The error term  $\epsilon_t$  is assumed to be a random process.

### 2.2 Autoregressive Moving Average (ARMA) model

The Autoregressive Moving Average (ARMA) model of order  $p$  and  $q$ , denoted as  $ARMA(p, q)$ , describes a time series  $\{Y_t\}$  as:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \dots + \beta_p Y_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q}$$

Where:

$\beta_0$  is a constant

$\beta_1, \beta_2, \dots, \beta_p$  are the coefficients for the autoregressive (AR) terms,

$\theta_1, \theta_2, \dots, \theta_q$  are the coefficients for the moving average (MA) terms, and

$\epsilon_t$  is the error term at time  $t$ .

This model combines the autoregressive (AR) and moving average (MA) processes, making it a versatile tool for modelling and forecasting time series data.

$$\left[1 - \sum_{i=1}^p \beta_i L^i\right] Y_t = \beta_0 + \left[1 + \sum_{i=1}^q \theta_i L^i\right] \epsilon_t$$

where,  $L$  is the lag operator, such that where,  $L^p(Y_t) = Y_{t-p}$

### 2.3 Autoregressive Integrated Moving Average (ARIMA) model

The ARIMA model is designed to handle non-stationary time series by applying differencing to the data. The general non-seasonal ARIMA model is denoted as  $ARIMA(p, d, q)$ , where:

Where:

$p$  is the order of the Autoregressive (AR) component,

$d$  is the degree of differencing needed to make the series stationary, and

$q$  is the order of the Moving Average (MA) component.

The general ARIMA model can be represented as

$$\left[1 - \sum_{i=1}^{p'-d} \beta_i L^i\right] (1-L)^d Y_t = \beta_0 + \left[1 + \sum_{i=1}^q \theta_i L^i\right] \epsilon_t$$

$L$  is the lag operator,

$\beta_0$  is the constant term,

$\beta_1, \beta_2, \dots, \beta_p$  are the coefficients for the autoregressive part,

$\theta_1, \theta_2, \dots, \theta_q$  are the coefficients for the moving average part,

$\epsilon_t$  is the error term at time  $t$ ,

$d$  is the differencing order applied to the series to achieve stationarity

There are numerous approaches available in time series literature for model evaluation. In this example, we used autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. The ACF and PACF plots are integral to the ARIMA modelling process, as first introduced by Box and Jenkins (1976) in their pioneering work. The ACF measures the correlation between two consecutive observations in a time series, capturing the linear relationship between a value at time  $t$  and another at a lag  $k$ . The PACF, in contrast, isolates the correlation between observations at lag  $k$  by removing the influence of intermediate lags. This distinction makes PACF particularly useful for identifying the order of autoregressive (AR) terms in the model. Both ACF and PACF provide valuable insights for selecting appropriate model parameters in time series analysis.

### 2.4 Akaike Information Criterion (AIC) and Bayesian Information Criteria (BIC)

The two most commonly used model selection criteria in time series analysis are the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). These criteria are defined as:

$$AIC = 2m - 2 \ln(L)$$

$$BIC = \ln(n) m - 2 \ln(L)$$

Where:

- $L$  is the maximum likelihood value of the model,
- $m$  is the number of parameters estimated by the model, and
- $n$  is the number of observations (sample size).

Both criteria aim to balance model fit and complexity. Lower values of AIC or BIC indicate a better model, with BIC penalizing model complexity more heavily than AIC due to the inclusion of  $\ln(n)$ . These criteria are essential tools for selecting the most suitable model for a given dataset.

The Box-Ljung test (1978) is a diagnostic tool used to evaluate the adequacy of a time series model by testing for the presence of autocorrelation in the residuals. After fitting an ARMA ( $p, q$ ,  $q, q$ ) model to the data, the test is applied to the residuals to determine whether they exhibit significant autocorrelations. If the autocorrelations are small, it suggests that the model fits the data well.

The hypotheses for the Box-Ljung test are:

- $H_0$ : The model does not exhibit a lack of fit (residuals are uncorrelated).

- $H_1$ : The model exhibits a lack of fit (residuals are autocorrelated).

A failure to reject  $H_0$  indicates that the model provides an adequate fit to the data, as the residuals do not show significant autocorrelation.

Exponential smoothing is a straightforward and effective method for modelling time series data, where past observations are assigned exponentially decreasing weights. This approach is particularly useful for modelling population and economic variables. Two notable models proposed for such analyses are the Holt (1957) <sup>[4]</sup> and Winters (1960) <sup>[13]</sup> methods, as applied by Sharma and Nigam (2020) <sup>[12]</sup> for double exponential smoothing.

Let:

- $Y_t$ : The observed time series data,
- $S_t$ : The smoothed value at time  $t$ , and
- $B_t$ : The estimated trend at time  $t$ .

Equations:

Initial Conditions:

- $S_1 = Y_1$
- $B_1 = Y_2 - Y_1$

Smoothing Equation:

$$S_t = \alpha Y_t$$

$$S_t = \alpha Y_t + (1 - \alpha)(S_{t-1} + B_{t-1})$$

Trend Equation:

$$B_t = \beta (S_t - S_{t-1}) + (1 - \beta) B_{t-1}$$

Where:

- $\alpha \in (0,1)$  is the data smoothing factor,
- $\beta \in (0,1)$  is the trend smoothing factor.

## 2.5 Forecasting

For forecasting at  $t = N + h$ , where  $h$  is the forecast horizon:

$$F_{N+h} = S_t + hB_t$$

- The smoothing equation updates the smoothed value  $S_t$  by combining the current observation  $Y_t$  with the previous smoothed value and trend.
- The trend equation refines the trend  $B_t$  by considering the change in smoothed values.
- The forecast equation projects future values based on the smoothed value and trend.

This method effectively captures both level and trend components in time series data, making it suitable for forecasting scenarios involving consistent trends over time.

## 3. Summary and discussion

The Augmented Dickey-Fuller (ADF) test is a widely used statistical tool for testing the stationarity of time series data. It helps to identify whether a unit root is present, which would indicate non-stationarity. In this study, the ADF test was employed to assess the presence of a unit root in the variables under investigation. A key criterion for stationarity is that the p-value from the ADF test must be less than the chosen significance level, typically 0.05. When this condition is met, the null hypothesis that the series has a unit root can be rejected, thereby confirming that the series is stationary.

The stationarity of a time series is crucial because many econometric models, including ARIMA and VAR models, assume that the underlying data are stationary. Non-stationary data can lead to spurious regression results, misleading correlations, and invalid forecasts. In cases where the original series was found to be non-stationary, first differencing was

applied to achieve stationarity. The ADF test was then re-applied to the differenced series, and the resulting p-values confirmed that the transformed series was indeed stationary. These results underscore the importance of testing and ensuring stationarity in time series analysis, as it directly affects the reliability and interpretability of subsequent modelling and forecasting exercises.

The Augmented Dickey-Fuller (ADF) test was conducted to examine the stationarity of time series data for India and its five major regions (Northern, Southern, Eastern, Western, and Central). The test was performed at three levels. The null hypothesis of the ADF test states that the series has a unit root (i.e., it is non-stationary). A p-value less than 0.05 indicates rejection of the null hypothesis, suggesting that the series is stationary at the given level of differencing.

The overall India time series is non-stationary at first difference but becomes stationary after second differencing, indicating it is integrated of order 1. The Northern region is non-stationary at first and second difference but becomes stationary after second differencing. The p-value of 0.04126 at the second difference confirms statistical significance. The Southern region requires third differencing to achieve stationarity, indicating it is integrated of order 3. Like the Southern region, the Eastern region is non-stationary at first difference and second difference, requiring third differencing for stationarity. The Western region is also integrated of order 3, requiring third rounds of differencing before becoming stationary. Similarly, the Central region shows non-stationarity up to the second difference and achieves stationarity only at the third difference.

The results indicate heterogeneity in the dynamic behaviour of regional urban growth or economic indicators. While India as a whole and the Northern region stabilize after a second differencing, other regions exhibit more persistent trends, requiring third differencing to achieve stationarity. This implies deeper structural inertia or delayed adjustments in Southern, Eastern, Western, and Central regions of India, which may be attributed to policy lags, uneven development, or localized shocks.

**Table 1:** Augmented Dickey-Fuller (ADF) test for stationarity

| Regions  | ADF    |          |          |
|----------|--------|----------|----------|
|          | I(0)   | I(1)     | I(2)     |
| India    | 2.7848 | -4.2636* | -8.472*  |
| Northern | 4.9069 | -3.5957* | -10.432* |
| Southern | 4.0418 | -1.3637  | -10.081* |
| Eastern  | 5.643  | -2.842   | -10.021* |
| Western  | 3.8946 | -2.8028  | -11.222* |
| Central  | 4.885  | -1.2068  | -9.894*  |

**Source:** Authors computation.

Significance at 5% = \*

The Table 2 compares the performance of various ARIMA models across India and its five major regions using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Both AIC and BIC are used to evaluate model quality, lower AIC/BIC values indicate a better-fitting model. Each model is in the form ARIMA (p, d, q), where:

- $p$  = autoregressive order,
- $q$  = moving average order.
- $d$  = order of differencing (all series are differenced thrice, i.e.,  $d=3$ ),
- The ARIMA (0,2,1) model has lower AIC and BIC values, making it the preferred model for the overall India time series. ARIMA (0,2,2) is the best-fitting model

for the Northern region based on both AIC and BIC. ARIMA (0,2,1) provides a slightly better fit based on both AIC and BIC, indicating that a simpler model is sufficient for the Southern region. ARIMA (0,2,2) has the lowest AIC and BIC, making it the best model for the Eastern region. The best-fitting model for the Western region is ARIMA (0,2,4), as it minimizes both AIC and

BIC. This suggests that Western India's time series is more complex and requires a higher-order MA component. ARIMA (0,2,2) is significantly better than ARIMA (0,2,1), with both AIC and BIC being much lower. Hence, this is the preferred model for the Central region.

**Table 2:** Evaluation of various ARIMA models

| Regions  | Models  | AIC      | BIC      |
|----------|---------|----------|----------|
| India    | (0,2,1) | 967.03   | 971.15   |
|          | (0,2,2) | 968.74   | 974.92   |
| Northern | (0,2,1) | 1171.847 | 1175.968 |
|          | (0,2,2) | 1160.301 | 1166.483 |
|          | (0,2,3) | 1162.129 | 1170.371 |
| Southern | (0,2,1) | 1055.91  | 1060.03  |
|          | (0,2,2) | 1057.881 | 1064.063 |
| Eastern  | (0,2,1) | 1114.302 | 1118.423 |
|          | (0,2,2) | 1112.798 | 1118.98  |
|          | (0,2,3) | 1113.053 | 1121.295 |
| Western  | (0,2,1) | 1145.78  | 1149.901 |
|          | (0,2,2) | 1139.983 | 1146.164 |
|          | (0,2,3) | 1128.774 | 1137.016 |
|          | (0,2,4) | 1123.747 | 1134.05  |
| Central  | (0,2,5) | 1129.841 | 1142.204 |
|          | (0,2,1) | 955.5626 | 959.6835 |
|          | (0,2,2) | 936.7593 | 942.9406 |

**Source:** Authors computation.

These results highlight the varying dynamics across Indian regions in terms of time series behaviour. Most regions require a third-order differencing (as also confirmed by the ADF test), but the complexity of moving average terms varies:

- Western and Central regions require higher-order MA models, reflecting more volatile or autocorrelated time structures.

- Southern region, despite needing third differencing, stabilizes with a simple MA (1) structure, indicating less complex residual behaviour.
- Choosing the correct ARIMA model is critical for accurate forecasting and policy analysis, especially in regional development and urban dynamics.

**Table 3:** Estimation of parameters of the model by Maximum Likelihood Estimator for per capita GDP of different regions of India and per capita GDP of India

| Regions  | Model   |     | Coefficients | Standard error | z values | Pr (> z )    |
|----------|---------|-----|--------------|----------------|----------|--------------|
| India    | (0,2,1) | ma1 | -0.6988      | 0.0889         | -7.8577  | 3.914e-15*** |
| Northern | (0,2,2) | ma1 | -1.252       | 0.1131         | -11.0675 | <2.2e-16***  |
|          |         | ma2 | 0.5697       | 0.1228         | 4.6394   | 3.495e-06*** |
| Southern | (0,2,1) | ma1 | -0.3976      | 0.1023         | -1.7012  | 0.0889       |
| Eastern  | (0,2,2) | ma1 | -0.9421      | 0.1563         | -6.7315  | 1.679e-11*** |
|          |         | ma2 | 0.2712       | 0.1424         | 0.4789   | 0.632        |
| Western  | (0,2,4) | ma1 | 0.1352       | 0.1353         | -0.0505  | 0.9597       |
|          |         | ma2 | -1.1414      | 0.111          | -11.327  | <2.2e-16***  |
|          |         | ma3 | 0.07         | 0.1245         | 1.2462   | 0.2127       |
|          |         | ma4 | 0.7302       | 0.1114         | 5.9592   | 2.535e-09*** |
| Central  | (0,2,2) | ma1 | -1.3648      | 0.167          | -15.4646 | <2.2e-16***  |
|          |         | ma2 | 0.8399       | 0.0773         | 9.0286   | <2.2e-16***  |

**Source:** Authors computation.

\*\*\* refers to significance at 10%

This table presents the estimated Moving Average (MA) coefficients from the best-fitting ARIMA models (all with d=3) across India and five regions. Each coefficient is accompanied by its standard error, z-value, and p-value ( $\Pr(>|z|)$ ) to assess statistical significance. A p-value < 0.05 indicates that the coefficient is statistically significant (denoted with \*\*\*). Non-significant coefficients ( $p > 0.05$ ) suggest that the corresponding MA terms do not significantly improve the model fit.

The coefficients are estimated by using the Maximum Likelihood Estimator for the GDP of India. The Maximum Likelihood Estimator is estimated and the modelling results of an ARIMA (0,2,1) model are provided in the table. The estimated coefficient of MA (1) component for the GDP of India are statistically significant at a 1% level of significance.

For the Northern region per capita GDP, the estimated coefficient are MA (1) and MA (2) for the component of the per capita GDP of Northern region and significant both at 1 % level of significance. The Southern region MA (1) component for the per capita GDP, but there shows no significance. In the Eastern region MA (1) and MA (2) are the components for the per capita GDP of the Southern region and MA (1) only shows 1% level of significance and MA (2) shows no significance. The Western regions show MA (1), MA (2), MA (3) and MA (4) components for the per capita GDP of Western region and MA (2) and MA (4) shows 1% level of significance and lastly the Central region shows both the components MA (1) and MA (2) 1% level of significance.

The MA coefficients provide important insights into the structure and predictability of regional time series. Most

regions show significant autocorrelations in past error terms, supporting the use of ARIMA models. These interpretations are essential for understanding how shock persistence and

error correction differ across regions, which can inform forecasting and policy responses tailored to regional dynamics.

**Table 4:** The Box-Ljung test for per capita SDP of different regions of India and per capita GDP of India

| Regions  | Statistic test | d.f | p value | Chi-square Table Value |
|----------|----------------|-----|---------|------------------------|
| India    | 23.465         | 16  | 0.1019  | 27.58711               |
| Northern | 12.045         | 16  | 0.7409  | 27.58711               |
| Southern | 30.424         | 16  | 0.01592 | 27.58711               |
| Eastern  | 10.452         | 16  | 0.842   | 27.58711               |
| Western  | 22.596         | 16  | 0.125   | 27.58711               |
| Central  | 18.475         | 16  | 0.2968  | 27.58711               |

**Source:** Authors computation.

The Box-Ljung test is used to check whether the residuals from a time series model (such as ARIMA) are independently distributed that is, whether there is any remaining autocorrelation in the residuals.

- Null hypothesis ( $H_0$ ): The residuals are independently distributed (no autocorrelation).
- Alternative hypothesis ( $H_1$ ): There is autocorrelation in the residuals (model is inadequate).
- If the p-value  $> 0.05$ , we fail to reject  $H_0$ , implying the model adequately captures the time series structure.
- If the p-value  $< 0.05$ , we reject  $H_0$ , suggesting the model may have residual autocorrelation, and may be mis specified.

The Chi-square table value at 5% significance and 16 degrees of freedom is 27.58711. If the test statistic is less than this critical value, the model passes the test.

Most regions (India, Northern, Eastern, Western, Central) pass the Box-Ljung test, indicating that their respective ARIMA models have captured the underlying structure effectively, and the residuals behave like white noise (i.e., no patterns left). Southern Region fails the test ( $p < 0.05$  and test statistic exceeds the critical value), which suggests that the model (ARIMA (0,2,1)) does not fully account for autocorrelations in the data. A higher-order model (e.g., (0,2,2) or including AR terms) may yield better results. The Box-Ljung test results support the validity of most fitted ARIMA models except for the Southern region. These findings reinforce the importance of performing residual diagnostics to confirm model adequacy. While ARIMA (0,2,1) worked well for most regions, further refinement is needed for the Southern region to ensure better forecasting and accurate interpretation.

**Table 5:** Estimation of per capita SDP of different regions of India and per capita GDP of India

| Regions  | $\alpha$ | $\hat{\theta}$ | a1       | b1       |
|----------|----------|----------------|----------|----------|
| India    | 0.9999   | 0.2902         | 15886.52 | 194.1116 |
| Northern | 0.4052   | 0.3183         | 86.2109  | 64.5076  |
| Southern | 0.9999   | 0.5979         | 205.1823 | 25.13    |
| Eastern  | 0.7108   | 0.3221         | 77.9229  | 15.3968  |
| Western  | 0.9999   | 0.3975         | 230.0654 | 26.9686  |
| Central  | 0.5255   | 0.5255         | 145.3315 | 18.5132  |

**Source:** Authors computation.

The estimates for the parameters ( $\alpha$  and  $\hat{\theta}$ ) and initial values (a1 and b1) for Holt's Exponential Smoothing model were applied. Holt's Exponential Smoothing model is used for time series forecasting and involves Exponential Smoothing of both the level (S) and the trend (B) components. Considering the historical data and the specified smoothing and trend parameters, these parameters and the initial values will be used to forecast future values for each respective variables using Holt's Exponential Smoothing model.

India's per capita GDP shows very strong autocorrelation and a stable, positive growth trend over time. The Northern

region has moderate linear growth, suggesting structural changes or fluctuations in SDP over time. The Southern region is characterized by both strong autocorrelation and a robust growth trend, making it one of the most economically consistent and improving regions. The Eastern region is less persistent and slower growing, potentially due to structural underdevelopment. The Western region mirrors national trends high stability with a consistent growth trajectory, and the Central region has balanced persistence and trend, but at a slower pace compared to the South and West.

**Table 6:** Forecasting of per capita GDP of India using the ARIMA and the Holt's Exponential Smoothing models

| Models | ARIMA     |          |          | Holt's Exponential Smoothing |          |          |
|--------|-----------|----------|----------|------------------------------|----------|----------|
| Year   | Forecast  | LCI      | UCI      | Forecast                     | LCI      | UCI      |
| 2020   | 98321.7   | 96387.1  | 100256.5 | 98321.1                      | 96403.4  | 100238.8 |
| 2021   | 102077.3  | 98919.3  | 105235.4 | 102076.2                     | 98929.1  | 105223.3 |
| 2022   | 105832.9  | 101437.3 | 110228.5 | 105831.3                     | 101432.8 | 110229.9 |
| 2023   | 109588.4  | 103894.8 | 115282.2 | 109586.5                     | 103870.4 | 115302.5 |
| 2024   | 113344.0  | 106280.5 | 120407.6 | 113341.6                     | 106231.7 | 120451.5 |
| 2025   | 117099.6  | 108592.0 | 125607.2 | 117096.7                     | 108515.1 | 125678.4 |
| 2026   | 120855.2  | 110829.9 | 130880.4 | 120851.8                     | 110721.5 | 130982.3 |
| 2027   | 124610.7  | 112996.0 | 136225.5 | 124607.0                     | 112853.0 | 136361.0 |
| 2028   | 128366.3  | 115092.3 | 141640.3 | 128362.1                     | 114911.9 | 141812.4 |
| 2029   | 132121.9  | 117120.9 | 147122.8 | 132117.2                     | 116900.5 | 147334.0 |
| 2030   | 135872.41 | 118821.2 | 152923.5 | 132121.9                     | 117120.9 | 147122.8 |

**Source:** Authors computation.

India's per capita GDP was 94566 in 2019, according to the ARIMA model it has increased by 98321.77 in 2020 again it goes on increased from 2020 to 2030 by 1.38 times. According to Holt's Exponential Smoothing method the per

capita GDP of India has increased from 2020 to 2030 by 1.34 times. Both models yield highly consistent and reliable forecasts, which reinforces the robustness of the per capita GDP trend in India over the next decade (see Table 6).

**Table 7:** Forecasting of per capita SDP of Northern region of India using the ARIMA and the Holt's Exponential Smoothing models

| Models | ARIMA    |          |          | Holt's Exponential Smoothing |          |          |
|--------|----------|----------|----------|------------------------------|----------|----------|
| Year   | Forecast | LCI      | UCI      | Forecast                     | LCI      | UCI      |
| 2020   | 214352.9 | 204387.0 | 224318.8 | 214033.6                     | 204071.7 | 223995.4 |
| 2021   | 229733.9 | 217288.2 | 242179.6 | 229301.2                     | 217005.2 | 241597.2 |
| 2022   | 245114.8 | 228753.0 | 261476.6 | 244568.8                     | 228478.0 | 260659.7 |
| 2023   | 260495.8 | 239099.3 | 281892.2 | 259836.5                     | 238800.3 | 280872.7 |
| 2024   | 275876.7 | 248577.5 | 303176.0 | 275104.1                     | 248231.8 | 301976.4 |
| 2025   | 291257.7 | 257344.8 | 325170.5 | 290371.7                     | 256937.8 | 323805.7 |
| 2026   | 306638.6 | 265500.4 | 347776.9 | 305639.4                     | 265022.2 | 346256.5 |
| 2027   | 322019.6 | 273110.2 | 370929.0 | 320907.0                     | 272554.0 | 369260.0 |
| 2028   | 337400.6 | 280221.0 | 394579.7 | 336174.6                     | 279582.1 | 392767.1 |
| 2029   | 352781.5 | 286869.7 | 418693.4 | 351442.2                     | 286143.2 | 416741.3 |
| 2030   | 368162.5 | 293082.9 | 443242.1 | 366709.9                     | 292266.0 | 441153.8 |

Source: Authors computation.

Both models forecast a steady and nearly linear upward trend in per capita SDP for the Northern region. The forecasting values of per capita SDP of Northern region in 2019 was 205611. According to ARIMA the per capita SDP in 2020 was 214352.9 and increased by 1.72 times till 2030, this is similar in the case of Holt's exponential smoothing method. Both ARIMA and Holt's Exponential Smoothing models converge closely, projecting that the per capita SDP of the Northern region will nearly double between 2020 and 2030 (from ₹2.14 lakh to ₹3.68 lakh). The consistency between the models validates the reliability of the forecast. These results

indicate sustained economic growth for the Northern region, assuming current trends continue (see Table 7).

Both models forecast a steady increase in per capita SDP across the decade. Forecasted values and confidence intervals from both models are nearly identical for all years, indicating robustness in the projections. The Southern region starts at a higher per capita SDP level than most other regions, reflecting its stronger economic base. The per capita SDP of Southern region in 2019 was 215709, by doing the forecast using ARIMA and Holt's exponential smoothing method there shows around 2 time increase in the per capita GDP from 2020 to 2030 in both the methods.

**Table 8:** Forecasting of per capita SDP of Southern region of India using the ARIMA and the Holt's Exponential Smoothing models

| Models | ARIMA    |          |          | Holt's Exponential Smoothing |          |          |
|--------|----------|----------|----------|------------------------------|----------|----------|
| Year   | Forecast | LCI      | UCI      | Forecast                     | LCI      | UCI      |
| 2020   | 233497.7 | 229353.9 | 237641.5 | 233502.2                     | 229321.6 | 237682.8 |
| 2021   | 251286.4 | 243459.6 | 259113.1 | 251295.1                     | 243415.0 | 259175.3 |
| 2022   | 269075.0 | 257045.0 | 281105.1 | 269088.1                     | 256990.2 | 281185.9 |
| 2023   | 286863.7 | 270129.8 | 303597.6 | 286881.0                     | 270065.6 | 303696.4 |
| 2024   | 304652.4 | 282752.1 | 326552.7 | 304674.0                     | 282678.6 | 326669.3 |
| 2025   | 322441.1 | 294946.0 | 349936.1 | 322466.9                     | 294863.3 | 350070.5 |
| 2026   | 340229.7 | 306740.2 | 373719.3 | 340259.8                     | 306648.0 | 373871.7 |
| 2027   | 358018.4 | 318158.6 | 397878.2 | 358052.8                     | 318056.8 | 398048.7 |
| 2028   | 375807.1 | 329221.7 | 422392.5 | 375845.7                     | 329110.1 | 422581.3 |
| 2029   | 393595.8 | 339947.1 | 447244.5 | 393638.7                     | 339825.4 | 447451.9 |
| 2030   | 411384.5 | 350349.8 | 472419.2 | 411431.6                     | 350217.7 | 472645.5 |

Source: Authors computation.

The Southern region's per capita SDP is forecasted to nearly double over the decade, underscoring its role as one of the most rapidly developing parts of India. Both ARIMA and

Holt's methods yield highly consistent results, suggesting that the region's growth path is strongly deterministic and trend driven (see Table 8).

**Table 9:** Forecasting of per capita SDP of Eastern region of India using the ARIMA and the Holt's Exponential Smoothing models

| Models | ARIMA    |          |          | Holt's Exponential Smoothing |          |          |
|--------|----------|----------|----------|------------------------------|----------|----------|
| Year   | Forecast | LCI      | UCI      | Forecast                     | LCI      | UCI      |
| 2020   | 157650.7 | 151354.1 | 163947.3 | 155469.3                     | 148805.2 | 162133.4 |
| 2021   | 173201.4 | 164002.1 | 182400.7 | 169237.3                     | 159656.4 | 178818.2 |
| 2022   | 189493.2 | 177531.0 | 201455.5 | 183005.4                     | 169839.7 | 196171.1 |
| 2023   | 206432.2 | 191433.2 | 221431.2 | 196773.5                     | 179503.6 | 214043.4 |
| 2024   | 223936.1 | 205421.7 | 242450.6 | 210541.6                     | 188729.9 | 232353.3 |
| 2025   | 241933.4 | 219303.6 | 264563.2 | 224309.7                     | 197569.2 | 251050.1 |
| 2026   | 260361.3 | 232944.4 | 287778.2 | 238077.7                     | 206056.3 | 270099.2 |
| 2027   | 279165.2 | 246250.2 | 312080.2 | 251845.8                     | 214217.1 | 289474.5 |
| 2028   | 298297.4 | 259155.7 | 337439.2 | 265613.9                     | 222071.8 | 309156.0 |
| 2029   | 317716.3 | 271615.3 | 363817.3 | 279382.0                     | 229636.9 | 329127.0 |
| 2030   | 337385.4 | 283598.0 | 391172.8 | 293150.1                     | 236926.4 | 349373.7 |

Source: Authors computation.

Both models forecast consistent year-on-year growth, reflecting an optimistic outlook for the Eastern region's economy. Holt's model generally gives slightly lower forecasts than ARIMA up to 2021, but the difference narrows and reverses slightly after 2024. In the Eastern region the per capita GDP in 2019 was 142949, after forecasting the values using ARIMA the per capita GDP of Eastern region has increased by 2.14 times from 2020 to 2030 and by using Holt's exponential method the per capita GDP is increased by 1.89 times from 2020 to 2030. The Eastern region, historically

lagging in economic indicators, is forecasted to more than double its per capita GDP over the next decade in both models. ARIMA suggests more optimistic growth, possibly reflecting recent infrastructure or industrial activity gains. Holt's model remains cautious, indicating steady but moderate growth, which might align more closely with past performance patterns. Policymakers can use the range between these forecasts to plan for realistic investment needs, development programs, and infrastructure provisioning (see Table 9).

**Table 10:** Forecasting of per capita GDP of Western region of India using the ARIMA and the Holt's Exponential Smoothing models

| Models | ARIMA    |          |          | Holt's Exponential Smoothing |          |          |
|--------|----------|----------|----------|------------------------------|----------|----------|
| Year   | Forecast | LCI      | UCI      | Forecast                     | LCI      | UCI      |
| 2020   | 328889.9 | 321994.5 | 335785.4 | 316273.3                     | 307222.2 | 325324.4 |
| 2021   | 353470.4 | 339009.9 | 367931   | 337893.3                     | 322340.0 | 353446.5 |
| 2022   | 378047.8 | 359896.8 | 396198.9 | 359513.2                     | 337021.9 | 382004.5 |
| 2023   | 405426.7 | 383712.7 | 427140.7 | 381133.1                     | 351138.5 | 411127.8 |
| 2024   | 431988.0 | 404339.1 | 459636.8 | 402753.1                     | 364683.9 | 440822.2 |
| 2025   | 458787.8 | 424023.7 | 493552   | 424373.0                     | 377677.2 | 471068.8 |
| 2026   | 485518.1 | 442467.5 | 528568.6 | 445993.0                     | 390142.4 | 501843.5 |
| 2027   | 512268.6 | 460020.1 | 564517.1 | 467612.9                     | 402103.2 | 533122.6 |
| 2028   | 539013.2 | 476757.1 | 601269.4 | 489232.8                     | 413581.7 | 564883.9 |
| 2029   | 565759.6 | 492777.1 | 638742.1 | 510852.8                     | 424597.9 | 597107.6 |
| 2030   | 592505.4 | 508137.9 | 676873.0 | 532472.7                     | 435169.9 | 629775.5 |

Source: Authors computation.

Both models forecast rapid and consistent growth in the Western region's per capita GDP. ARIMA gives higher forecasts throughout the period and Holt's model is more conservative, but the trend direction is the same. In the Western region the per capita GDP was 294654 in 2019, later by doing the forecasting using the ARIMA and Holt's exponential smoothing methods the results shows that there is 2 times increase in per capita GDP of Western region is found

from 2020 to 2030. The Western region, which includes industrial and commercial hubs like Mumbai, Ahmedabad, Pune, and Surat, shows high forecasted economic performance. The faster growth predicted by ARIMA may reflect: Past economic momentum, strong infrastructure and investment base, contribution of high growth sectors (IT, finance, logistics, trade) (see Table 10).

**Table 11:** Forecasting of per capita GDP of Central region of India using the ARIMA and the Holt's Exponential Smoothing models

| Models | ARIMA    |          |          | Holt's Exponential Smoothing |          |          |
|--------|----------|----------|----------|------------------------------|----------|----------|
| Year   | Forecast | LCI      | UCI      | Forecast                     | LCI      | UCI      |
| 2020   | 96725.0  | 95313.5  | 98136.5  | 96747.6                      | 95209.4  | 98285.7  |
| 2021   | 103943.9 | 101888.2 | 105999.6 | 103695.7                     | 101464.3 | 105927.0 |
| 2022   | 111155.2 | 108144.0 | 114166.5 | 110643.8                     | 107348.6 | 113939.0 |
| 2023   | 118363.3 | 113991.0 | 122735.6 | 117591.9                     | 112975.6 | 122208.3 |
| 2024   | 125570.0 | 119471.5 | 131668.6 | 124540.1                     | 118404.8 | 130675.4 |
| 2025   | 132776.1 | 124643.5 | 140908.8 | 131488.2                     | 123667.8 | 139308.6 |
| 2026   | 139982.0 | 129552.8 | 150411.3 | 138436.3                     | 128783.9 | 148088.7 |
| 2027   | 147187.8 | 134232.1 | 160143.5 | 145384.4                     | 133766.5 | 157002.4 |
| 2028   | 154393.5 | 138705.2 | 170081.9 | 152332.6                     | 138625.2 | 166039.9 |
| 2029   | 161599.3 | 142989.6 | 180208.9 | 159280.7                     | 143367.9 | 175193.5 |
| 2030   | 168804.9 | 147098.9 | 190511.0 | 166228.8                     | 148000.8 | 184456.8 |

Source: Authors computation.

The Central region includes states like Madhya Pradesh and Chhattisgarh, generally considered lower in economic development relative to Southern and Western regions of India. Both models project a steady and linear rise in per capita GDP across the forecast period. The per capita GDP of Central region for the year 2019 was 89488. By forecasting these per capita GDP values from 2020 to 2030 by using ARIMA and Holt's exponential smoothing method the results

shows that there is a nearly 2 times increase in the per capita GDP from 2020 to 2030 in both the methods. The Central region, which has historically lagged in industrialization and infrastructure, is forecasted to experience significant but moderate economic growth. Both models suggest that by 2030, the per capita GDP will be around ₹1.66-1.68 lakh, up from ₹96,700 in 2020 (see Table 11).

**Table 12:** Test for Accuracy and Bias for ARIMA and the Holts Exponential Smoothing models

|          | Arima  |         | Holt's Exponential Smoothing |         |
|----------|--------|---------|------------------------------|---------|
| Regions  | MAPE   | MALPE   | MAPE                         | MALPE   |
| India    | 2.3759 | -0.4222 | 2.3869                       | -0.4458 |
| Northern | 8.5117 | -4.6071 | 10.9553                      | -1.1477 |
| Southern | 4.5761 | -1.8320 | 4.7071                       | -1.6969 |
| Eastern  | 6.5548 | -2.9701 | 7.1764                       | -2.7596 |
| Western  | 6.7071 | -2.2164 | 5.8451                       | -2.4105 |
| Central  | 0.8916 | -0.3027 | 0.9511                       | -0.4337 |

Source: Authors computation.

The test for the accuracy and bias is tested by using MAPE and MALPE for both the models ARIMA and Holt's Exponential Smoothing models for all the regions of India including India and the results shows that for the MAPE for the ARIMA shows lower values than the Holt's Exponential Smoothing model for the per capita GDP of India and per capita SDP for different regions of India except Western region. The MALPE values for both the models shows underestimation. Forecast accuracy and bias diagnostics across Indian regions reveal that the ARIMA model consistently delivers more accurate and less biased forecasts than Holt's Exponential Smoothing in most cases. ARIMA achieves the lowest MAPE in the Central region (0.89%) and performs best in four of the five regions. Both models exhibit mild to moderate underprediction bias (negative MALPE), with the Northern region showing the highest bias under ARIMA (-4.61%). Notably, the Western region is the only case where Holt's model marginally outperforms ARIMA in forecast accuracy. These results reinforce the suitability of ARIMA for regional economic forecasting, especially where data exhibit autocorrelated patterns (see table 12).

#### 4. Conclusion

This study aimed to forecast the per capita State Domestic Product (SDP) of India and its major regions using two time series models ARIMA and Holt's Exponential Smoothing and to evaluate their performance in terms of accuracy and bias.

The forecasting results (Tables 6-11) clearly show that all regions are expected to experience steady economic growth from 2020 to 2030. Among them, the Western and Southern regions demonstrate the most significant increases in per capita SDP, reflecting their stronger industrial base and service sector expansion. In contrast, the Eastern and Central regions, while starting from lower base values, also project consistent upward trends, indicating gradual economic convergence.

Model-wise, both ARIMA and Holt's methods captured the general growth trajectories well. However, ARIMA consistently provided slightly higher and more dynamic forecasts, especially in the Western and Northern regions, where historical economic momentum and structural developments are likely better captured through lagged effects.

The Box-Ljung test results confirmed that the residuals of the selected ARIMA models were not significantly autocorrelated (except marginally in the Southern region), validating their adequacy for forecasting purposes. The estimation results also showed that most moving average terms were statistically significant, especially in the Northern and Western regions, suggesting that past shocks have a lasting influence on current SDP levels.

Crucially, the forecast accuracy diagnostics (Table 12) reveal that ARIMA models outperformed Holt's models in four out of five regions (India, Northern, Southern, Eastern, and Central), both in terms of lower Mean Absolute Percentage Error (MAPE) and less biased forecasts (MALPE). The Central region, often considered underdeveloped, showed the lowest forecast error (MAPE, 0.89%), indicating strong model performance and potentially improving data reliability in this region.

In summary, the findings suggest that ARIMA is the more robust forecasting model for regional economic projections in India. While Holt's model performs adequately especially in smoother trends like those seen in the Western region

ARIMA's ability to account for autocorrelation and past dynamics provides more reliable and nuanced predictions. These insights are valuable for regional economic planning, infrastructure investment, and targeted policy interventions aimed at reducing inter-regional disparities and fostering balanced growth across the Indian subcontinent.

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