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Does Distance Matter in Convergence among Indian States?

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CHITRAKALPA SEN & SUBARAN ROY
O P JINDAL GLOBAL UNIVERSITY
https://jgu.edu.in/

Does *Distance* Matter in Convergence among Indian States?

Chitrakalpa Sen*& Subaran Roy†

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Abstract

In this paper we investigate the existence of convergence among Indian states over a period of thirty five years (1981-2016) by employing *distance* of any state from the leader (*in terms of per-capita income*) as our variable of interest. The study primarily focuses on the role of three major sectors, namely, agriculture, manufacturing and infrastructure, while examining the existence of convergence or lack of it. *Prima facie,* we do not find evidence of convergence among Indian states. However, our unit root tests results both at state and in panel data confirms existence of convergence. In the next step we take into account the three aforementioned sectors, our findings become even stronger. Our empirical results indicate that an increase in the relative income gap with the leader is associated with a decrease in the *distance* variable. This is consistent with the notion of convergence. Agriculture, manufacturing, and infrastructure variables all demonstrate statistically significant relationships with *distance*.

JEL Classification: O15, O40, O53

*Professor of Economics, Jindal Global Business School, Jindal Global University. *Email*:c.sen@jgu.edu.in

†Professor of Economics, Jindal School of Government and Public Policy, Jindal Global University. *Email*:subaran@jgu.edu.in

Introduction and Literature Survey

Since 1991, India has undergone a remarkable economic transformation, fuelled by a series of liberalization, privatization, financial, banking, fiscal, and infrastructural reforms. As a result of this reforms-led progress, India's GDP reached $2.6 trillion (current US$) in 2022, the fifth largest in the world (The World bank). The per-capita income has increased substantially as well, from a meagre $300 in 1991 to over $2200 in 2022 (The World bank), putting the country in the bracket of lower-middle income countries, up from the low-income countries category. Between 2003 and 2018 (excluding 2008), Indian GDP grew at an impressive average of 7.3% annually (The World bank). However, the growth in per capita income has been largely uneven across Indian States and union territories. This often raises the question about the convergence dynamics of Indian states. In this paper we take a fresh look at the Indian regional convergence, it's extent and the key drivers behind the convergence or lack of it.

Solow's (1956) neoclassical growth model suggests that poorer economies tend to grow faster than richer ones, leading to a convergence in per capita income levels over time, commonly known as the "catch-up effect". However, this convergence hypothesis remains an extensively debated topic in growth economics, with empirical studies presenting mixed evidence supporting or refuting the hypothesis. The literature distinguished two types of convergence: β convergence, which measures the proportionate growth in per capita income relative to its initial level, and σ convergence, that measures the cross-sectional dispersion of per capita incomes. β convergence can be further divided into conditional and absolute convergence. The former is apparent only after other accounting for other factors which may cause variation in steady states while the latter is a stronger kind of convergence, where initially poor states grow faster, regardless of any differences in initial conditions (Trivedi, 2002). In absolute convergence, all economies, irrespective of their initial conditions, eventually converge to the same steady-state level of per capita income. On the other hand, according to conditional convergence, economies with similar characteristics and structures converge to their own unique steady-state levels (Barro & Sala-i-Martin, 1992).

Empirical studies on convergence have produced mixed results. Early cross-sectional studies, such as those by Baumol (1986) and Barro (1991), found evidence of convergence among OECD countries. However, these studies were criticized for their lack of robustness and inability to account for unobserved country-specific effects (Quah, 1993). Subsequent panel data studies, such as those by Islam (1995) and Caselli, Esquivel, and Lefort (1996), addressed these concerns and provided further support for conditional convergence.

Despite the evidence in favor of conditional convergence, some studies have reported divergence or lack of convergence among economies. For example, Pritchett (1997) argued that the world's distribution of per capita income became more dispersed between 1960 and 1990, with a growing gap between rich and poor countries. Similarly, Quah (1996) highlighted the presence of multiple convergence clubs, wherein economies converge to different steady-state levels depending on their initial conditions and other factors.

Policy-related variables, such as trade openness, financial development, and macroeconomic stability, have been identified as important determinants of convergence as well (Frankel & Romer, 1999; King & Levine, 1993). Openness to trade can facilitate the diffusion of technology and knowledge, promote specialization, and enhance the efficiency of resource allocation, thereby contributing to convergence (Sachs & Warner, 1995). Financial development is found to act as a catalyst for more efficient allocation of capital and enhance productivity, while macroeconomic stability can create a conducive environment for investment and growth (Aghion, Bacchetta, Rancière, & Rogoff, 2009).

The literature on state and regional income convergence within countries generally supports the notion that income disparities tend to decrease over time, with poorer states or regions growing faster than richer ones. Barro and Sala-i-Martin (1991) pioneered the study of this phenomenon in the U.S., while Islam (2003) provided a comprehensive review of the literature focusing on several countries, including the United States, Canada, Europe, and Japan. Studies exploring income convergence in different contexts, such as those by da Mata et al. (2007) in Brazil, Caselli et al. (1996) in Italy, and Magrini (2004) in Europe, have consistently found evidence of convergence and emphasized the importance of factors such as human capital, physical capital, technology diffusion, and investments in infrastructure in achieving convergence. However, the rate of convergence can differ significantly between regions and countries. For instance, Bernard and Durlauf (1995) found that convergence across U.S. states was conditional on initial income levels, suggesting the presence of convergence clubs. Meanwhile, Ramos and Suriñach (2017) highlighted the role of economic growth periods and investments in human and physical capital in driving convergence within Spanish regions. Gennaioli et al. (2014) extended the analysis to a large sample of regions across 110 countries, uncovering within-country convergence alongside persistent between-country disparities and emphasizing the role of national institutions in shaping convergence patterns.

In the context of India, understanding the convergence dynamics among states is crucial for policy formulation, as it has implications for regional equity and inclusive growth. There is extensive empirical evidence on income and state-level per capita GDP convergence among Indian states. While the majority of studies find support for conditional convergence, some evidence suggests divergence or the presence of convergence clubs. The factors influencing the convergence process are complex and multifaceted, involving structural, institutional, and policy-related variables, as well as spatial effects. Early studies by Nagaraj et al. (1998) and Ghosh et al. (1998) found evidence of absolute convergence among Indian states during the 1960s and 1970s, suggesting that poorer states were catching up with their richer counterparts. However, these studies were based on cross-sectional data and did not account for unobserved state-specific effects or other potential sources of heterogeneity.

More recent studies have employed panel data techniques, such as panel unit root tests, panel cointegration analysis, and dynamic panel data models, to investigate the convergence hypothesis among Indian states (Bajpai & Sachs, 1996; Cashin & Sahay, 1996; Kar & Pentecost, 2000; Nayyar, 2008; Panagiotidis & Chortareas, 2018). These studies generally find evidence of conditional convergence, implying that Indian states with similar characteristics and structures tend to converge to their own unique steady-state levels of per capita income. For example, Bajpai and Sachs (1996) found after accounting for state-specific variables such as investment, education, and the sectoral composition of output, Indian states with lower initial levels of per capita income experienced accelerated growth compared to states with higher initial per capita income levels. Similarly, Nayyar (2008) reported conditional convergence among Indian states, with evidence of convergence clubs based on states' initial conditions and other characteristics.

Several factors have been identified as determinants of the convergence process among Indian states. These factors can be broadly categorized into structural, institutional, and policy-related variables (Ahluwalia, 2000; Purfield, 2006; Bajpai and Sachs, 1996; Nayyar, 2008; Romer, 1990; Lucas, 1988; Rodrik and Subramanian, 2004; Trivedi, 2002, Acemoglu et al., 2001; Easterly and Levine, 2003; Sachs et al., 2002).

While there is substantial evidence supporting the conditional convergence hypothesis among Indian states, some studies have reported divergence or a lack of convergence in certain contexts. For instance, Ghosh et al. (1998) and Kurian (2000) found that income disparities among Indian states increased during the 1980s and 1990s, coinciding with the period of economic liberalization. Spatial effects have also been found to play a role in the convergence process among Indian states. Studies by Cashin and Sahay (1996), Purfield (2006), and Thirlwall (2013) reported that geographical proximity and regional spillovers in- fluenced the convergence dynamics among Indian states, with spatially contiguous states exhibiting similar growth patterns and convergence trends

To address these limitations, our study employs a comprehensive panel dataset covering 29 Indian states and union territories from 1981 to 2016, providing a more nuanced understanding of the convergence process. We focus on the role of three major sectors of Indian economy in the process of convergence employing the *distance* variable.

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To address these limitations, our study employs a comprehensive panel dataset covering 22 Indian states and union territories from 1981 to 2016, providing a more nuanced understanding of the convergence process. We utilize advanced econometric techniques, including panel unit root tests to investigate the presence of both absolute and conditional convergence.

An Overview of Data

As of 2023, India is divided into 28 states and 8 union territories. We consider the annual data for a period of thirty-five years, from 1981 to 2016. limitation of relevant comparable data restricts our sample to 22 states/territories[1]. Our variable of interest - the growth of Gross State Domestic Product (GSDP) is calculated using the available values of GSDP provided in Indian Public Finance Statistics (IPFS) published by Government of India. In this study, we introduce a variable *distance*, defined as one minus the ratio of the per capita income of a given state Y_i to the per capita income of Delhi Y_{Del}.[2] The *distance* variable serves as a comparative measure of each state's per capita income relative to that of a "benchmark" region, Delhi. We have chosen Delhi as the benchmark, because of its consistent ranking in state per

[1] The list of these /territories is provided in Appendix 1.The sample represents more than 90% of Indian economy

[2] We follow the hypothesis of Nelson and Phelps (1966). Specifically, our measure of distance is given by $distance = (1 - \frac{Y_i}{Y_{Del}})$.

capita income across the sample periods (rank 2 in 1980, rank 1 in 2016; Table -2). A value of *distance* approaching 1 indicates that the per capita income of the respective state is far from that of Delhi. Conversely, a *distance* value significantly close to zero suggests that the per capita income of the state in question is considerably closer to Delhi. This approach provides a normalized comparison of per capita incomes across states, using Delhi as the benchmark. In order to investigate non-linearity, we additionally create a new measure of distance, $distance - new$, as proposed by Benhabib and Spiegel (2005).In this scenario $distance - new = (1 - \frac{Y_i}{Y_{Del}})\frac{Y_i}{Y_{Del}}$.The multiplicative term, $\frac{Y_i}{Y_{Del}}$, here helps capture the non-linear nature of sensitiveness for changes in both Y_i and Y_{Del} .

Table 1 presents the per capita Gross State Domestic Product (GSDP) for all states and territories spanning the period from 1980 to 2016. Upon examining the 25-year average of per capita GSDP, it becomes evident that certain states have consistently outperformed other

Table 1. Average Per Capita GSDP between 1980-2016 (values in Indian Rupees)

State	Per Capita GSDP
Andhra Pradesh	58392.5
Assam	25942.6
Bihar	23619.4
Delhi	204425.5
Gujarat	98964.9
Haryana	80467.8
Himachal Pradesh	53594.1
Karnataka	65746.7
Kerala	53994.7
Madhya Pradesh	36030.5
Maharashtra	108405.2
Manipur	33981.1
Meghalaya	34585.2
Nagaland	54457.5
Orissa	30164.4
Pondicherry	65631.1
Punjab	38364.1
Rajasthan	280449.2
Sikkim	71637.5
Tamil Nadu	72273.4
Tripura	26567.7
Uttar Pradesh	54065.4
West Bengal	58392.5
Average	**71443.6**

During the observed period, the economic performance of the majority of states has been suboptimal, as summarized in Table 2. Of the 22 states in the sample, 10 have experienced a decline in their per capita GDP rankings, while 5 have remained stagnant. Notably, only 7 states have risen in the rankings. Sikkim, which held the top position in 2016, has been the second-best performing state, experiencing a remarkable 35-times increase in its per capita GDP, rising from Rs. 15,710 to Rs. 545,188.4. Delhi, formerly the leader, has been slipped to the second position, succeeded by Maharashtra, Gujarat, Haryana, and Tripura. Tripura has exhibited the most significant improvement during this period, climbing 12 ranks and witnessing more than a tenfold increase in its per capita GDP, from Rs. 13,070 to Rs. 131,476.8. Conversely, West Bengal and Punjab have each fallen by 8 ranks, followed by Manipur, which has declined by 6 ranks.

Of particular concern is the performance of the five lowest-ranking states in 2016-17: Bihar (22nd), Assam (21st), Uttar Pradesh (20th), Orissa (19th), and Manipur

(18th). Rankings of both Uttar Pradesh and Bihar have been static since the 1980s. Orissa and Assam, which were already in the bottom half of the raking in the 1980s (ranked 17th and 21st, respectively), have further declined by 2 ranks. Manipur has experienced an 8-rank drop.

The performance of majority of the states during this time-period has been less than satisfactory (Table 2). 10 out of the 22 states have slipped in their per capita state GDP ranking, 5 states have shown no change, and only 7 states have climbed up in the ranking. Sikkim's per capita GDP has increases the most between 1980-81 and 2016-17 (from Rs.1571 to Rs.54518.84), while Assam's increase has been the lowest (from Rs.1284 to Rs. 3904.52).

Table 2. Ranking of Indian States According to Their PCSGDP (in Rs.) between 1980 and 2016

State	1980-81	2016-17	Rank 1980-81	Rank 2016-17	Change in Ranking
Andhra Pradesh	13800	102985.1	13	11	2
Assam	12840	39045.2	19	21	-2
Bihar	9170	38068.9	22	22	0
Delhi	40300	368551.1	1	2	-1
Gujarat	19400	178529.8	5	4	1
Haryana	23700	137235.7	4	5	-1
Himachal Pradesh	17040	90148.2	7	8	-1
Karnataka	15200	116293.4	9	9	0
Kerala	15080	92909.5	10	13	-3
Madhya Pradesh	13580	58481.1	16	16	0
Maharashtra	24350	192460.4	3	3	0
Manipur	14190	53772.2	12	18	-6
Meghalaya	13610	55560.4	14	17	-3
Nagaland	12715	96199.1	15	12	3
Orissa	13140	47188.87	17	19	-2
Punjab	26740	104522.2	2	10	-8
Rajasthan	12220	64508.2	21	15	6
Sikkim	15710	545188.4	8	1	-7
Tamil Nadu	14980	128294.1	11	7	4
Tripura	13070	131476.8	18	6	12
Uttar Pradesh	12780	40355.5	20	20	0
West Bengal	17730	90400.8	6	14	-8

In the next section we discuss briefly the unit root tests which we conducted and the estimation techniques we used in this study.

Unit Root Tests & Estimation Approach

First, we look at convergence pattern using the *distance* variable without taking into consideration of any other control variables. We conduct unit root tests to investigate the convergence. Absence of unit root in the series implies a mean reversion process and thus convergence with respect to the leader state in our case. Specifically, we employ two unit root tests to each series. Namely these tests are a) Dicky-Fuller and b) Phillips-Perron unit root tests.

The Dickey-Fuller test is based on the $AR(1)$ process $y_t = \rho y_{t-1} + v_t$. It is stationary when $|\rho| < 1$, and, when $|\rho| = 1$, it becomes the non stationary random walk process. Hence, one way to test for stationarity is to investigate the value of ρ. In other words, we test whether ρ is equal to one or significantly less than one. To verify this procedure, the method concedes an $AR(1)$ process:

$$y_t = \rho y_{t-1} + v_t \tag{1}$$

where the v_t are independent random errors with zero mean and constant variable σ_v^2. We can test for non stationarity by testing the null hypothesis $\rho = 1$ against the alternative that $|\rho| < 1$, or simple $\rho < 1$. This one tail (left) test can be constructed in a more prudent form by subtracting y_{t-1} from both sides of (2) to obtain

$$y_t - y_{t-1} = \rho y_{t-1} - y_{t-1} + v_t \tag{2}$$

$$\Delta y_t = (\rho - 1) y_{t-1} + v_t \tag{3}$$

$$\Delta y_t = \gamma y_{t-1} + v_t \tag{4}$$

where $\gamma = \rho - 1$ and $\Delta y_t = y_t - y_{t-1}$. Then, the hypotheses can be expressed in terms of either ρ or γ :

$$H_0 : \rho = 1 \Leftrightarrow H_0 : \gamma = 0$$
$$H_0 : \rho < 1 \Leftrightarrow H_0 : \gamma < 0$$

Thus the null hypothesis reflects that the series is non-stationary. In other words, if we do not reject the null, we conclude that it is a non-stationary process; if we reject the null hypothesis that $\gamma = 0$, then we conclude that series is stationary in nature.

We also conduct Phillips–Perron (PP) unit root tests of stationarity. The Phillips–Perron unit root tests primarily differ from other tests in how they treat serial correlation and heteroskedasticity in the error terms. We briefly discuss the test regression, test statistic and the estimates of the variance parameters before explaining the panel unit root tests. The test regression for the PP tests is

$$\Delta y_t = \beta \mathbf{D}_t^{'} + \pi y_{t-1} + u_t \tag{5}$$

where u_t is $I(0)$ and may be heteroskedastic and $\mathbf{D}_t$ is a vector of deterministic terms. The PP tests correct for any serial correlation and heteroskedasticity in the errors u_t of the test regression by clearly modifying the test statistics t_π and $T_{\hat{\Pi}}$. These modified statistics, denoted Z_t and Z_π, are given by

$$Z_t = \left(\frac{\hat{\sigma^2}}{\lambda^2} \right)^{\frac{1}{2}} .t_{\pi=0} - \frac{1}{2} \left(\frac{\lambda^2 \hat{-} \hat{\sigma^2}}{\hat{\lambda^2}} \right) . \left(\frac{T.SE(\widehat{\pi})}{\widehat{\sigma^2}} \right) \tag{6}$$

$$Z_\pi = T_{\widehat{\pi}} - \frac{1}{2} \frac{T^2.SE(\widehat{\pi})}{\widehat{\sigma^2}} (\lambda^2 \hat{-} \hat{\sigma^2}) \tag{7}$$

The terms $\hat{\sigma^2}$and $\hat{\lambda^2}$are consistent estimates of the variance parameters

$$\sigma^2 = lim_{T \to \infty} T^{-1} \sum_{t=1}^{T} E \left[u_t^2 \right] \tag{8}$$

$$\lambda^2 = lim_{T \to \infty} \sum_{t=1}^{T} E \left[T^{-1} S_T^2 \right] \tag{9}$$

where $S_T = \sum_{t=1}^{T} u_t$. The sample variance of the least square residual is $\hat{u}_t$ is a consistent estimator of σ^2, and the Newey-West long run variance estimate of of u_t using $\hat{u}_t$ is a consistent estimator of λ^2.

Under the null hypothesis that $\pi = 0$, the PP Z_t and Z_π statistics have the identical asymptotic distributions as Augmented Dickey Fuller t-statistic and normalized bias statistics. One benefit of the PP tests is that the PP tests are robust to general form of heteroskedasticity in the error term u_t. Also, we do not have to specify a lag length for the test regression in PP test.

Next we conduct the panel unit root tests to identify the existence of any convergence in terms of distance among states. Specifically we conduct panel unit root tests proposed by Levin, Lin and Chu (2002) & Im, Pesaran and Shin (2003). We briefly explain the tests below. We consider a simple panel data model with a first order autoregressive component:

$$y_{it} = \rho_i y_{i,t-1} + \mathbf{z}_{it}^{'}\gamma_i + \epsilon_{it} \tag{10}$$

where $i = 1, ..., N$ indexes panels; $t = 1, ..., T$ indexes time; y_{it} is the variable of interest that is being tested; and $\epsilon_{it}$is a stationary error term. The $\mathbf{z}_{it}$ term reflect panel specific variables. Panel unit root tests are used to test the null hypothesis $H_0 : \rho_i = 1$ for all i versus the alternative $H_a : \rho_i < 1$. Depending on the test, H_0 may hold, for one i, a fraction of all i or all i. Levin-Lin-Chu (LLC) test considers the simplifying assumption that all panels have the same autoregressive parameter so that all panels share the unique autoregressive parameter so that $\rho_i = \rho$ for all i. Equation (10) is often reformulated as

$$\Delta y_{it} = \phi y_{i,t-1} + \mathbf{z}_{it}^{'}\gamma_i + \epsilon_{it} \tag{11}$$

so that the null hypothesis is then $H_0 : \phi_i = 0$ for all i versus the alternative $H_a : \phi_i < 0$. The LLC test (11) starts with the restriction that all panels share a common autoregressive parameter. In a regression equation like (11), ϵ_{it} is potentially serially correlated. In order to address this, LLC augment the model by adding lags of the the dependent variable:

$$\Delta y_{it} = \phi y_{i,t-1} + \mathbf{z}_{it}^{'}\gamma_i + \sum_{j=1}^{p} \theta_{ij} \Delta y_{i,t-j} + u_{it} \tag{12}$$

The number of lags, p, can be specified employing the one of several information criteria. The LLC test assumes that ϵ_{it} is independently distributed across panels.

The LLC test we have briefly explained assume that all panels share a common autoregressive parameter, ρ. On the other hand Im, Pesaran and Shin (IPS) developed set of tests that relax the assumption of a common autoregressive parameter. The starting point for the IPS test is a set of Dickey-Fuller regression of the form

$$\Delta y_{it} = \phi_i y_{i,t-1} + \mathbf{z}_{it}^{'} \gamma_i + \epsilon_{it} \tag{13}$$

Equation (13) differs from (11) in terms of ϕ. In equation (13) ϕ is panel specific, indexed by i, where as in (11), ϕ is constant. IPS assume that ϵ_{it} is independently distributed normal for all i and t, and they allow ϵ_{it} to have heterogeneous variances σ_i^2 across panels. One way to differentiate between the IPS and LLC tests is that here we employ (13) to each panel individually and average the resulting t statistics, whereas in the LLC test we pool the data before fitting an equation such as (11) and calculate a test statistic based on the pooled regression results.

Next, we conduct panel estimation after conducting these tests. Specifically, we employ random effect model to our panel data set. The estimation method for the approach are discussed briefly. Let's assume the data on individual state i is:

$$y_{it} = \beta_{1i} + \beta_2 x_{2it} + \beta_{3it} + x_{3it} + ... + \beta_{kit} x_{kit} + e_{it} \tag{14}$$

We estimate random error component model after confirming the stationarity. We treat the individual state differences as random rather than fixed. Random individual differences can be included in the model by specifying the intercept parameters β_{1i}. In order to capture this, one way to construct β_{1i} is to comprise of a constant part that represents the population average, $\bar{\beta_1}$,and random individual differences from the population average, u_i. In equation form β_{1i} is

$$\beta_{1i} = \beta_1 \bar{+} u_i \tag{15}$$

The random individual differences u_i, which are popularly termed as random effects, are similar to random error terms, and we make the standard assumptions about them - namely that they have zero mean, are uncorrelated across individual observations, and have a constant variance σ_u^2, so that $E(u_i) = 0, cov(u_i, u_j) = 0$ for $i \neq j$ and $var(u_i) = \sigma_u^2$. Now if we substitute (15) in (14) we have

$$y_{it} = (\bar{\beta_1} + u_i) + \beta_2 x_{2it} + \beta_{3it} + x_{3it} + ... + \beta_{kit} x_{kit} + (e_{it} + u_i) \tag{16}$$

In this expression $\overline{\beta_1}$ is a fixed population parameter, and u_i is a random effect. We rearrange (16) to make it look like a familiar regression equation,

$$y_{it} = \overline{\beta_1} + \beta_2 x_{2it} + \beta_{3it} + x_{3it} + ... + \beta_{kit} x_{kit} + v_{it} \tag{17}$$

where $\overline{\beta}_1$is the intercept parameter and the error term is v_{it} is composed of a component u_i that represents a random individual effect and the component e_{it} which is the usual regression random error. The combined error is v_{it} =(e_{it}+u_i). Because the random effects regression has two components, one for the individual and one for the regression, the random effects model is also known as error components model. We estimate the model using the Generalized Method of Moments (GMM) estimation technique. Specifically, we estimate the following regression equation:

$$y_{it} = \sum_{j=1}^{\rho} \rho_j y_{it-j} + x_{it}^{'} \beta + e_{it} + u_i \tag{18}$$

where y_{it} is the *distance*, $|\rho| < 1$,x_{it} is $(k-1)$ vector of regressors, i is the number of states, $i = 1, ...N$; t is time period $t = 1, ...T$; and u_{it} is the unobserved time-invariant error, and $e_{it}\sim$ $iid(0, \sigma_e^2)$ is the idiosyncratic error. In the next section we report our results and discuss the same.

Results and Discussion

Table 3 shows results from Dickey-Fuller test provides strong evidence that the *distance* variable is stationary for all states/territories. All the p-values are less than 0.05 except for Tripura. Similarly, when we conduct Phillips Perron test we observe similar pattern. All p-values remain less than 0.05 again except for Tripura.[3]

[3]The p-value is 0.09 for Tripura.

The overall results indicate that *distance* variable is stationary in process. In the next step we employ the panel unit root tests described above.

Table-3:-State-Wise Stationarity Results of Distance

State	***DickeyFullerTestStat.***	$p-value$	**PhillipsPerronTestStat.**	$p-value$
Andhra-Pradesh	-4.313***	0.000	-4.332***	0.000
Assam	-3.957***	0.001	-4.067***	0.001
Bihar	-3.736***	0.003	-3.717***	0.003
Gujarat	-5.440***	0.000	-5.419***	0.000
Haryana	-4.526***	0.000	-4.489***	0.000
Himachal Pradesh	-4.815***	0.000	-4.882***	0.000
Karnataka	-3.848***	0.002	-3.842***	0.002
Kerala	-4.302***	0.000	-4.291***	0.000
Madhya Pradesh	-4.639***	0.000	-4.792***	0.000
Maharashtra	-4.017***	0.001	-3.995***	0.001
Manipur	-4.365***	0.000	-4.355***	0.000
Meghalaya	-3.797***	0.002	-3.805***	0.002
Nagaland	-3.612***	0.005	-3.700***	0.004
Orissa	-5.350***	0.000	-5.325***	0.000
Punjab	-4.056***	0.001	-4.011***	0.001
Rajasthan	-6.521***	0.000	-6.503***	0.000
Sikkim	-3.106**	0.026	-3.170**	0.021
Tamil Nadu	-4.592***	0.000	-4.424***	0.000
Tripura	-2.373	0.149	-2.568*	0.099
Uttar Pradesh	-4.255***	0.000	-4.226***	0.000
West Bengal	-3.362**	0.012**	-3.366**	0.012

*** significant at 1% level, ** significant at 5% level, *significant at 10% level

Table-4:-State-Wise Stationarity Results of Distance New

State	$DickeyFullerTestStat.$	$p-value$	**PhillipsPerronTestStat.**	$p-value$
Andhra-Pradesh	-4.270***	0.000	-4.211***	0.000
Assam	-3.881 ***	0.002	-3.782***	0.003
Bihar	-4.138***	0.000	-4.085***	0.001
Gujarat	-3.440***	0.001	-5.369***	0.000
Haryana	-5.386***	0.000	-4.689***	0.000
Himachal Pradesh	-4.739 ***	0.000	-5.805***	0.000
Karnataka	-5.793***	0.000	-4.299***	0.000
Kerala	-4.249 ***	0.000	-4.206***	0.000
Madhya Pradesh	-5.055***	0.000	-5.150 ***	0.000
Maharashtra	-4.173***	0.000	-4.134***	0.001
Manipur	-4.530***	0.000	-4.510***	0.000
Meghalaya	-3.905***	0.002	-3.904***	0.002
Nagaland	-3.437 ***	0.009	-3.458***	0.009
Orissa	-5.310 ***	0.000	-5.286***	0.000
Punjab	-4.172***	0.001	-4.070***	0.001
Rajasthan	-6.925***	0.000	-6.957***	0.000
Sikkim	-3.285 **	0.015	-3.295**	0.015
Tamil Nadu	-4.679***	0.000	-4.575***	0.000
Tripura	-2.320	0.165	-2.498	0.115
Uttar Pradesh	-4.976***	0.000	-4.956***	0.000
West Bengal	-3.568**	0.006**	-3.564**	0.006

The Dickey-Fuller and Phillips-Perron unit root tests both overwhelmingly indicate that the *distance new* variable is stationary for nearly all Indian states. The test statistics are predominantly negative and statistically significant, with p-values close to zero, strongly rejecting the null hypothesis of a unit root. The notable exception is Tripura, where the series may not be stationary. These results have significant implications for the study of income convergence across states; the stationarity of the *distance new* variable suggests that the relative income disparities between states and Delhi are not time-dependent, thereby supporting the notion of convergence in per capita incomes across Indian states.

Table 5 reports the results of panel unit root tests on the data-set. The LLC test returned a test statistic of -9.486, while the IPS test produced a test statistic of -11.930. In both instances, the associated p-values were indistinguishable from zero. This robustly rejects the null hypothesis of a unit root, providing strong evidence of stationarity in the *distance* variable across the entire panel of states.

Table-5: Panel Data Stationarity Results of Distance[4]

Test	Statistic	$p-value$
LLC	-9.486***	0.000
IPS	-11.930***	0.000

*** significant at 1% level, ** significant at 5% level, *significant at 10% level

Table-6: Panel Data Stationarity Results of Distance New

Test	Statistic	$p-value$
LLC	-10.883***	0.000
IPS	-9.830***	0.000

*** significant at 1% level, ** significant at 5% level, *significant at 10% level

[4] We also conducted Breitung & Harris Tzavalis unit root tests. Both tests rejected the null hypothesis at 1% significance level. Results on request.

The results from Table-6, which presents panel data stationarity tests for the *distance new* variable, further corroborate the findings from the state-wise tests. Both the Levin-Lin-Chu (LLC) and Im-Pesaran-Shin (IPS) tests yield negative and statistically significant test statistics at the 1% level, with p-values of zero. These results robustly reject the null hypothesis of a unit root in the panel, affirming the stationarity of the *distance new* variable across the panel of states.

The stationarity of the *distance* variable, as confirmed by both the LLC and IPS tests, suggests that the relative disparities in per-capita income between each state/territories and Delhi do not exhibit a time-dependent structure. And if we take stationarity as a proxy for convergence, then our result is consistent with the notion of convergence. The variable *distance* appears to fluctuate around a constant mean, suggesting that no state is consistently growing faster or slower than Delhi.

Table 7: Random Effect Estimation Results with Distance

Variables	**(1)**	**(2)**	**(3)**	**(4)**
Distance	-0.630***	-0.621***	-0.602***	-0.612***
	(0.084)	(0.082)	(0.083)	(0.083)
Agriculture		-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)
Manufacturing			0.004**	0.004**
			(0.000)	(0.000)
Infrastructure				0.006**
				(0.000)
Constant	0.050***	0.093***	0.102***	0.096***
	(0.003)	(0.007)	(0.000)	(0.010)
Number of Obs.	770	770	770	770
Number of Groups	22	22	22	22
Wald χ^2	55.59	104.27	106.17	109.12
$Prob > \chi^2$	0.000	0.000	0.000	0.000

*** significant at 1% level, ** significant at 5% level, *significant at 10% level

Table 8: Random Effect Estimation Results with Distance New

Variables	**(5)**	**(6)**	**(7)**	**(8)**
Distance New	-.0645***	-0.632***	-0.621***	-0.624***
	(0.000)	(0.000)	(0.000)	(0.000)
Agriculture		-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)
Manufacturing			0.003**	0.050*
			(0.081)	(0.091)
Infrastructure				0.022**
				(0.084)
Constant	0.049***	0.088***	0.094***	0.089***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of Obs.	770	770	770	770
Number of Groups	22	22	22	22
Wald χ^2	65.82	113.53	114.72	118.00
$Prob > \chi^2$	0.000	0.000	0.000	0.000

*** significant at 1% level, ** significant at 5% level, *significant at 10% level

The results from Table 7 presents the random effect estimation outcomes using the *distance* variable while Table 8 summarized the random effect estimation using the *distance new* variable. Across all eight models, the *distance* variable (*distance* in models (1) – (4) and *distance new* in models (5) – (8)) shows a negative and statistically significant relationship at the 1% level with itself, reinforcing the notion of income convergence. The "Agriculture" variable consistently exhibits a small but statistically significant negative impact, suggesting that a greater emphasis on agriculture is associated with reduced convergence. The "Manufacturing" variable shows a positive effect, significant between 1% and 10% levels in different models, indicating that manufacturing contributes positively to convergence. Similarly, "Infrastructure" also shows a positive and statistically significant effect at the 5% level, underscoring its role in convergence. The Wald $\chi 2$ statistics and their corresponding p-values further confirm the robustness of these findings. Overall, the results provide substantial evidence supporting the hypothesis of income convergence across states, while highlighting the sectoral influences on this convergence across Indian states.

Table 9 shows the random effect estimation results incorporating the variable *distance* along with six interaction terms. In model (1), both *distance* and agriculture exhibit significantly negative coefficients, while manufacturing and infrastructure display significantly positive coefficients. Model (1) includes only one interaction term, *distance**agriculture, which also yields a significantly negative coefficient. Overall it points towards a phenomenon switch underscores the importance of the manufacturing and infrastructure sector towards convergence. In our earlier models (Table 7 and 8) we found that greater emphasis on agriculture is usually associated with reduced convergence. To enhance the model's robustness, model (2) introduces an additional interaction term *distance**manufacturing. The results remain consistent with Model (1), and the newly added interaction term also shows a significantly negative coefficient. Model (3) incorporates another interaction term, *distance**infrastructure, which reveals a significantly positive coefficient, maintaining the signs of other coefficients. In Model (4), three new sectoral interaction terms are introduced. While the existing variables maintain their signs and levels of significance, the interaction term manufacturing*infrastructure is significantly positive. The other two sectoral interaction terms, although negative, are not statistically significant.

A discernible pattern emerges from these results. Any interaction term involving "agriculture" consistently shows a negative coefficient, suggesting that an increased focus only on the primary sector impedes convergence. The interaction term *dis-*

*tance**manufacturing is also consistently negative, indicating that even if a state emphasizes manufacturing, a large income gap relative to the leading state can negate any growth benefits. This is supported by the empirically observed positive relationship between per capita income and productivity; low per capita income correlates with low productivity levels, adversely affecting manufacturing.

Infrastructure however plays a pivotal role in promoting convergence. Greater emphasis on infrastructure can lead the states towards the convergence path. In fact, a simultaneous emphasis on both manufacturing and infrastructure yields a significantly positive impact, steering states toward the path of convergence.

The robustness of these findings is solidified by the highly significant Wald chi-square test statistics across all models, underscoring the collective impact of these sectors on the relative income disparities with Delhi. This provides a rich tapestry of insights, spotlighting the multifaceted economic dynamics at play in the quest for income convergence across Indian states.

Table-9:-Random Effect Estimation Results - Distance with Interaction Terms

Variables	**(1)**	**(2)**	**(3)**	**(4)**
Distance	-0.151*	-0.334*	-0.607*	-0.598*
	(0.116)	(0.250)	(0.364)	(0.289)
Agriculture	-0.010***	-0.011***	-0.010***	-0.012***
	(0.000)	(0.000)	(0.000)	(0.000)
Manufacturing	0.056***	0.058***	0.061***	0.057***
	(0.000)	(0.000)	(0.000)	(0.000)
Infrastructure	0.026*	0.028*	0.031*	0.030*
	(0.000)	(0.000)	(0.000)	(0.000)
Distance*Agriculture	-0.020**	-0.017**	-0.016**	-0.014**
	(0.007)	(0.008)	(0.007)	(0.008)
Distance*Manufacturing		-0.088**	-0.103**	-0.101**
		(0.007)	(0.005)	(0.004)
Distance*Infrastructure			0.032***	0.031***
			(0.003)	(0.003)
Manufacturing* Infrastructure				0.002**
				(0.000)
Agriculture* Infrastructure				-0.001
				(0.050)
Agriculture* Manufacturing				-0.001
				(0.041)
Constant	0.091***	0.091***	0.092***	0.086***
	(0.009)	(0.009)	(0.009)	(0.020)
Number of Observations	770	770	770	770
Number of Groups	22	22	22	22
$Wald\chi^2$	115.87	117.28	118.36	118.39
$Prob > \chi^2$	0.000	0.000	0.000	0.000

*** significant at 1% level, ** significant at 5% level, *significant at 10% level

Table-10:-Random Effect Estimation Results - Distance New with Interaction Terms

Variables	**(1)**	**(2)**	**(3)**	**(4)**
Distance New	-0.179**	-0.259*	-0.604*	-0.689*
	(0.046)	(0.019)	(0.256)	(0.368)
Agriculture	-0.031***	-0.011***	-0.021***	-0.022**
	(0.000)	(0.000)	(0.000)	(0.050)
Manufacturing	0.052**	0.065*	0.065*	0.058*
	(0.039)	(0.023)	(0.000)	(0.021)
Infrastructure	0.022*	0.018*	0.041**	0.045*
	(0.089)	(0.015)	(0.001)	(0.085)
Distance New *Agriculture	-0.019**	-0.018**	-0.012*	-0.020*
	(0.010)	(0.021)	(0.001)	(0.010)
Distance New *Manufacturing		-0.053**	-0.033*	-0.038*
		(0.0011)	(0.007)	(0.015)
Distance New *Infrastructure			0.041**	0.036**
			(0.003)	(0.016)
Manufacturing* Infrastructure				0.003**
				(0.001)
Agriculture* Infrastructure				0.000
				(0.000)
Agriculture* Manufacturing				-0.002
				(0.000)
Constant	0.090***	0.091***	0.092***	0.087***
	(0.009)	(0.009)	(0.009)	(0.019)
Number of Observations	770	770	770	770
Number of Groups	22	22	22	22
$Wald\chi^2$	125.39	125.87	127.47	127.49
$Prob > \chi^2$	0.000	0.000	0.000	0.000

*** significant at 1% level, ** significant at 5% level, *significant at 10% level

The results from Table-10 incorporates interaction terms in the random effect estimation models using the *distance new* variable. The *distance new* variable remains negatively correlated with itself across all four models, albeit at lower significance levels (5% and 10%), reinforcing the notion of convergence. The sectoral variables—Agriculture, Manufacturing, and Infrastructure—continue to exhibit statistically significant effects, with Agriculture negatively impacting convergence and Manufacturing and Infrastructure positively impacting it. The interaction terms *distance new**Agriculture and *distance new**Manufacturing are negatively significant, suggesting that the impact of these sectors on convergence varies with the distance from Delhi's per capita income. Conversely, *distance new* *Infrastructure is positively significant, indicating that infrastructure's positive impact on convergence is amplified as the distance from Delhi increases. The Wald $\chi 2$ statistics and their corresponding p-values affirm the robustness of these models. Collectively, these results offer a multifaceted view of the factors influencing income convergence, emphasizing not only the role of individual sectors but also their interactive effects with the relative income levels of states compared to Delhi.

Conclusion

This paper introduced a fresh perspective by examining the "*distance*" in income from the leading state, Delhi, to understand convergence patterns among Indian states. The results affirm a catching-up phenomenon, indicating states are progressively narrowing the income gap with Delhi. The analysis spotlighted three critical sectors: agriculture, manufacturing, and infrastructure. It was found that an enhanced focus on manufacturing and infrastructure emerges as a positive force driving convergence, potentially through forward and backward linkages that spur broader economic activity. Forward linkages refer to the demand these sectors create for other industries, while backward linkages relate to the demand they create for raw materials and inputs from other sectors.

On the flip side, a heavier reliance on agriculture is associated with a widening income disparity with Delhi, hinting at a slower pace of convergence for agriculture-dominant states. While manufacturing and infrastructure investments are found to play a favorable role in bridging the gap, the less encouraging outlook for the agricultural sector despite government interventions underscores a pressing need for a balanced multi-sectoral approach to ensure convergence and foster inclusive growth across states.

India's trajectory in bolstering manufacturing and infrastructure is visible through initiatives like 'Make in India' and numerous infrastructure development projects. These sectors are becoming engines of growth, contributing to the convergence process. However, agriculture lags, despite government interventions to augment the sector. This sector's slower pace signals a potential area for policy redirection to ensure balanced sectoral growth and hasten convergence.

Connecting mildly with Rostow's stages of economic growth, the shift towards manufacturing and infrastructure echoes the movement from agrarian focus to pre-conditions for take-off, although a full alignment is limited due to the lack of analysis on the tertiary sector. In summary, the "distance" metric employed here unveiled key insights about income convergence across Indian states. It underlines the need for a balanced growth strategy across sectors to accelerate the convergence process and ensure no state lags significantly in the journey towards economic affluence. The findings call for policy dialogues that not only seeks sectoral advancements but also aims for an equitable spatial distribution of growth catalysts across states.

APPENDIX

List of Indian States and Territories

1. Andhra 7. Himachal Pradesh 14. Nagaland 2. Assam 8. Karnataka 15. Orissa 3. Bihar 9. Kerala 16. Punjab 4. Delhi 10. Madhya Pradesh 17. Rajasthan 5. Gujarat 11. Maharashtra 18. Sikkim 6. Haryana 12. Manipur 19. Tamil Nadu 13. Meghalaya 20. Tripura 21. UP 22. West Bengal

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