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SPATIAL ANALYSIS OF REGIONAL DIVERGENCE IN INDIA: INCOME AND ECONOMIC STRUCTURE PERSPECTIVES

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ABSTRACT

Two research methods – exploratory spatial data analysis and structural divergence analysis – are used to provide empirical support for the fact that GSDP per capita in 30 States in India continue to diverge in the post-reform period 1993–2004. First, exploratory spatial data analysis reveals the evidence of spatial clustering, such that rich forward States are located near other forward States (High-High Clusters), while backward States are located near other backward States (Low-Low Clusters). The local indicators of spatial autocorrelation suggest that the spatial dependence of GSDP per capita in 30 States in India is dominated by Low-Low clusters throughout the period. Second, structural divergence analysis reveals that the sector's contribution to the aggregate divergence is led by industry (60.26%), and followed by services (54.34%), while agriculture plays a role of buffer and offsets the rate of aggregate divergence (−11.81%). The positive spatial autocorrelation of income from services and industry persists, but negative spatial autocorrelation of income from agriculture is observed throughout the period 1993–2004. Therefore, the similarity of High-High (South of India) and Low-Low (BIMARU States) clusters location for economy-wise and sector-wise analysis highlights that the aggregate divergence in India is caused by structural divergence.

Key words: *States of India, regional GSDP per capita divergence, exploratory spatial data analysis, structural divergence analysis*

JEL Classification: O18, R11, C31

SPATIAL ANALYSIS OF REGIONAL DIVERGENCE IN INDIA: INCOME AND ECONOMIC STRUCTURE PERSPECTIVES

1. Introduction

In recent decades the so-called new economic geography and issues of regional economic convergence have increasingly channeled the interest of economists to the empirical analysis of regional and spatial data. It should be noted that spatial effects, particularly spatial autocorrelation and spatial heterogeneity, must be taken into account when analyzing convergence processes at regional scale.

There are a number of factors – trade between regions, technology and knowledge diffusion and more generally regional spillovers – that lead to geographically dependent regions. Therefore, geographical location is important in accounting for the economic performances of regions owing to intensive spatial interactions between regions.

In the 1997–98 financial year, the 9 forward States (Punjab, Maharashtra, Haryana, Gujarat, West Bengal, Karnataka, Kerala, Tamil Nadu, Andhra Pradesh) accounted for 58%, while the 6 backward States (BIMARU States: Bihar, Madhya Pradesh, Rajasthan, Uttar Pradesh, as well as Orissa and Assam) accounted for nearly 27% of the national income in India. As of 2004, the share of forward States is 60%, and share of backward States is only 25% in total Net State Domestic Product. In other words, the forward States were becoming more forward or richer, while the backward States were becoming more backward and poorer.

Removal of regional disparity had been an acknowledged goal since the Second (1956–61) and Third (1962–66) Five Year Plans of India. Moreover, the issue of regional balance has been directly or indirectly addressed in almost every Five Year Plan in India since the Second Plan (1956–1961) till the recent Tenth Plan (2002–2007). The adoption of planning and a strategy of State-led industrialization were intended to lead to a more balanced growth in the country. This approach has being realized through policies designed to facilitate more investments in the relatively backward areas. It was expected that inter-State disparities would be minimized in the long run. However, the perception is that regional imbalances have actually been accentuated, particularly over the period of economic reforms 1991–2004.

Earlier studies recognize the importance of space and geography in India’s economic development. For instance, one of the outstanding studies presented disaggregated details of the spatial patterns of pre-reform (before 1991) and post-reform industrial investment in India (Chakravorty, 2006). However, none of the earlier studies have used techniques that have been specifically focused on GDP values and GDP structure and tailored to take spatial effects into account. Moreover, the geographical scope of regional studies in India is limited by only 14–16 major States. In this paper we hope to fill that gap and report the additional information – derived from 1) the application of the exploratory spatial data analysis (ESDA), and 2) decomposition of the rate of divergence into sectors' contribution – to the analysis of income divergence in India.

Our goal is to describe the space-time dynamics of Gross State Domestic Product (GSDP) across 30 States in India for the post-reform period 1993–2004, and to explain why clusters occur in specific locations. In line with existing literature, it will be shown that spatial dependence (autocorrelation) and spatial heterogeneity represent potential features of regional growth in India.

More specifically, spatial autocorrelation can be defined as the coincidence of value similarity with location similarity (Anselin, 2001). There is positive spatial autocorrelation when high or low values of a random variable tend to cluster in space and there is negative spatial autocorrelation when geographical areas tend to be surrounded by neighbors with very dissimilar values. There are at least three possible explanations. One reason is that there is a simple spatial correlation relationship, showing what is causing an observation in one location also causes similar observations in nearby locations. Another possibility is spatial causality, meaning that something at a given location directly influences it in nearby locations. A third explanation is spatial interaction: the movement of people, goods or information creates apparent relationships between locations.

Spatial heterogeneity means in turn that economic behavior is not stable across space and may generate characteristic spatial patterns of economic development under the form of spatial regimes: a cluster of forward States (rich regions, the core) being distinguished from a cluster of backward States (poor regions, the periphery). The methodology of exploratory spatial data analysis (ESDA) is applied to find the evidence of spatial autocorrelation and spatial heterogeneity. The estimation of global spatial autocorrelation (Moran's I) and local spatial autocorrelation (LISA) will indicate how economic activities are located in India during the reform period 1993–2004. Moreover, local spatial statistics confirms the existence of spatial heterogeneity and, consequently, raises an agenda behind the differential growth profile of forward States and backward States.

At the final stage, methodology of the exploratory spatial data analysis is applied to three sectors, namely agriculture, industry and services in order to discover spatial autocorrelation and spatial heterogeneity in 1993–2004.

It is of great importance to see whether economic structure (share of agriculture, industry, services in GSDP) has an impact on the economic performance of States in India, and consequently, on regional divergence. The sector decomposition framework will break down the rate of GSDP divergence into the contribution made by various sectors in 1993–2004.

Specifically, we pose the following research questions and test the corresponding hypotheses:

H1. Gross State Domestic Product values in period 1993–2004 are spatially correlated as opposed to spatial randomness.

H2. Gross State Domestic Product in period 1993–2004 values cluster in geographically specific, positively spatially auto-correlated locations within the country.

H3. Aggregate divergence in India is caused by structural divergence. GSDP sectors are also spatially correlated in India, confirming the existence of spatial externalities.

This paper is organized as follows. In section 2, methodology and data sources are explained. The results for the economy-level analysis of regional divergence in India in the post-reform period 1993–2004 are presented in section 3. Section 4 is devoted to the results of GSDP sectors contribution to regional divergence in India in 1993–2004. Finally, conclusions and policy recommendations are provided in section 5.

2. Methodology

2.1. Exploratory Spatial Data Analysis (ESDA)

The exploratory spatial analysis framework is based on the spatial aspects of the database, allowing visualization and exploration of data where space matters. ESDA deals directly with the idea of spatial dependence and spatial heterogeneity. The objective of this method is to describe the spatial distribution, the patterns of spatial association (spatial clusters), verify the existence of different spatial regimes and identify non-typical observations (outliers). It is possible to extract measures of spatial autocorrelation and local autocorrelation from these methods (Anselin, 1998).

2.1.1. Global Spatial Autocorrelation

Spatial dependence exists when the value associated with one location is dependent on those of other locations. Spatial dependence can result from spatial interaction effects (e.g., externalities or spill-over effects) or from measurement error (e.g. related to a mismatch between the scale at which a phenomenon occurs and how it is measured). Summarizing, the “first law of geography” (Tobler 1979) says that “everything is related to everything else, but closer things more so”.

The spatial autocorrelation is positive when like values cluster together (that is high values are proximate to high values, and low values are proximate to low values), which is a clear expectation of geographers, or negative (when high and low values are proximate) which is rare and difficult to explain.

We attempt to test the spatial element of this law at the regional level in India, using the spatial distribution of Gross State Domestic Product in section. A popular method of specifying spatial correlation is the spatial lag operator, which is the product of spatial observations (Y) and a matrix of spatial weights (W). Therefore, the spatial lag (Wy) is a weighted average of the values in neighboring regions (States of India in this paper) of each observation, with the matrix W defining the concept of 'neighbors' and the specific spatial dependence that is assumed between regions. Thus, if an observation on a variable y (NSDP) at location "i" (State of India) is denoted by y_i, then its spatial lag is $\sum_j w_{ij} y_i$, with i≠j, w_{ij} the elements of spatial weight matrix W, and i, j = 1, …., n.

At the first step, we use Moran's I statistics (Moran 1948) to estimate and test hypotheses related to clustering. By doing this, spatial analysis will explore the degree to which GSDP in one region is in some sense dependent or influenced by that of its neighbors. The concept of clustering was further developed by Anselin (1988; 1995) and includes the well-known Moran's I and Moran scatter plot. Moran's I is derived from equation:

$$I = \frac{n}{s} \frac{\sum_i \sum_j w_{ij} (x_i - \mu)(x_j - \mu)}{\sum_i (x_i - \mu)^2} \qquad (1)$$

where n is the number of cases or observations

w_{ij} is the element in the spatial weights matrix corresponding to the observation pair i,j

x_i and x_j are observations for locations i and j (with mean μ),

s is a scaling constant (that is the sum of all spatial weights).

Consequently, for the purpose of this study Moran's I takes the form

$$I_i = \frac{n}{s} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} z_i^2} \quad \forall \text{ all } t = 1,2,\dots T \qquad (2)$$

where n is the number of regions (States) , z_i and z_j are normalized vectors of the natural logarithm of per capita GSDP in study period 1993–2004, and s is the sum of all elements of w. The weight matrix w has a dimension of ($n \times$ n), with a typical element w_{ij} representing the interaction between region i and j. Element w_{ij} is equal to 1 if i and j share common borders, and 0 otherwise.

The theoretical mean of Moran's I is −1/(n−1), which is nominally negative but tends to 0 when n increases. As a measure of global spatial autocorrelation, Moran's I values around +1 represent strong and positive (clustering of similar values) spatial dependence, while values around −1 show negative spatial correlation (clustering of different values). Positive spatial dependence refers to the existence of clusters in the data set.

Summarizing applicability issues, the results from Moran's I test statistic provide an overall picture of the degree of spatial dependency across States of India. Global autocorrelation statistics – global Moran's I – provide a single measure of spatial autocorrelation for an attribute in a region as a whole. Being a test of global spatial autocorrelation, Moran's I indicates the clustering of the whole system. Moran's I is less informative in identifying areas of local spatial association or dependence.

Therefore, while the strength of Moran's I is its simplicity, its major limitation is that it tends to average local variations in the strength of spatial autocorrelation. This drawback has motivated emergence of local indicators spatial association. The latter category of tools examines the local level of spatial autocorrelation in order to identify areas where values of the variable are both extreme and geographically homogeneous.

2.1.2. Local Spatial Autocorrelation

Local spatial autocorrelation is analyzed by means of Moran Scatter-plot and local indicators of spatial association (LISA). Given the space limitations, we shall focus on LISA.

Local Moran's I decomposes the global spatial pattern and indicates to which extent the geographic region is surrounded by similar or dissimilar values, forming the geographical pattern. This implies that some structure is present in the data, which can be considered as additional information.

At the second step we calculate the local Moran in order to get more precise results, because local indicators of spatial association (LISA) maps provide information on statistically significant clusters and outliers compared to the spatial randomness. In the case of local spatial association there may be no clustering effects compared to a global mean, but they may very well show spatial dependence when compared to a local mean (Anselin 1995). According to Anselin (1992: 23-2) "these statistics allow for the decomposition of a global measure of spatial association into its contributing factor by location. They are thus particularly suitable to detect potential non-stationarities in a spatial data set (like the case when the spatial clustering is concentrated in one sub-region of the data only).

According to Anselin (1995) LISA satisfy two criteria: 1) LISA has to provide for each observation an indication of significant spatial clusters of similar values around the observation unit (region, State, province), and 2) the sum of LISA for every region is proportional to the indicator of global spatial autocorrelation.

Local Moran is calculated by the formula:

$$I_i = \frac{z_i \sum_j w_{ij} z_j}{\sum z_i^2 \ /n} = \frac{(x_i - \mu_x) \sum_j w_{ij} (x_j - \mu_x)}{\sum_i (x_i - \mu_x)^2 / n} \tag{3}$$

where $(x_i - \mu_x)$ - deviation of region I value from the mean

$\sum_j w_{ij}(x_j - \mu_x)$ – deviation of neighboring area *j* values from the mean

$\sum_i (x_i - \mu_x)^2 / n$ – average area squared deviations from the mean.

In respect to property (2) of local Moran, the sum of all local indices is proportional to the global value of Moran's statistics. Thus, it can be written: $\sum_i I_i = \gamma.I$ (4)

Summarizing, local indicators of spatial association are most useful when, in addition to global trends in the entire sample of observations, there exist also pockets of localities exhibiting homogeneous values that do not follow the global trend. This leads to identification of "hot spots" (regions where the considered phenomenon is extremely pronounced across localities) as well of spatial outliers.

From an overall applicability perspective, LISAs detect significant spatial clustering around individual locations and pinpoint States that contribute most to an overall pattern of spatial dependence of Net State Domestic Product in India. Particular attention will be given to the positive spatial association, i.e. positive, significant LISAs located near other positive significant LISAs ("hot spots").

Finally, Global Moran's I accounts for all combinations of the variable X at all States in India. In its turn, Local Moran's I focuses on the correlation between the value of the variable X at State *i* and its neighboring values.

2.2. Methodology of Structural Divergence Analysis

The aim of this section is to quantify the contribution of agriculture, industry, and services to overall trends in regional inequality by decomposing them into respective trends of sectoral components. In order to estimate how much each of the sectors contribute to the aggregate divergence, the first step is to quantify the rate of divergence. We follow the approach of Kar and Sakthivel (2006) and Jenkins (1995) in formalization and algebraic treatment of the postulate that degree of divergence is determined by the extent of the increase in the coefficient of variation. The rate of divergence is determined as the growth rate of inequality, i.e., the growth rate of the coefficient of variation of output over time.

$$D=\triangle C(X_{i)} / C(X_i)$$ [1] (5)

where X_i is (regional output) GSDP per capita, $C(X_i)$ – coefficient of variation of regional output per capita, and D – rate of divergence.

If there are n regions, the output of each region is given by X_i, i = 1….n. If there are m sectors that contribute to each region's output X_i, the output of each sector in each region is given by X_{ij}, i =1…n, j = 1…m.

[1] The estimating equation inference is similar to See Kar and Sakthivel (2006)

Thus, $X_i = \sum_j X_{ij}$

Let $\overline{X}$ be the arithmetic mean of X_i and $\overline{X}_j$ be the arithmetic mean of X_{ij}.

$$\text{Thus, } \overline{X} = \frac{1}{n}\sum_i X_i = \frac{1}{n}\sum_i\sum_j X_{ij} = \sum_j \frac{1}{n}\sum_i X_{ij} = \sum_j \overline{X}_j \quad (6)$$

The above equation indicates that the average output for the economy is equal to the sum of the average output of each of the sectors. Next, define P_j as the ratio between the average output of the *j* sector and the average output of the economy. Thus, $P_j = \overline{X}_j / \overline{X}$.

Next, let us also assume that $\sigma(X_i)$, $Var(X_i)$, $Cov(X_{ij},X_{ik})$ and $r_{ij,ik}$ are the symbols for the standard deviation, variance, covariance and the correlation coefficient of the corresponding variables, respectively.

By definition, $Var(X_i) = \frac{1}{n}\sum_i (X_i - \overline{X})^2 = \frac{1}{n}\sum_i (X_{ij} - \sum_j \overline{X}_j)^2 =$

$$\frac{1}{n}\sum_i\left[\sum_j (X_{ij} - \overline{X}_j)^2\right] = \sum_j\left[\frac{1}{n}\sum_i\left\{(X_{ij} - \overline{X}_j)(\sum_k X_{ik} - \overline{X}_k))\right\}\right]_{k=1....m} = \sum_j\left[\sum_k (Cov(X_{ij}, X_{ik}))\right]$$

$$\text{Or } Var(X_i) = \sum_j Cov(X_{ij}, X_i) \quad (7)$$

Now by definition, the coefficient of variation is given by,

$$C(X_i) = \frac{\sigma(X_i)}{\overline{X}} = \frac{Var(X_i)}{\sigma(X_i) * \overline{X}} \quad (8)$$

Substituting equation (7) in equation (8) we get,

$$C(X_i) = \frac{\sum_j Cov(X_{ij}, X_i)}{\sigma(X_i) * \overline{X}} = \sum_j \frac{\sigma(X_{ij}) * r_{ij,i}}{\overline{X}} = \sum_j \left(\frac{\sigma(X_{ij})}{\overline{X}_j} * \frac{\overline{X}_j}{\overline{X}} * r_{ij,i}\right)$$

Thus, the estimating equation has the form

$$C(X_i) = \sum_j C(X_{ij}) * P_j * r_{ij,i}) \quad (9)$$

where $r_{ij,i}$ is the correlation coefficient.

Equation (9) breaks up the coefficient of variation of aggregate output into its sectoral components, and postulates that the level of aggregate inequality (measured by the coefficient of variation of aggregate output) is equal to the sum of contribution from three sectors – agriculture, industry, services. The contribution of each sector is equal to the product of: (i) the inequality in the sector, (ii) the average regional output of the sector as a share of the average regional output, and (iii) the correlation coefficient between the sector and the whole economy (Kar and Sakthivel, 2006).

As to the size of the sectors (ii), it adds a scale effect to the sectoral inequality, i.e, a larger sector adds more to the economy's inequality compared to a smaller sector. As to the inter-linkages of a sector with the whole economy (iii), high correlation coefficient between any sector and the economy implies that a region that has a relatively high output from that sector also has a relatively high aggregate output, while a region that has a relatively low output from that sector also has a relatively low aggregate output. Thus, for a given level of inequality in the sector, an increase in the correlation coefficient increases the economy's inequality (Kar and Sakthivel, 2006).

Having differentiated with respect to time, and then divided by $C(X_i)$ both sides of equation (9) , we obtain the growth rate of coefficient of variation in order to derive the rate of divergence:

$$\frac{\Delta C(X_i)}{C(X_i)} = \sum_j \left[\left(\frac{\Delta C(X_{ij})}{C(X_{ij})} + \frac{\Delta P_j}{P_j} + \frac{\Delta r_{ij,i}}{r_{ij,i}} \right) * \left(\frac{C(X_{ij}) * P_j * r_{ij,i}}{C(X_i)} \right) \right] \tag{10}$$

Therefore, the aggregate divergence is equal to the weighted sum of growth rates of the three components in equation (9). In each case, the weights are the particular sectors' contribution to the economy's initial levels of inequality ($C(X_{ij}) * P_j * r_{ij,i}$), as a ratio of the economy's initial levels of inequality ($C(X_i)$). Since these weights correspond to the relative contribution of each sector in the initial period, they are referred to as initial conditions.

3. Regional Divergence in India: Income Perspective

3.1. Results of Exploratory Spatial Data Analysis, Period 1993–2004

As an intermediate exercise within ESDA analysis, we performed a visual inspection of the geographical pattern of the GSDP in the initial year (1993) and in the final year (2004). Both maps display a spatial trend with a marked core-periphery pattern. In fact, the higher GSDP values in both years are concentrated in West and South with a smooth decline towards the lower values that may be observed in BIMARU region and the North, East and North-East of India. One additional growth pole is located around New Delhi in the North-West of India.

The percentile map identifies a small Union territory of Chandigarh as the top outlier in 1993 and similarly in 2000. On the opposite side, the role of lower outlier belongs to Bihar (Bihar in its new borders, after carving out of southern regions and establishment of Jharkhand in 2000) at the beginning and end of the study period. It is today home to more than 80 million Indians. The State has lost some of the enviable mineral resource base due to the creation of Jharkhand. The opportunity is that Bihar is one of the largest producers of fruit and the second largest producer of vegetables in the country. Building on its comparative advantage in agro-climatic and human resources Bihar has been embarking upon a path to become a vibrant economy.

Again, the above analysis allows presumption of the existence of spatial dependence in economic development in India in the post reform-period 1993–2004.

3.1.1. Global Spatial Autocorrelation, Period 1993-2004

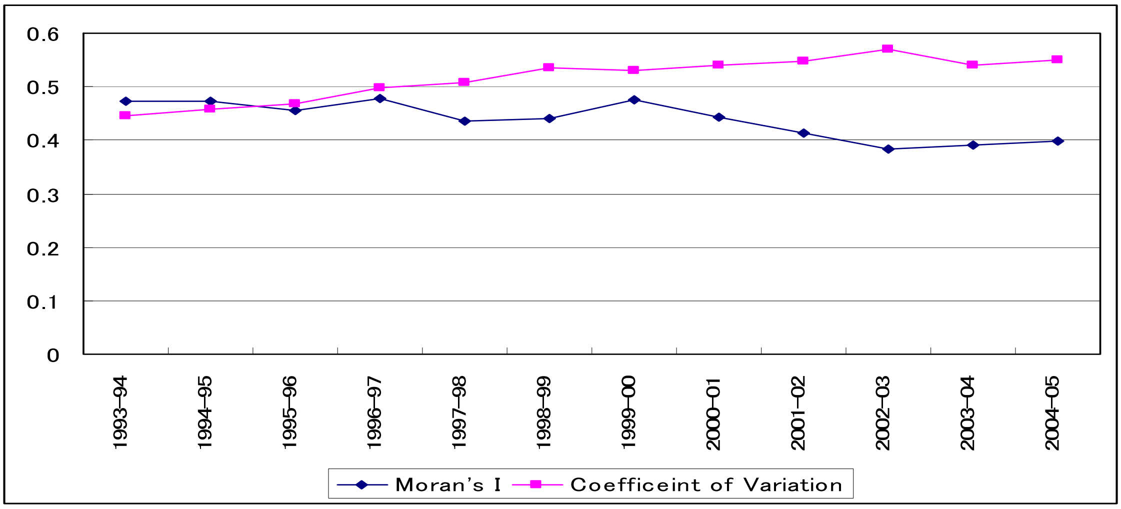
Let us continue with a descriptive analysis based on Moran's I and σ- convergence of Indian States during the period considered. Figure 1 shows the coefficient of variation's dynamics over the period 1993–2004. We observe the increasing trend of the coefficient of variation, and, hence, an increase of economic disparities between States in India.

Moran's I for 30 States has a decreasing trend in 1993–2004. However, Moran's I values are very high – around 0.45. Therefore, the current situation suggests stronger real spatial dependence of GSDP per capita in India in the reform period.

3.1.2 Local Indicators of Spatial Autocorrelation, Period 1993–2004

It is possible to observe the LISA results for GSDP per capita for year 1993 in Figure 2. The main characteristics are as follows. Both in 1993 and 2004, a Low-Low cluster was located in the East of India, and formed by Uttar Pradesh, Bihar, Jharkhand, West Bengal. Firstly, the local patterns of spatial association reflect the global trend towards positive spatial autocorrelation since 100% of the significant LISA fall Low-Low of the scatter-plot. Secondly, the distribution between the associations of High-High and Low-Low types is not balanced since the majority of the States fall into quadrant Low-Low.

Figure 1. Moran's I for Regional GDP per Capita in India, Financial Year 1993–94 to 2004–05

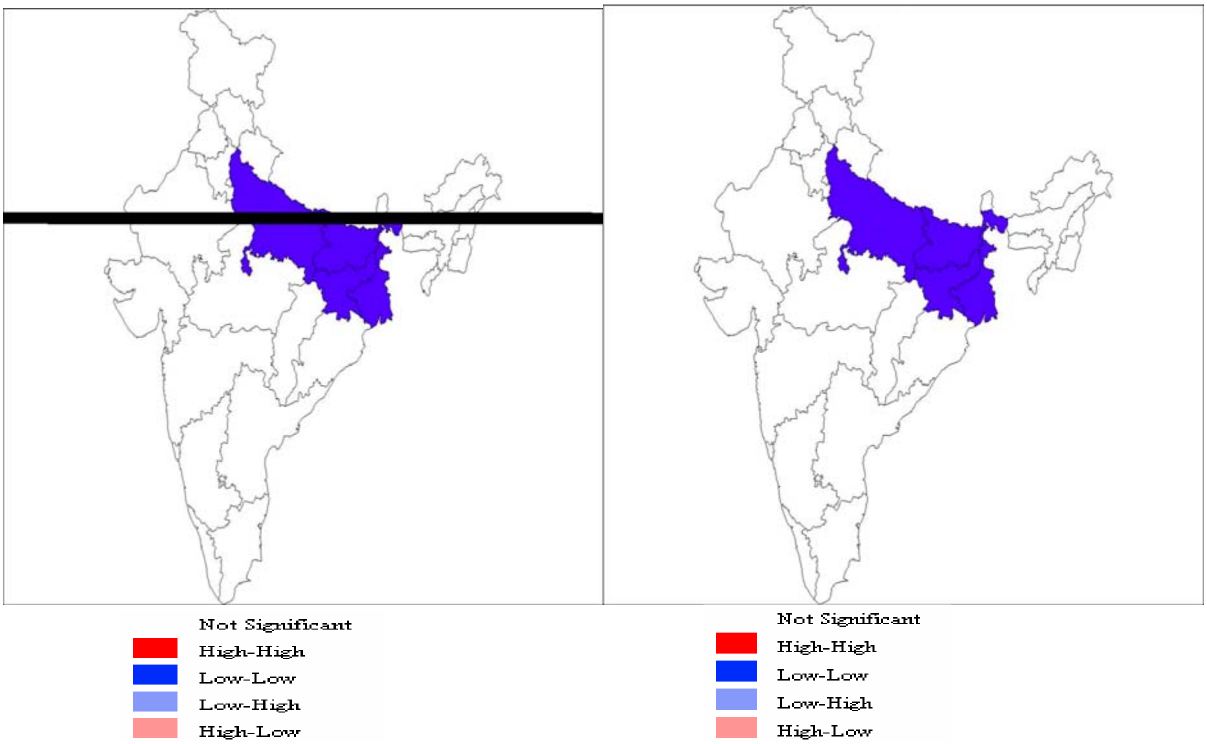


Source: Author's calculations based on the methodology

Thirdly, the regions formed by States with low GSDP surrounded by States with low values for GSDP per capita are concentrated in the North and East of the country. Thus, from spatial perspective the development in the reform period 1993–2004 is dominated by Low-Low cluster of peripheral, backward States.

Figure 2. LISA Cluster Maps. GSDP per capita in India

Figure 2.1. LISA 1993 **Figure 2.2. LISA 2004**



Source: Author’s calculations based on methodology

Finally, the outcomes of exploratory spatial data analysis (ESDA) for 30 States in India for period 1993–2004 can be summarized as follows. The study of the spatial distribution of GSDP in India over the period 1993–2004 highlights the importance of spatial interactions and geographical location in regional growth issues. ESDA reveal the characteristics of economic development of each State in relation to those of its geographical neighbors. The overall picture is one of spatial autocorrelation and spatial heterogeneity in the distribution of GSDP per capita GDP.

In section 5, it was attempted to explain briefly specific results of regional divergence in India from income perspective. Firstly, ESDA reveals significant positive global spatial autocorrelation, which persisted throughout the post-reform period 1993–2004: regions with relatively high GSDP per capita are and remain localized close to other States regions with relatively high per capita GSDP. Respectively, regions with relatively low GSDP per capita are and remain localized close to other States regions with relatively low per capita GSDP. In spite of the visual decline in Moran’s I graph for the period 1993–2004, spatial dependence is great and equals 0.4421 in year 2000 in the case of the recent administrative map of India. Secondly, statistics show clustering of high and low values, persistent throughout the period, confirming the South-West plus North-West versus BIMARU, East and North-East polarization of Indian States. More interestingly, LISA maps confirm the persistence of Low-Low cluster in BIMARU region (Bihar, Jharkhand, Uttar Pradesh) and East (West Bengal) of India in benchmark years 1993 and 2004 for 30 States configuration.

4. Regional Income Divergence: Economic Structure Perspective

4.1. Exploratory Spatial Data Analysis for GSDP Sectors, Period 1993–2004

The sector composition of the economy has undergone a structural shift in individual States and India on the whole from 1993 to 2004. The share of agriculture in GSDP per capita reduced from 27.13% in 1993 to 17.57% in 2004, while the share of industry slightly increased from 27.04% in 1993 to 30.64% in 2004, and role of services significantly increased from 45.83% in 1993 to 51.79% in 2004. From the economic structure point of view, the spatial pattern of development for the Indian economy can be summarized as follows. The Western region (Maharshtra, Goa, Gujarat) is industrialized and prosperous; the North-West (Haryana, Punjab, Himachal Pradesh) is agriculturally prosperous, and East (West Bengal, Sikkim, Nagaland, Arunachal Prasesh, Meghalaya) is moderately prosperous in agriculture. The South and South-East (Karnataka, Andhra Pradesh, Tamil Nadu) are high-tech industry and services regions, the South-West (Kerala) is characterized by high human and social development.

By contrast, Central BIMARU States (Bihar, Madhya Pradesh, Rajasthan and Uttar Pradesh) are known as the backward States. BIMARU States are underperforming in all three sectors, namely agriculture, industry, services. For instance, Bihar is the lowest outlier in two categories: industry share in GSDP per capita and services share in GSDP per capita, resulting in the worst position among States in GSDP per capita.

Therefore, good performance of the West, South and North-West regions in industry and services is at the core of prosperous development of these regions. In addition, the agricultural sector is contributing to the development of the North-west region.

From the historical perspective, the success of the Western region in comparison with the Eastern region in industrial development was influenced by two policy measures: 1) the ‘Freight Equalization Policy’ for the control, distribution and pricing of key industrial products, and 2) industrial licensing scheme. As to the former policy measure, the prices of key industrial products, such as cement, steel and coal, were made equal throughout the country and this took away the natural competitive advantage of the Eastern region and benefited the Western, southern and northern regions (Sekhar, 1983 and Mohan, 1997). The services sector is also unevenly distributed among States of India, targeting primarily metropolitan cities in the West, South, South-East and North-West of India.

The increasing returns come about primarily as a result of spatial arrangements; this is because density is the principal source of increasing returns Chakravorty (2006). Firstly, increasing the scale of certain operations, especially in industrial production or transportation, leads to more efficient division of labor and use of inputs, consequently rising productivity. Secondly, increasing returns also arise from other kinds of density because of the increasing intensity of interaction, knowledge exchange and spillovers, and proximity to other firms and individuals in the same business (buyers, suppliers and specialized labor). These are called economies of agglomeration, and are external to the firm (Chakravorty, 2006: 176). Increasing returns to scale and economies of agglomeration drive the development of industry and services sector in India at the current stage. At the same time increasing returns in urban and metropolitan regions represent the primary reason for the existence and persistence of regional inequalities in India.

The manufacturing belt and farm belt, the existence of cities and clusters – all these concentrations form and survive because of some form of agglomeration economies, in which spatial concentration itself creates the favorable economic environment that supports further or continued concentration (Fujita et al, 2006).

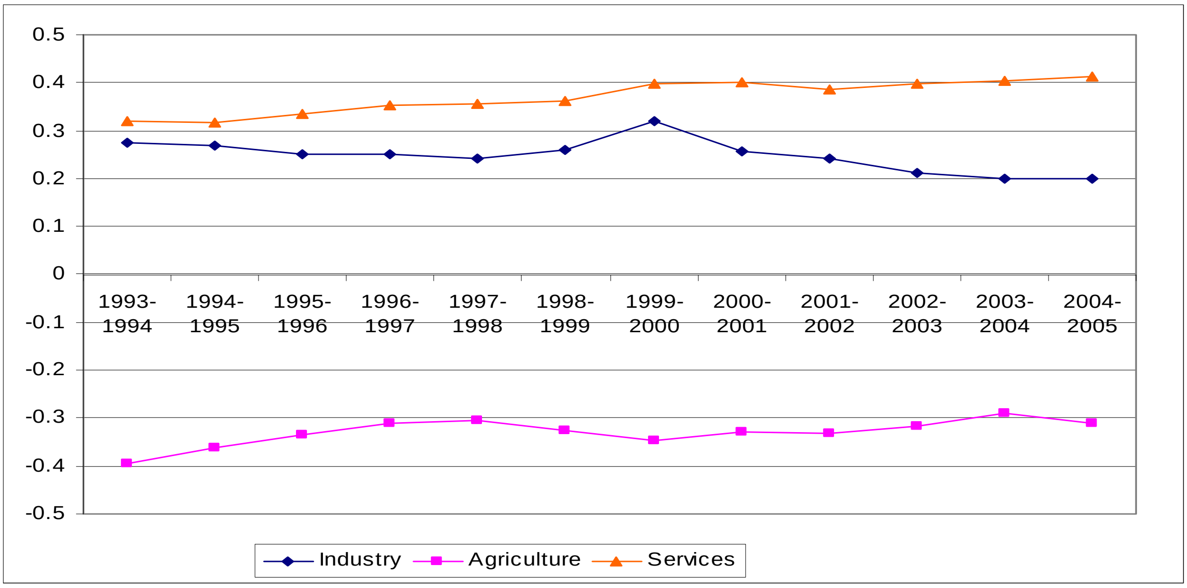
4.1.1. Global Spatial Dependence for GSDP Sectors, Period 1993–2004

Based on the above theoretical underpinnings, we tested the hypothesis of spatial dependence in all three sectors of the economy, namely agriculture, industry, services (Figure 3).

The analysis suggests persistence of spatial dependence in industry and services sectors. In the case of industry, spatial dependence can disclose itself when technology spillovers, movement of goods and migration of population can tie the performance and fortune of one region to another. It might be the case when two neighboring States in India have several industrial linkages in their value chains. Besides, spatial dependence can disclose itself when economic boundaries do not correspond to administrative borders. It is very common for the economic growth of a particular State in India to be determined not only by the economic and social factors within its borders. This spatial relationship implies that the realization of industrial output for these neighboring States is jointly determined.

In accordance with Figure 3, increase in Global Moran's I points out increased spatial association in the services sector from around 0.3 in year 1993 to around 0.4 in year 2004. Although the overall trend for spatial dependency in the industrial sector has downward slope, it is still significant. It should be noted that services and industry sectors have similar spatial dependence in 1993, but currently Moran's I = 0.4116 for services share in GSDP per capita is twice as high in comparison with Moran's I = 0.1989 industry share in GSDP per capita. There is no spatial dependence in agriculture share GSDP per capita (negative Moran's I values), indicating the absence of the nearest-neighbor bond in similarity of development in 1993–2004.

Figure 3. Moran's I for Sector-wise Gross State Domestic Product (GSDP) per capita in India



Source: Author's calculations based on the methodology

Summarizing, the services sector to a greater extent and the industrial sector to a lesser extent are characterized by spatial dependence and benefit from spill-over effects.

4.1.2. Local Indicators of Spatial Association for GSDP Sectors in India, 1993–2004

In accordance with Figure 4, LISA maps confirmed the existence of industry cluster in the South in 2004. By contrast, BIMARU States centered around Uttar Pradesh, and East States centered around West Bengal experience problems in industrial dynamism. Jharkhand and Himachal Pradesh, classified as High-Low, perform better than their neighboring States. In its turn, Kerala is a Low-High outlier, lagging behind neighboring States in the South of India in industry achievements.

Figure 4.2 warns about services sector performance in BIMARU States, qualifying Uttar Pradesh, Bihar, Jharkhand and Chhattisgarh as having Low-Low statistically significant spatial association. West Bengal is a High-Low outlier in services share in GSDP per capita classification in 2004.

Fig.4.1 LISA Map for Industry Share in GSDP

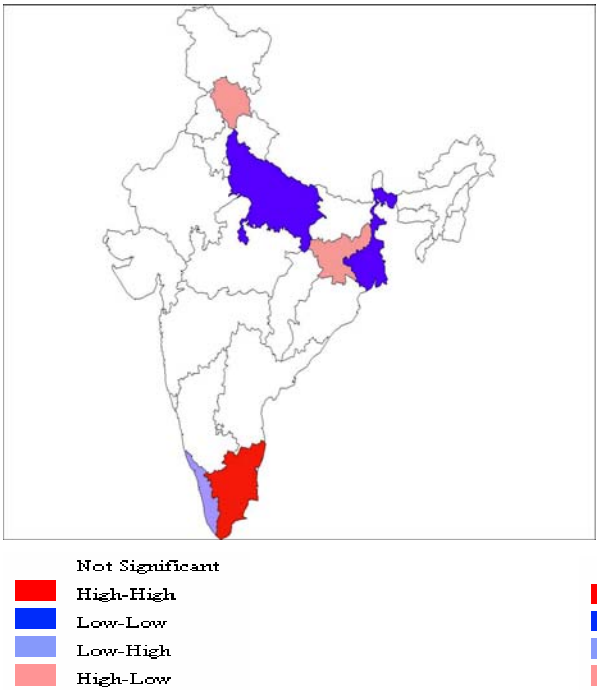
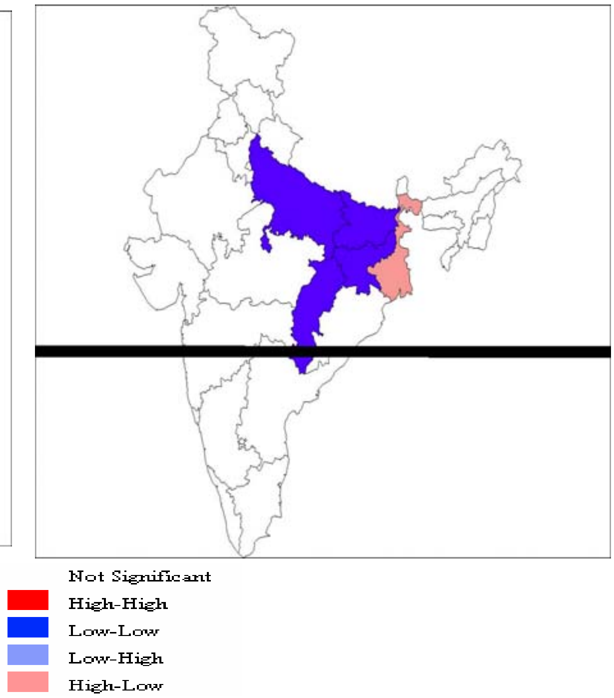


Fig. 4.2 LISA Map for Services Share in GSDP



Source: Author's calculations based on the methodology

We proved that the economic structure of the region and its neighboring States is the key to the State-wise GSDP per capita performance in India in 1993–2004. In 2004, the list of top performers in industry and services sectors is headed by the same 10 States. It presupposes the spillover effects within High-High industry cluster, within High-High services cluster, as well as some growth impulse from industry to services, and from services to industry. The success in industrial development and services provision in the West, South and North-West regions of India pre-determined the advanced development of these States in comparison with the rest of the country. It is high time to quantify the role of economic structure and its dynamics to GSDP divergence in India, which is the task tackled in the next section.

4.2. Sector Decomposition Framework of Regional Divergence in India, 1993–2004

This section is devoted to study of regional economic structure contribution to regional inequalities in India from Financial Year 1993–94 to 2004–05. The comparative contribution of agriculture, industry, services through: 1) sector's inequality, 2) sector's share in output, 3) sector's correlation with the whole economy are quantified.

The state-wise data on GSDP (Gross State Domestic Product) were obtained from Ministry of Statistics and Program Implementation. The details obtained by industry of origin are used in the construction of the aggregate and sector output of the individual States. The agriculture output combines the following sub-sectors: agriculture, forestry and logging and fishing. The industry sub-sectors comprise mining and quarrying, registered and unregistered manufacturing, construction and electricity, gas and water supply. The services sector encompasses transport, storage and communication, trade, hotels and restaurants, banking and insurance, real estate, ownership of dwellings and business services, public administration and other services.

Firstly, Table 1 outlines the inequality at the sector (agriculture, industry, services) level and aggregate level.

Table 1. Aggregate and Sector Divergence Rates (1993–2004)

	Coefficient of Variation of per Capita Income			
	GSDP	Agriculture	Industry	Services
1993–94	0.4450	0.4315	0.5951	0.7168
1994–95	0.4577	0.4359	0.5869	0.7455
1995–96	0.4676	0.4388	0.5661	0.7662
1996–97	0.4990	0.4523	0.6307	0.7991
1997–98	0.5072	0.4334	0.6860	0.7886
1998–99	0.5364	0.4239	0.7466	0.7813
1999–00	0.5303	0.4436	0.7382	0.7646
2000–01	0.5391	0.4709	0.7633	0.7528
2001–02	0.5479	0.4462	0.8025	0.7517
2002–03	0.5707	0.4685	0.8509	0.7562
2003–04	0.5403	0.4675	0.8216	0.7431
2004–05	0.5504	0.4847	0.8228	0.7484
Rate of Divergence	1.9511	1.0632	2.9895	0.3925
Weights		-0.0013	0.3094	0.6426
Sector Contribution		-0.0014	0.9250	0.2522
Sector Contribution (Percentage)		-0.0726	47.4085	12.9285

Source: Author's calculations

The year-wise coefficient of variation of GSDP per capita for 30 States from 1993–94 to 2004–05 can be seen at the top of Table 1. More specifically, Column 2 provides the coefficient of variation for GSDP per capita, and Columns 3–5 deal with the coefficient of variation for GSDP per capita from agriculture, industry and services respectively.

In accordance with 1993–94 classification, the highest inequality is in services sector (0.72), followed by industry (0.60) and agriculture (0.43). In accordance with 2004–05 classification the rating has changed as follows. The highest inequality is in the industry sector (0.82), followed by services (0.75), and agriculture (0.48).

As to the inequality growth dynamics, Table 2 reveals the fact of increased inequality for the aggregate economy (Column 2) as well as all the sectors during this period. The greatest rise in coefficient of variation of about 38% from 1993–94 to 2004–05 is observed in the industry sector. By contrast, the modest rise in coefficient of variation of 12% is attributed to the agriculture sector. The services sector has witnessed a sharp increase in the coefficient of variation from 1993–94 to 1996–97, and followed-up stabilization. The coefficient of variation in the services sector increased around 4% between 1993–94 and 2004–05. We can conclude that the aggregate as well as sector divergence of incomes per capita among States in India has increased from 1993–94 to 2004–05. Perhaps most important, the degree of divergence has been different in various sectors, with the greatest divergence in industry.

The contribution of each of the sector divergences towards aggregate divergence is presented in the bottom part of Table 1. In accordance with the methodology, the rates of divergence are equal to the inequality growth from 1993–94 to 2004–05. This is the average annual compound growth rate (CAGR) of the coefficient of variations between 1993–94 and 2004–05. As mentioned above, weights or initial conditions represent the sector's contribution to the economy's initial levels of inequality as a ratio of the economy's initial levels of inequality. Going further, the sector divergence is the product of the sector divergence rates and the weights. Finally, the sector contribution as a percentage of aggregate divergence is shown below.

The results of Table 1 suggest that the services sector had the lowest rate of divergence (0.39% per year), and the agricultural sector 1.06% per year. Quite opposite, the industrial sector experienced significantly higher rate of divergence, 2.99% per year. Consequently, the rate of divergence of the economy was 1.95% per year in period 1993–94 to 2004–05. Secondly, the weights or initial conditions are significantly different for the three sectors. The differences in these initial conditions indicate that the contribution of the sectors in explaining the level of inequality at the beginning of period (1993–94) was significantly different, with agriculture having the lowest contribution – 0.0013%, followed by industry (31%), while services had the highest contribution (64%). As a result, the initial conditions have a significant impact on contribution from the sector's inequality to the overall inequality. The contribution of the agricultural sector divergence is a negative minor value −0.0014, industrial sector 0.93, and services sector 0.25. In percentage terms, sector contribution equals −0.07 in agriculture sector, 47.41 in industry, and 12.93 in services.

Table 2 quantifies the second component of aggregate inequality – the average regional output of the sectors as a proportion of the average regional output (denoted Pj in the methodology). The average GSDP per capita of each sector as a proportion of the average GSDP per capita from 1993–94 to 2004–05 is displayed at the top of Table 2. The figures indicate the relative size of each sector, namely agriculture, industry, services. The data by industry of origin enables us to gauge the nature of structural changes taking place in State economies. For instance, the proportion of per capita GSDP for an average State produced in agriculture decreased from 30.66% in 1993–94 to 21.78% in 2004. Most of all, the share of services increased from 43.37% in 1993–94 to 49.27% in 2004–05 most of all, while the share of industry moderately increased from 25.97% to 28.95% in the same period. Therefore, even in 1993–94, the economy was dominated by services (43.37%), followed by agriculture (30.66%) and industry (25.97%). In the reform period India continued structural transformation of the economy, which is currently dominated by 1) the services sector, followed by 2) industry and, then with a growing gap, by 3) agriculture.

The calculations procedures in the lower part of Table 2 are similar to those in Table 1. The obtained results lead to the following conclusions. Reflecting changes in the relative size of the sectors, agriculture is characterized by the negative growth rate of Pj (agriculture output as a proportion of the average regional output), industry and services sectors have the positive growth rate. The magnitude of the growth rate is highest in the agricultural sector, followed by the services, and then by industry. However, the initial conditions (weights) have corrected the final picture. As a result, the biggest contribution is attributed to the services sector (38.41%), which is two times higher than the contribution of the industrial sector (15.73%). The agricultural sector provided only marginal contribution (0.21).

Table 2. Changes in the Relative Size of the Sectors

	Average Sector-wise per Capita Output as a Proportion of Average per Capita Output		
	Agriculture	Industry	Services
1993–94	0.3066	0.2597	0.4337
1994–95	0.3037	0.2644	0.4319
1995–96	0.2891	0.2697	0.4412
1996–97	0.2875	0.2689	0.4435
1997–98	0.2661	0.2816	0.4523
1998–99	0.2615	0.2801	0.4584
1999–00	0.2528	0.2776	0.4697
2000–01	0.2423	0.2827	0.4751
2001–02	0.2442	0.2742	0.4815
2002–03	0.2254	0.2861	0.4886
2003–04	0.2268	0.2852	0.4880
2004–05	0.2178	0.2895	0.4927
Rate of Growth	−3.0602	0.9917	1.1661
Weights	−0.0013	0.3094	0.6426
Sector Contribution	0.0041	0.3069	0.7493
Sector Contribution (Percentage)	0.2089	15.7269	38.4061

Source: Author’s Calculations

Table 3 is focused on the third element of aggregate inequality, namely the inter-linkage of the sectors with the economy ($r_{ij,i}$), measured by the correlation coefficient between each of the sectors and GSDP. Is can be observed that the services sector has the strongest links with GSDP, and the magnitude of correlation is stable in the period from 1993–94 to 2004–05. Industry is also integrated with the economy, but the links decreased from 0.89 in year 1993–94 to 0.84 in year 2004–05. The weakest link belongs to agriculture and it continued to decline from 1993–94 to 2004–05.

The last four rows of Table 3 are similar to those in Table 1, and calculate the contribution of the changing linkages between the sectors and the whole economy. The product of correlation coefficient growth rate and initial conditions results in the biggest contribution of industry (−8.90%), followed by agriculture (−2.82%), and followed with a significant gap by services (−0.09%).

Table 4 summarizes the results of Tables 1–3 and is structured in the next order. Horizontally, Table 4 specifies the total contribution of each of the three components in equation (10), namely: 1) contribution from sector divergences; 2) contribution from changes in relative size of the sectors; 3) contribution from changing linkages between the sectors and GSDP (See Rows 2–4). Vertically, Table 4 highlights the contribution of each of the sectors, namely 1) agriculture, 2) industry, services (See Column 2–4). The bottom line provides the total contribution of each of the sectors. Respectively, Column 5 indicates the total contribution of each of the three components. There is an error term in the decomposition exercise, based on equation 10, due to the measurement in discrete time (and consequently non-negligible values of the cross products arising from extension of equation 9). Having said this, Column 6 shows the error as a percentage of total divergence.

The error is 2.80%, which is almost three and a half times lower and accurate than in analysis presented by Kar and Sakthivel (2006). Therefore the decomposition of trends in regional inequality into their sector components performed here explains about (97%) of the aggregate divergence.

Table 3. Changing Linkages between the Sectors and GSDP

	Correlation Coefficient between Sectors and GSDP		
	Agriculture	Industry	Services
1993–94	−0.0045	0.8909	0.9199
1994–95	−0.0615	0.9135	0.9280
1995–96	−0.0762	0.8940	0.9294
1996–97	−0.0859	0.8798	0.9312
1997–98	−0.1696	0.8423	0.9300
1998–99	−0.1513	0.8840	0.9312
1999–00	−0.1335	0.8731	0.9309
2000–01	−0.1404	0.8760	0.9344
2001–02	−0.1672	0.8813	0.9329
2002–03	−0.1543	0.8649	0.9260
2003–04	−0.1813	0.8364	0.9137
2004–05	−0.2013	0.8374	0.9196
Rate of Growth	41.3277	−0.5614	−0.0027
Weights	−0.0013	0.3094	0.6426
Sector Contribution	−0.0550	−0.1737	−0.0017
Sector Contribution (Percentage)	−2.8210	−8.9021	−0.0877

Source: Author's calculations

It is high time to summarize the contribution of three components of aggregate inequality (equation 9) one by one. Firstly, sector divergence contributes 60.26% of aggregate divergence with dominated influence of industry. Secondly, the average regional output of the sectors as a proportion of the average regional output added 54.34% to aggregate divergence. The structural transformation in the economy of India is the reason behind the second important component of aggregate divergence. Thirdly, the dynamics of correlation between sectors and GSDP played a role of buffer with value of −11.81% in aggregate divergence.

Finally, it is necessary to outline the role of sectors in the aggregate divergence. The agricultural sector is characterized by negative sector contribution (−0.07), shrinking size of the sector (0.21%), and significant negative inter-linkages with the economy (−2.82%). This composition results in the total negative contribution of agriculture to the aggregate divergence (−2.68%). Therefore, agriculture played a role of buffer in period 1993–94 to 2004–05, and offset −2.68% of the aggregate divergence. The industrial sector is distinguished by the highest sector contribution (47.41%), medium growth in its relative size (15.73%), and negative inter-linkages with the economy (−8.90%). As a result, industry made the biggest (54.23%) contribution of the three sectors to the aggregate divergence. The services sector is characterized by the sector divergence of 12.93%, highest growth in the relative size of the sector (38.41%), and negative inter-linkages with the economy (−0.09%). The outcome of the above factors is the second largest contribution by services sector (51.25%) to the aggregate divergence.

Table 4. Components of the Aggregate Divergence (Percentage)

	Agriculture	Industry	Services	Total	Error
Contribution from Sector Divergences	−0.07	47.41	12.93	60.26	
Contribution from Changes in Relative Size of the Sectors	0.21	15.73	38.41	54.34	
Contribution from Changing Linkages between the Sectors and GSDP	−2.82	−8.90	−0.09	−11.81	
Total Sector Contribution	−2.68	54.23	51.25	102.80	2.80

Source: Author's calculations

In this section we attempted to quantify the sector contribution to aggregate divergence in 30 States in India from 1993–94 to 2004–05. The study concluded on the persistence of divergence at the aggregate level as well as in each of the three sectors, namely agriculture, industry, and services in the reform period 1993–94 to 2004–05. The uneven development of industry and services in 30 States of India is the key reason behind the aggregate divergence. The final contributions of sectors to the aggregate divergence is led by industry, and followed by services, while agriculture played a role of buffer and offset the rate of aggregate divergence. The rating of three components of divergence is topped by the sector divergence, followed by the changing relative size of the sectors (structural divergence), compensated by the changing linkages (correlation) between the sectors and the economy.

5. Conclusions and Policy Recommendations

This paper reported the research results on regional economic development in India in two dimensions, namely regional divergence in India from income and economic structure perspectives. First, GSDP per capita in 30 States in India continue to diverge in the post-reform period 1993–2004. The rich forward States have experienced faster growth rates than backward States. The forward States in India have steadily increased their share in the national economy due to favorable geographic position, resource endowments, higher investment, better infrastructure and knowledge economy. The forward States, classified in accordance with their higher growth rate, include: Punjab, Maharashtra, Haryana, Gujarat, West Bengal, Karnataka, Kerala, Tamil Nadu, Andhra Pradesh. The backward States include: Orissa and Assam, BIMARU States – Bihar, Madhya Pradesh, Rajasthan, Uttar Pradesh. Second, while the economic structure of forward States is characterized by a significant share of industry and services sectors, the economic structure of backward States is dominated by agriculture.

We confirmed three hypotheses and elaborated on them. Firstly, GSDP per capita values in period 1993–2004 are spatially correlated as opposed to spatial randomness. The rise of Moran's I in divergence post-reform period 1993–2000 suggests that the number of States in Low-Low Cluster increased.

Secondly, GSDP per capita values in period 1993–2004 cluster in geographically specific, positively spatially auto-correlated locations within the country. The spatial dependence of income in India is characterized by persistence of both High-High and Low-Low clusters, but dominated by Low-Low clusters. LISA maps highlighted statistically significant clusters and outliers compared to the spatial randomness. LISA maps for GSDP per capita in 30 States in India revealed only persistence of Low-Low cluster: Uttar Pradesh, Bihar, Jharkhand, West Bengal at the beginning (1993) and end (2004) of reform period.

Thirdly, exploratory spatial analysis of three GSDP sectors, namely agriculture, industry and services revealed spatial dependence of income from services and industry, but negative spatial autocorrelation of income from agriculture. More specifically, a rise in Global Moran's I points to increased spatial association in the services sector from around 0.3193 in 1993 to 0.416 in 2004. Although Global Moran's I shows decreased spatial dependence in the industry sector from 0.2734 in 1993 to 0.1989 in 2004, it is still significant. Most interestingly, the services and industry sectors have similar spatial dependence in 1993, but currently it is twice as high in services as in industry.

LISA maps for services share in GSDP indicate the Southern State of Tamil Nadu as the center of High-High cluster, and Uttar Pradesh and West Bengal as the center of Low-Low cluster in 2004. As to spatial outliers, Himachal Pradesh and Jharkhand are classified as High-Low cluster, because they perform better in comparison with their neighboring States. By contrast, Kerala is seen as the Low-High cluster, because it under-performs in comparison with other South States with high concentration of software services.

LISA maps for industry share in GSDP show that significant territory of BIMARU States – Bihar, Jharkhand, Uttar Pradesh, Chhattisgarh – is associated with Low-Low cluster. There is no industry growth pole as such in the absence of High-High cluster. As to outliers, West Bengal with its industrial base is classified as High-Low cluster.

It can be concluded that the similarity of High-High (South of India) and Low-Low (BIMARU States) clusters location for economy-wise and sector-wise analysis suggests that the aggregate divergence in India is caused by structural divergence. More specifically, sector divergence contributed 60.26% of aggregate divergence with dominated influence of industry; sectors' share in regional output added 54.34%; and compensated by correlation between sectors and GSDP (−11.81%). The final contributions of sectors to the aggregate divergence is led by industry (54.23%), and followed by services (51.25%), while agriculture played a role of buffer and offset the rate of aggregate divergence (−2.68%). Therefore, differences in GSDP per capita and persistent divergence of income per capita in 30 States in India in the post-reform period 1993–2004 are explained by uneven geographical distribution of industry, including industrial investment, and services sector enterprises in India.

The first policy implication is that the emergence of regional imbalances is accompanied by faster growth in all regions. This is also good for the periphery and creates a tension between the static loss due to relocation and the dynamic gain due to faster growth. Therefore, regional polices at the national level that seek to avoid geographic concentration of industry may cost the country as a whole in international competitiveness and growth terms. The second policy implication deals with trade-off between specialization in industry and services on the one hand, and agriculture on the other hand. The research has shown that the modern industry and services sectors have higher productivity and growth prospects in comparison with agriculture, but the agricultural sector is the only one that offsets divergence in India. The further development of industry and services sectors is necessary to guarantee exports and growth in India. The third policy implication is that the Low-Low cluster, formed by West Bengal and BIMARU States – Uttar Pradesh, Bihar, Jharkhand – need to get a growth impulse. One of the solutions is "Delhi Mumbai Industrial Corridor". The fourth policy implication covers a wide range of topics. India still needs to improve governance, State-wise financial discipline, and social coherence.

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