Exploring Convergence of Human Capital in India: A Disaggregated Analysis

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Dedicated to
My Parents

CERTIFIED THAT THE THESIS ENTITLED

"Exploring Convergence of Human Capital in India: A Disaggregated Analysis" submitted by me for the award of the Degree of Doctor of Philosophy in Arts at Jadavpur University is based upon my own work carried out under the Supervision of **Prof. Sushil Kumar Haldar**. Neither this thesis nor any part of it has been submitted before for any degree or diploma anywhere/elsewhere.

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CHAPTER-1

INTRODUCTION

1.1 Background of the study

Low level equilibrium trap or vicious circle of poverty is the result of failure of convergence hypothesis. Due to low-level investment in physical capital, the economy may experience the problem of low-level equilibrium trap or vicious circle of poverty (Nurkes 1953, Nelson 1956). According to the neoclassical growth model developed by Solow (1956), it is hypothesized that heterogeneous countries attain a similar steady state over the long-run growth process due to diminishing returns to physical capital. This implies that the poor countries catch up with richer counterparts due to competitive forces and inter-regional migrations; regional inequalities will gradually vanish because of equalizations of factor prices (Solow 2000; Paas et al. 2007; Stefanoudakis 2011). The failure of many poor economies to catch up with the rich ones should not primarily be seen as the result of inadequate investments in physical capital; rather, the problem is associated with lack of effective human capital or knowledge endowment (Lucas 1988, Romer 1986, 1990). Instead of physical capital, the endogenous growth model gives emphasis on human capital and the argument of global convergence (of neoclassical growth theory) is not fully supported by Lucas (1988) and Romer (1990).

Even the new growth theory based on economic geography developed by Fujita, Krugman and Venables (2001), Bloom et al (2003) and Fujita (2012) refute the "catching up" hypotheses of Solow's growth model; their growth models have considered the issues or factors of economic geography. Poor countries do suffer from "technological capabilities" as well as "social capabilities" comprising provision of education, culture, quality of governance, spread of social values, beliefs and institutions; lack of these capabilities lead to underdevelopment and persistence poverty trap (Woolcock and Narayan 2000; Fagerberg and Srholec 2009). Numerous theoretical models have already been developed relating to the existence of low level trap caused primarily by inadequate human capital accumulation (Kraay and McKenzie 2014). The existence of imperfect competition especially credit market imperfections, economic dualism, market failures of merit goods like health and education, existence of strategic complementarities in human capital investment, lack of efficient institutional framework and social capabilities (which include factors like quality of social institutions and good governance) lead to the emergence of "good" and "bad" equilibrium (Murphy et al. 1989; Kremer 1993; Galor and Zeira 1993;

Matsuyama 1995; Acemoglu 1997; Basu and Van 1998; Basu and Tzannatos 2003; Azariadis and Stachurski 2005, Santosh 2009; Ray and Chatterjee 2013; Kraay and McKenzie 2014; Sanchez Carrera 2016, 2019). Under globalization, the foreign direct investment (FDI) generates asymmetric incentives to innovation that disproportionately favors leading countries and underdevelopment persists (Mayer –Foulkes 2007). The empirical support towards global income convergence is still a debatable issue; cross-country growth empirics provide mixed results.

Recent growth empirics have stressed the existence of “middle income trap (MIT)”; this term MIT has been a buzz word in empirical growth economics introduced by Gill and Kharas (2007). The identification of trap was based on the level of outcome not on growth. My research study does not aim to highlight the existence of income trap based on growth or level rather, I have tried to explore the chronic presence of human capital trap using convergence analysis. The present study is motivated by two seminal works –The first one is “mortality trap”carried out by Bloom and Canning (2007) and the second one is poverty trap developed by Kraay and McKenzie (2014).

Initially, the concept of human capital is confined within individual’s education, training, knowledge, skills and abilities that provide individual economic and social benefits; Neoclassical growth model (developed by Solow 1956) was first extended by Mankiew, Romer and Weil (1992) to include human capital like education. Health as human capital is considered much later; the seminal work of Grossman’s (1972) optimal investment in health in which health is defined as durable goods that individuals possess which has intrinsic as well as instrumental value largely influences the broad concept of human capital (Bloom et al 2001; Becker 2007). The importance of health is well established in numerous cross-country growth empirics (Fogel 1994; Barro1996; Gallup and Sachs 2000; Arora 2001; Sala-i-Martin 2005). Health is generally deemed as a fundamental feature for human well-being, one of the basic capabilities introduced in measuring human development; health and education complements to each other and country’s development outcomes are jointly determined by health and education along with income (UNDP 1990, 2010; Sen 1992). Based on the importance of health, Knowles and Owen (1995) again extended the neoclassical growth model by incorporating both health and education as human capital.

Now, the basic question is: How is to measure human capital comprising education and health? A robust quantitative measure of human capital, known as human capital index(HCI) across 122 countries is first introduced by the World Economic Forum (WEF) in 2013; the HCI is based on 4 pillars, comprising a total of 51 indicators: 3 core determinants of human capital are education, health and employment comprising 12, 14 and 16 indicators respectively; plus those factors that allow these three core determinants to be translated into greater return is termed as enabling environment consisting 9 indicators (WEF 2013). The second measure of HCI is developed by the World Bank in 2019 for 157 countries; it is based on three dimensions- survival as measured by under 5 mortality rate, expected years of quality adjusted schooling comprising two indicators like quality and quantity aspect of education and health environment consisting two indicators like adult survival rate and the rate of stunting for children under age 5 (World Bank 2018). Our estimation of HCI is more or less similar to World Bank (2018), however, there are some dissimilarities originated from inadequacy of data, but not in principle or methodological framework as such. In this study, instead of considering only on the child health dimension, we have also focused on the reproductive and general health dimensions. In order to capture the education dimension of human capital, I have considered the complete years of each schooling level and gross enrolment ratio along with literacy rate. Using these two dimensions of human capital, I have examined the performance of Indian states as well as her districts in terms of human capital along with its components over the last 23 years and 10 years respectively.

Thus, my first objective is to construct a new measure of human capital index across Indian states and for four time points [viz. 1992-93(NFHS-1), 1998-99(NFHS-2), 2005-06(NFHS-3) and 2015-16(NFHS-4)]. I have extended the same type of analysis at the district level for three time points [NFHS-3(2005-06), CENSUS 2011 and NFHS-4(2015-16)]. Based on the performance of each state as well as district, I have tried to identify the presence of ‘chronic low level human capital trap’. It is expected that my findings may help policy makers and development practitioners to take appropriate measures towards breaking the chronic low level trap in India.

1.2 Literature Review

Most of the literatures both in cross country or state level analysis (in India) are based on income convergence. A very few studies have focused on convergence in socioeconomic variables (i.e., health or education). In cross country analysis, literatures have focused on human capital convergence along with income convergence as they have argued that human capital is the only path of income convergence. In India, no such study is available on human capital rather the studies have focused on the impact of human capital on economic growth. I have discussed relevant literatures on convergence on human capital across countries since last three decades.

Tamura (1991) has explained the income convergence across heterogeneous agents (Country) via convergence in human capital and consumption. According to this literature, the country or state with below average human capital have a higher rate of return than country or state with above average human capital. At the end, all these heterogeneous countries will converge in terms of human capital. This will lead the convergence in income or per capita income.

Babini (1991) has examined the presence of convergence or divergence on education system across the countries. She has used enrolment rates to primary, secondary and tertiary levels of education to examine the convergence in education. She has used coefficient of variation for education indicators for a sample of countries over the period 1960 to 1983. Decreasing trend in coefficient of variations implies the presence of convergence. She has concluded that these indicators are converging as the coefficient of variation has decreased and the speed of convergence is found to be the maximum at the primary level.

Ingram (1994) has used 16 different social indicators along with GDP level and GDP growth to examine the presence of convergence across different groups of countries (Low, Middle and High). The study has covered 1960-1985 time period and 109 countries (both industrialized and developing countries). He has used three different measures of convergence for this analysis. First one is elasticity of the social indicators obtained by the regression-based approach, second one is coefficient of variation and last one is the disparity in mean values of each indicator. He has found that life expectancy, primary school enrolment, calorie intake and urbanization are found to be converging over time.

O'Neill (1995) has examined the presence of income convergence along with the role of human capital towards economic convergence across 29 developed and 68 less developed countries for the period of 1967-85. He has used gross enrolment ratio to secondary school as human capital. According to this literature, the convergence in education levels promotes the income convergence across developed countries. However, this relationship does not hold when the study considers all countries simultaneously (developed & less developed).

Ram (1995) has investigated the presence of human capital convergence across 88 less developed countries for the period of 1960-1986. He has used education as human capital and examine the convergence both for inter as well as intra-country level. He has constructed a weighted inequality index for enrolment rates. He has found that inequality seems to be diminishing in regard to primary and secondary education and the inter-country convergence estimation showed the evidence of convergence at all educational levels.

Barro (1996) has found the existence of conditional convergence for 100 countries. The study has considered several conditional indicators like, initial schooling, life expectancy, lower fertility, lower government consumption, better maintenance of the rules of law, lower inflation and terms of trade. The study shows that all these conditioning variables enhance the growth over time.

Hobijn and Franses (2001) have examined the presence of convergence in respect of infant survival rate, literacy rate and life expectancy at birth along with supply of calories and protein in daily basis. The study has used different sample of countries for examining club convergence in terms of above variables. The study has found the presence of club convergence across countries rather than the catch-up process.

Sab and Smith (2002) have used enrolment ratio to primary, secondary and tertiary level of education and life expectancy and infant survival rate as the human capital. Using 3SLS approach they have found the presence of convergence in both health and education for the time period 1970-90 across 100 countries. The results support the convergence of health and education.

Petrakis (2002) has explored the effect of human capital on growth across 24 countries during the period 1977-82 to 1989-94. The study has used completion rate of different education level as human capital. The study has divided total countries into three different groups (advanced, developed and less developed countries). It has found the evidence of strong relationship between human capital and economic growth but this relationship is found to vary across different groups of countries. The study reveals that the growth in less development country is highly influenced by the primary and secondary education.

Neumayer (2003) has explained cross-country convergence of human capital indicators over the period from 1960 to1999 and finds strong evidence of convergence of life expectancy, infant survival, educational enrolment, literacy as well as telephone and television availability.

Mazumdar (2003) has covered a long period, 1960-1995 and classified 92 countries into 4 respective income groups; the study has considered infant survival rate, life expectancy, adult literacy rate, and calories intake; her study reveals that for the full sample as well as for three income groups (except high income) for all the indicators (like infant survival rate, life expectancy at birth, adult literacy rate) divergence is observed rather than convergence.

Petrakis (2005) has constructed an enhanced human capital to define the level of human capital across different group of countries (advanced, developed and less developed) during the period 1990-2001. The study has used enrolment ratio to primary, secondary and higher level, expenditure on different education level, number of teachers in different education level, number of books in public libraries and number of researchers per million populations to define human capital. The empirical result shows the presence of moderate convergence among countries.

Ram (2006) has examined the presence of convergence in terms of life expectancy across 163 countries for the period 1980 to 2000. The study has created two different models with and without conditioning factors. The results show that there exists divergence in life expectancy due to HIV/AIDS.

Observing the non-linearity of data of life expectancy, a robust cross-country panel study based on 192 countries over a long period from 1950 to 2005 is conducted by Bloom and Canning (2007) and they have rejected the convergence hypotheses of life expectancy, rather their findings support club convergence with distinct twin peaks manifesting countries with low and high mortality.

Viswanath and Pandit (2009) have found that how human capital enhance the net state domestic product for 25 Indian states. In this study they have used mean years of schooling as a proxy of human capital. Along with productive capacity, mean years of schooling positively influences the net state domestic product.

Mayer-Foulkes(2010) has analyzed the convergence of components of human capital (of HDI) like life expectancy, literacy and gross enrolment ratio across 111 countries over 1970-2005; he has concluded that the components of human capital initially diverges and then converges. The analysis show that life expectancy divergence replaces convergence in the late 1980's because of adult mortality differences.

The same result of convergence of life expectancy and infant survival is found by Clark (2011) who has considered 195 countries over a long-time span, 1955-2005. This result of convergence of life expectancy and infant survival stands in stark contrast to the conclusions drawn by Mazumdar (2003), Hobijn and Franses (2001).

Pelinescu (2015) has examined the impact of human capital on growth of GDP. In this study he has used education expenditure in GDP, number of employees with secondary education, export of goods and services and number of patents. The study has found that capacity of human capital including number of patents and numbers of employee with secondary education positively influence the economic growth.

Some of the cross-country analysis have considered human development index to measures the human well-being (HDI); the studies have examined the presence of convergence of HDI over time and have found the result of **β** convergence (Mazumdar 2003; Sutcliffe 2004; Edwards and Tuljapurkar 2005; Noorbakhsh 2006; Cuaresma et al. 2008; Mayer- Foulkes 2010; Yang et al. 2019; Mendez-Guerra 2018). Using decennial census data (1981–2001), Roy and Bhattacharjee (2009) have found **β** convergence but **σ** divergent of HDI across major Indian states. More or less, the same results are found in respect of **β** and **σ** convergence in HDI in India (Ghosh 2006; Mukherjee and Chakraborty 2007, 2011; Roy 2012). Research shows that the human development index (HDI) across 15 major states in India does not show the same increase in regional inequality, as in the case of per capita net state domestic product (PCNSDP) (Singh et al. 2003; Dholakia 2003; Banerjee and Kuri 2015). However, the assumption of linearity is questioned by many authors. Various econometric specifications like quadratic form of regression, quantile regression, semi-parametric specification of partially linear model (PLM), nonparametric stochastic kernel have already been suggested in order to capture nonlinearity of growth of HDI and its components (Mazumdar 2003; Mayer-Foulkes 2010; Jorda and Sarabia 2015). Following these literatures on convergence of human well-being, I have examined the presence of human capital convergence based on its sub component both at the aggregate as well as disaggregate levels in India.

1.3 Research Gap and My Contribution

Existing literature has revealed a new area of convergence analysis based on the limitation of convergence hypothesis under the theory of neo classical growth model. Endogenous growth model answered the unexplained portion of exogenous growth model using the introduction of human capital. My study considers the convergence of the determinants of the outcome of income. Existing literatures suggest a strong relationship between human capital convergence and income convergence. Most of the convergence studies are based on cross country analysis using both education as well as health outcomes. But, no studies are found in Indian context on convergence of human capital. Majority of the studies are more concerned about the role of human capital or investment in human capital as determinants of convergence of income. Recently, few studies in India have explored the convergence of health indicators across states (Hembram et al 2019). So, in India, I have an ample scope to examine the convergence of human capital across states (vis a vis across districts) both at the aggregate as well as disaggregate level. Since, education and health jointly determine the human capital, it is important to focus on the components of human capital also. It can be observed that most of the existing literatures have considered only one component (either education or health) as human capital. They have used regression or dispersion-based approach to explore the convergence in terms of human capital across countries. My study is different from the earlier studies on following grounds.

First, in this study, I have used human capital using both education and health jointly. I have constructed the human capital index (HCI) following the methodology developed by World Bank (2018). Second, I have tried to cover entire education and health dimensions rather than considering only one or two indicators arbitrarily. Third, I have used non-parametric approach to explore convergence or club convergence. Fourth, earlier studies could not focus on human capital trap. Using non-parametric approach, I have tried to explore the chronic low-level trap. Fifth, I have explored the trap or club based on geographical influence. Sixth, from this analysis, I am able to identify the backward states as well as districts where 'big push' is required. I have explored the low-level human capital trap across states and districts. This disaggregated analysis will help the policy maker to implement appropriate policies for breaking the low-level trap. This is assumed to be an important contribution of my dissertation.

1.4 Major Research Questions

Following the scope of the study, I have formulated the following research objectives.

- Construct the Education Index, Health Index and Composite Human Capital index based on some selected indicators from Health and Education dimension across 26 Indian states using NFHS I (1992-93), NFHS II (1998-99), NFHS III (2005-06) and NFHS IV (2015-16) data.

- The same is to be estimated across the Districts in India for three time points [NFHS 3 (2005-06), Census (2011), NFHS- 4 (2015-16)]

- Examine the presence of convergence in terms of Education, Health and Composite Human Capital index (HCI) both in states and districts in India using Regression and Dispersion based approaches.

- Examine the regional inequality in respect of Education, Health and Composite Human Capital Index (HCI) for Indian states as well as districts using Generalized Entropy Measures of inequality.

- Explore the chronic low-level Education, Health and Composite Human Capital trap across the states using Distributional Dynamics Approach.

- Explore the chronic low-level Education, Health and Composite Human Capital trap across the districts using Distributional Dynamics Approach.

- Final objective is to examine the role of space towards formation of clubs or groups of States vis a vis Districts in India.

1.5 Data and Methodology

1.5.1 Data

In order to construct Education Index, I have focused on disaggregate education level i.e., complete years of schooling at different education level (education level less than primary, complete only primary school, complete only middle school, complete high school and complete years of schooling above high school) and gross enrolment ratios to different education level (Gross enrolment ratio to primary, Gross enrolment ratio to upper primary, Gross enrolment ratio to higher secondary, Gross enrolment ratio to higher education)along with literacy rate across 26 states for four time points. The data are drawn from District Information System for Education (DISE), School Report Card (SRC) and Annual Report 1993-94, Part I, Ministry of Human development, Department of Education, Government of India, Annual Report 1998-99, Ministry of Human development, Department of Education, Government of India.

In order to construct health index, I have focused on child, reproductive and general health dimensions. Under child health dimension I have considered Infant Survival Rate and Nutritional level of children. In reproductive health, I have used Lower Total Fertility Rate and percentage women who are non-anaemic whereas under general health, I have used data on Body Mass index and life expectancy at birth. All these data are drawn from four round of National Family Health Survey (NFHS I-IV) and Reserve Bank of India (RBI).

I have used Per Capita Education Expenditure (PCEE), Per Capita Health Expenditure (PCHE), Physical Infrastructure and Social Infrastructure Index as the determinants of conditional convergence analysis. The data for determinants of convergence are drawn from various issues of Handbook of statistics on Government Finance and State Finances: A study of State Budget, Reserve Bank of India, Ministry of Road transport and highways, Health and Family Welfare statistics in India, Niti Aayog and some School Report Cards and Annual Report on Education, Ministry of Education and Human Resource Development.

1.5.2 Methodology

I have used the following econometric techniques and statistical tools in my research study.

Construction of Human Capital Index (HCI)

Since the Human capital Index is comprised of health and education, therefore, first I have constructed the education and health on the basis of selective indicators.

To make all the indicators scale free, I have used the relative distance methods. Initially compute the range of each indicator from each dimension (category). For example, the j-th indicator belonging to the r-th dimension (category), the range R^*_{rj} can be written as follows;

$$\left(X_{\underset{i,t}{rjMax}} - X_{\underset{i,t}{rjMin}} \right) = R^*_{rj} \tag{1.1}$$

where, $\left(X_{\underset{i,t}{rjMax}} \right)$ and $\left(X_{\underset{i,t}{rjMin}} \right)$ are the maximum and minimum values for the j-th indicator in the r-th dimension (r=1, 2 and 3) over time(t=1, 2, 3 and 4) and space(state(i)). Compute, $\left(X_{rji(t)} - X_{\underset{i,t}{rjMin}} \right)$ and divide each value by R^*_{rj}, we thus obtain the scale-free values of the j-th indicators as:

$$\frac{\left(X_{rji(t)} - X_{\underset{i,t}{rjMin}} \right)}{R^*_{rj}} \tag{1.2}$$

for all i (i=1,2……25, t=1,2..4).

Then following the methodology of HDI (UNDP 2010), I have calculated each dimensional index which is basically the weighted arithmetic mean of each indicator. However, education and health dimensions have different sub-dimensions. So, first I have calculated the sub dimensional index for each dimension using appropriate indicators. Finally using these sub-dimensions, I have constructed education, health index and human capital index respectively. The details of construction of education, health and human capital index are given in the respective chapters.

Education Index (EI) $=[GERI * YSI * LRI]^{0.333}$ (1.3)

Where, GERI is Gross Enrolment Ratio Index, YSI is Years of Schooling Index and LRI is Literacy Rate Index.

Health Index (HI)=$[CHI * RHI * GHI]^{0.333}$ (1.4)

Where, CHI is the Child Health Index, RHI is the Reproductive Health Index and GHI is the General Health Index.

Finally, the Human Capital index (HCI) = $[EI * HI]^{0.5}$ (1.5)

Where, EI represents the Education Index and HI represent the Health Index.

In order to construct all the indices, I have followed the methodology developed by UNDP (2010) to construct human development index. According to new methodology, HDI is the geometric mean of all sub-indices. This new methodology is more acceptable than the old one. Poor performance of any sub-dimension can directly be captured by the geometric mean. In geometric mean, the marginal contribution of each dimension is not fixed. Here, the marginal contribution captures the endogeneity among the dimensions. This index satisfies all the properties of an ideal index like transitivity, substitutability, homogeneity, convexity and sub-group decomposability (see, Appendix 1A.1).

Method of Convergence Study: Regression and Dispersion Based approaches

Now, based on this index, I have examined the presence of β, σ and club convergence. Following Barro and Sala-i-Martin (1992), I have used the least square panel regression model to examine the presence of absolute β convergence.

$$\left(\frac{1}{\tau}\right) ln\left[\frac{Y_{it}}{Y_{i(t-1)}}\right] = \alpha + \beta\, ln(Y_{i(t-1)}) + U_{it} \tag{1.6}$$

Here, τ is the time interval, Y_{it} is the observed variable (i.e. Education Index / Health Index /Human Capital Index),U_{it} is error term which is assumed to be normally distributed; β represents the partial correlation between growth of human capital and its initial value.

$$\left(\frac{1}{\tau}\right) ln\left[\frac{Y_{it}}{Y_{i(t-1)}}\right] = \alpha + \beta\, ln(Y_{i(t-1)}) + \gamma Z_{it} + U_{it} \tag{1.7}$$

In above two equations (1.6 and 1.7), Y is our observed variable of interest (Education Index/ Health Index / Human Capital Index) whose convergence is studied in respective chapters. Now, sigma (σ) convergence occurs across the states(or districts)if the dispersion of the variable (for example human capital index) falls over time. It can be defined as follows;

$$SD_t < SD_{t-1} \tag{1.8}$$

If it happens, then we can say σ convergence. It can be proved that β convergence is necessary but not sufficient condition for σ convergence (Sala-i-Martin 1996) (see, Appendix 1A.2). These two measures of convergence have some limitations. Both are descriptive measures and these are highly affected by extreme values or outliers. At the same time, these measures of convergence do not provide the pattern of distribution; the existence of multiple modes or the non-linearity of data cannot be captured by β (and σ) convergence (Quah 1993, 1996, 1997). Sigma (σ) convergence is based on dispersion which considers the whole distribution but in reality, the rate of decline of different parts of distribution might differ. If the mean changes over time, it becomes pointless to look at the standard deviation (SD) as it is naturally bigger in absolute amount if the mean increases. In order to correct this anomaly, one can consider the changes in the coefficient of variation over time. This is uniquely captured by the Entropy Class of inequality. The mean log deviation, Theil Index and coefficient of variation belong to the Entropy Class measure of inequality; the generalized entropy measure of inequality is shown in equation (1.9).

$$GE(\alpha) = \frac{1}{n(\alpha^2 - \alpha)} \sum \left[\left(\frac{Y_i}{\bar{Y}} \right)^{\alpha} - 1 \right] \tag{1.9}$$

Where, $\alpha$are the sensitivity parameter capturing different parts of the distribution; $\bar{Y}$ is the grand mean of Y (observed variable) and *n* stands for number of states(or districts). Since, Gini coefficient is distribution insensitive and it is not perfectly sub-group decomposable, therefore, we objectively consider the Entropy measure. For lower values of α, *GE* is more sensitive to changes in the lower tail of the distribution and for higher values, GE is more sensitive to changes that affect the upper tail (Litchfield 1999, Cowell 2003). It can be proved that GE (0), GE (1) and GE (2) correspond to mean log deviation, Theil Index and half of the squared coefficient variation respectively (Appendix1A.3).

$$GE(0)=\text{Mean Log Deviation}=\frac{\sum ln\left(\frac{\bar{Y}}{Y_i}\right)}{n}, \tag{1.10}$$

$$GE(1)=\text{Theil Index}=\frac{\sum \frac{Y_i}{\bar{Y}} ln\left(\frac{Y_i}{\bar{Y}}\right)}{n} \tag{1.11}$$

$$GE(2)=\frac{1}{2}.\frac{\frac{1}{n}\sum\left(Y_i-\bar{Y}\right)^2}{(\bar{Y})^2} = 0.5.\, CV^2 \tag{1.12}$$

The GE measures of inequality is more comprehensive than sigma convergence or divergence. It provides the information about inequality as well as it helps guessing the pattern distribution. Now, in order to find out the sources of inequality, we decompose the GE(α) measures as follows:

$$GE(\alpha) = \frac{1}{n(\alpha^2-\alpha)} \sum_{j=1}^{k} \sum_{i=1}^{n_j} \frac{Y_{ij}}{\bar{Y}} \left[\left(\frac{Y_{ij}}{\bar{Y}} \right)^{\alpha} - 1 \right] = GE(\alpha)_W + GE(\alpha)_B \tag{1.13}$$

where, k be the number of groups, n_j be the number of populations in the j-th group, given that $\sum_{j=1}^{k} n_j = n$, $GE(\alpha)_W$ and $GE(\alpha)_B$are the within and between inequality respectively. The$GE(\alpha)_W$and$GE(\alpha)_B$are defined as follows where $\overline{Y_j}$be the mean of Yof j-th group.

$$GE(\alpha)_W = \sum_{j=1}^{k} \frac{n_j.Y_j}{n.\bar{Y}} \left(\frac{\bar{Y}_j}{\bar{Y}} \right)^{\alpha} .GE(\alpha)_{Wj} \tag{1.13.1}$$

$$GE(\alpha)_B = \frac{1}{(\alpha^2-\alpha)} \sum_{j=1}^{k} \frac{n_j.\bar{Y}_j}{n.\bar{Y}} \left[\left(\frac{\bar{Y}_j}{\bar{Y}} \right)^{\alpha} - 1 \right] \tag{1.13.2}$$

Analysis of Non-Parametric approach

Parametric approaches of convergence analysis are average in nature, they fail to capture the dynamics of the distribution of observed variable over time, at the same time, they cannot identify the transition of individual state over time. The *GE* measure of inequality also fails to capture the stability or mobility of states (districts) to their respective classes. In order to understand the intra-distributional dynamics of observed variable, I have followed the non-parametric approach of convergence analysis. The distribution dynamics approach of club convergence based on Kernel density estimation and Markov process of transition developed mainly by Quah (1993, 1996, 1997) is adopted in this study because it has several merits and it overcomes many limitations of the parametric approach of neoclassical growth model based on β and σ convergence; moreover, the distribution dynamic approach is consistent with the endogenous growth model developed by Romer (1986) and Lucas (1988) as argued by Bernard and Durlauf (1996). Firstly, this approach easily captures the dynamics of the distribution over time. Secondly, non-parametric approach does take care of the extreme outliers in the distribution and it focuses on the intra-distributional dynamics of the underlying distribution of any variable. Thirdly, it can clearly identify the mobility as well as stability of the state-level (district level) units over time. It is purely a non-parametric approach in the sense that let the data speak for themselves, providing a better understanding on the trends, patterns and division they might conceal. Moreover, it can estimate the stability index, mobility index and speed of convergence (viz. half-life) in the short-run as well as in the long-run; it can check and predict the ergodic nature (corresponding to the steady state) of the distribution.

The stochastic Kernel allows the space of the variable to be a continuum of states and observes probability densities to study the distributional dynamics (Quah 1993, 1996, 1997; Monfort 2008; Hembram et al 2020). It is a visual inspection of club convergence across economies based on observed variable. Generally, there are three parts of any distribution (Low, Middle and High), but based on the continuous nature of the distribution, I have considered 5 non-overlapping classes of the distribution (extreme low, low, lower middle, upper middle and high). Under this approach, each data point is normalized and a density function is derived, referred to as the Gaussian (stochastic) kernel. The non-parametric kernel density estimation is given by:

$$f_k(y) = \frac{1}{nh}\sum k\left(\frac{y-y_i}{h}\right) \tag{1.14}$$

Where, $k(y)$ usually chosen as a symmetric probability density function satisfying the condition.

$\int_{-\infty}^{+\infty} k(y)dy = 1$, $k(y) = k(-y)$, where, $k(y) = 0$, for $|y| > 1$

There are two important problems that one has to consider while using the Kernel density estimation. First one is the choice of Kernel function and second one is choice of the optimum bandwidth. There are several Kernel functions[1.1], however the choice of Kernel function is not a very sensitive problem whereas choice of bandwidth is very important task here. Optimum bandwidth is the factor which ensures the smoothness of the density function. The optimum bandwidth that makes a balance between bias and variance in the estimation[1.2]. A large bandwidth may reduce the bias of the estimation but at the same time increases the variance, whereas, a small bandwidth works in the opposite direction. This problem is partially solved by Silverman (1986); another limitation of kernel plots is that it will not help in tracking the movement of the states within distribution; however, Markov chain analysis can be applied to estimate the transition dynamics if the distribution is evolving (Quah 1996, 1997; Pellegrini 2002; Monfort 2008; Hembram et al 2020);

Therefore, we can argue that Markov process of probability transition and Kernel density act as complement to each other. As, I have mentioned earlier that, in the empirical analysis of Kernel, I have normalized the observed variable of all 26 states for each time point; I multiply the normalized value by 100 and add 10 such that the value of observed variable of a state (or district) lies between 10 to 110. We divide it into five equi-spaced classes- Extreme low (10-30), Low (30-50), Lower middle (50-70), Upper Middle (70-90) and Higher (90-110).

Following the standard literature on Markov process, we assume that the relative observed variable follows a finite first-order Markov chain with stationary transition probabilities. A group-space of *m* non-overlapping groups (or classes) is defined (in my study *i* = 1, …5) and each group (or class) represents an interval of relative values of observed variable. Let Y_r^t be the relative observed variable of a state viz. regional unit (r). If the sequence $\{Y_r^0, Y_r^1, \ldots\ldots\ldots Y_r^n\}$ satisfies the relation:

$$P\{Y_r^{t+1} = j \mid Y_r^0 = i_0, Y_r^1 = i_1 \ldots\ldots\ldots\ldots\ldots Y_r^t = i\} = P\{Y_r^{t+1} = j \mid Y_r^t = i\} = P_{ij} \tag{1.15}$$

for all intervals (groups or classes) and states (viz. regional-level units), then it is defined as a discrete-time Markov chain process. This means that the probability for a states, *r* to move from group *i* at time *t* to a group *j* at time *t*+1 depends only on the state's (geographical unit) group *i* at time *t* but not on the group at previous points in time. If the transition probability, P_{ij} is independent of time (*t*), then it is called a time stationary Markov chain as shown in ***P*** matrix as follows.

$$P = \begin{pmatrix} P_{11} & P_{12} & P_{13} & P_{1m} \\ P_{21} & P_{22} & P_{23} & P_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ P_{m1} & P_{m2} & P_{m3} & P_{mm} \end{pmatrix}$$

Given that $\sum_{i=1}^{m} P_{1i} = 1; \sum_{i=1}^{m} P_{2i} = 1;\ \ldots \sum_{i=1}^{m} P_{mi} = 1;$ the elements of **P** is estimated as: $P_{ij} = \frac{n_{ij}}{\sum_{j=1}^{m} n_{ij}}$, where n_{ij} is the number of transitions from group *i* to group *j*, thus P_{ij} is the probability transition that a state(geographical unit) will move from group *i* to group *j* in the next period. Mathematically, the Markov process can be described as:

$$M^{t+1} = P.M^{t} \tag{1.16}$$

where, **P** is defined as probability transition matrix (**TPM**), a square matrix (*m* x *m*) of transitional probabilities (P_{ij}); M^{t+1} and M^{t} are the distribution of the variable (say, EI, HI and HCI) at time (*t*+1) and *t* respectively. The generalized distribution for any time, (t+λ) can be written as:

$$M^{t+\lambda} = P^{\lambda}.M^{t} \tag{1.17}$$

Similarly, iterating the system up to infinity, we get the steady-state long-run (ergodic) distribution as follows:

$$M^{*} = \lim_{\lambda \to \infty} P^{\lambda} M^{t} \tag{1.18}$$

Therefore, the M* (ergodic distribution) can be applied to predict the future distribution of any variable and to explore the possibility of stratification, polarization and convergence in the future. Stratification occurs if we have more than two modes, polarization is associated with bi-modal distribution whereas convergence occurs if M* shows a tendency towards a point of mass. Following Quah (1996, 1997) and Pellegrini (2002), we can estimate the stability index (**SI**) which determines the probability that a state will remain in the same group over time as shown in equation (1.18):

$$SI = \frac{trace(P)}{m} \tag{1.19}$$

Here, *trace* (***P***) is the sum of diagonal elements or probabilities and *m* is the dimension of matrix, ***P***. The high value of **SI** implies that the transition process is low. There is another measure developed by Shorrocks (1978) pertaining to mobility of a country from one group (class) to another over time; this is known as mobility index (**MI**) as shown in (1.19).

$$MI_p(P) = \frac{m - tr(P)}{m - 1} \tag{1.20 }$$

Where, ***P*** is the probability transition matrix (TPM) and $tr(P)$ denotes a trace of **P**. There exists another measure of mobility index defined by Bibby 1975; Prais, 1955; this measures of mobility index can be used in the presence of fully mobile case, that means the sum of diagonal elements will be equal to zero. In that situation the overall mobility can be captured by using following index;

$$MI_p(P) = \frac{m - tr(P)}{m} \tag{1.21}$$

This index (MI) is opposite of stability index (SI). A higher value of Mobility Index (MI) means stability to a particular class is low. The speed of convergence (half-life) can be calculated from the **TPM** and λ_2 (the second Eigen value of matrix **P**). The low value of the half-life indicates a quick convergence to steady state value(s). The derivation of half-life is given in Appendix 1A.4.

$$Half - life = \frac{- \ln 2}{\ln|\lambda_2|} \tag{1.22}$$

Since, Markov chain analysis is based on discrete approach, it suffers from one limitation like arbitrary discretization. One major drawback in the discrete Markov process of transition is that the number of groups or classes is chosen arbitrarily. How many groups are to be chosen optimally? This is difficult to answer. However, for my analysis, I have used the groups such that extreme trap is identified for policy intervention.

Analysis of Variance

I have constructed five non overlapping classes to examine the presence of club convergence. Using analysis of variance, I have examined the presence of significance difference among the different classes. The hypothesis of significance difference can be observed for both aggregate as well as at the specific groups also.

For aggregate difference in group mean, the null hypothesis can be written as follows;

$H_0 = \mu_1 = \mu_2 = \cdots = \mu_n$

Whereas the alternative hypothesis can be written as follows:

$H_1 = \mu_1 \neq \mu_2 \neq \cdots \neq \mu_n$

From the significance F-statistics one can take the decision about the acceptance or rejection of the null hypothesis. F-statistic can be obtained from the ratio of between and within variation across the groups.

Therefore, the F-statistics can be written as; $F = \frac{Average\_SSB}{Average\_SSE}$ (1.23)

Where, SSB is between sum of square and SSE is within sum of square or error sum of square.

$$SSB = \sum r_j(\bar{x}_j - \bar{X}_G)^2 \quad (1.23.1)$$

and $SSE = \sum_i^r \sum_j^c (\bar{x}_{ij} - \bar{x}_j)^2$ (1.23.2)

G stands for aggregate, j is the total number of group and r is the total number of variable in j-th group.

Using Fisher test or Scheffe's test one can examine the presence of group specific significance mean difference. For both calculations, we need critical difference (CD). The test statistics of CD for Fisher's test can be written as follows;

$$CD = MSE^{\frac{1}{2}} * (\frac{1}{n_A} + \frac{1}{n_B})^{\frac{1}{2}} * t_{0.025(n-k)df} \quad (1.24)$$

The Scheffe's test is more or less similar to Fisher's test, but here it contains F value to estimate the critical distance (CD).

$$CD = MSE^{\frac{1}{2}} * (\frac{1}{n_A} + \frac{1}{n_B})^{\frac{1}{2}} * [(k-1) * F_{(k-1),(N-k),\alpha}]^{\frac{1}{2}} \quad (1.25)$$

Where n_A and n_B are the number of individuals in group A and B respectively; *k* is the number of groups and MSE is the mean sum of error.

Spatial Analysis

Quah (1996) for the first time has focused on the importance of space towards club formation. Following Quah, Rey and Monouri (1999) and Fischer and Claudia (2005), I have examined the role of space towards analysis of convergence. Kraay and McKenzie (2014) have explained how does space create the trap across economies. In India also, several literature have used space as a determinant of convergence. Pushparaj (2013) has examined the presence of spill-over effect across 17 major states in India. Sofi and Durai (2015) and Lolayekar and Mukhopadhyay (2019) have explored the impact of space towards convergence across states.

One can examine the presence of spatial autocorrelation based on Global and Local Moran's Index. Following Anselin (1988, 1995) and Hongfei, Calder and Noel (2007), we define Moran's Index (MI):

$$MI = \frac{N}{W} \cdot \frac{\sum_i \sum_j w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2} \tag{1.26}$$

where, N=number of spatial units indexed by i and j (state/district), $W = \sum_i \sum_j w_{ij}$=sum of spatial weights, $w_{ij}$is a matrix of spatial weights with zeros on the diagonal ($w_{ii} = w_{jj} = 0$), X be the variable of interest, $\bar{X}$ =mean of the variable. The spatial weight matrix can be defined in many ways but the Queen contiguity matrix[1.3] is assumed to be a better approach (Anselin 1988) as it captures all possible borders. I have adopted Queen contiguity matrix; by geographic proximity I construct a binary matrix, in which, $w_{ij} = 1$if two states (districts) share borders, otherwise zero. The weight matrix has been row standardized. For statistical significance testing, we can calculate Z-statistics along with p-values (Appendix 1A.5).

GMI is an aggregate index value showing the presence of global spatial autocorrelation. Local Moran's index shows the individual spatial dependency with its neighbour. It is very similar to that of Global Moran's I, as mentioned below:

$$MI_i^L = \frac{X_i - \bar{X}}{S_i^2} \sum_{j=1, i \neq j} w_{ij} \left(X_j - \bar{X} \right) \tag{1.27}$$

where, $S_i^2 = \frac{\sum_{j=1, i \neq j}^{N} w_{ij}}{N-1} - \bar{X}^2$.

Now, for statistical testing, we can estimate the z-statistics (Appendix 1A.5).

In regression analysis, if spatial dimension is neglected, the usual panel data estimators can be greatly affected; omitting the spatial dependence in an econometric analysis would lead to biased estimation (Anselin 1988, Baltagi and Pirotte 2010). Therefore, following Anselin (1988), Anselin et al (1998), Kelejian et al (2006), we propose here basic two models of spatial panel regression: (a) Spatial Lag Panel Model (SLPM) and (b) Spatial Error Panel Model (SEPM). Incorporating SLPM and SEPM, LeSage and Pace (2009) suggest another model known as Spatial Panel Durbin Model (SPDM); however, I will only estimate SLPM and SEPM.

We assume that the observed variable (Education Index / Health Index / Human Capital Index) in the i-th state at time t, namely y_{it} , is generated according to the following Spatial Durbin Lag Model(SDLM):

$$y_{it} = \rho \sum_{j=1}^{N} W_{ij} y_{jt} + X_{it}\beta_1 + \beta_2 \sum_{j=1}^{N} W_{jt} X_{jt} + \mu_i + \varepsilon_{it} \tag{1.28}$$

i=1,2…N; *t=1,2…..T*

where ρ is the spatial autoregressive parameter, β is the (*K x 1*) parameters, X_{it} stands for (*1 x K*) vector of explanatory variables. In standard panel data regression, μ_i captures individual (state/region) specific characteristics and it is fixed effect but in spatial panel, μ_i becomes random (Anselin and Bera 1998, Baltagi and Griffin 1997), with zero mean and constant variance,$IID(0,\sigma^2)$;ε_{it} is white noise,$IID(0,\sigma^2)$; *W* is the spatial standardized weight matrix of order (*N x N*) defined earlier. The term,$\sum_{j=1}^{N} W_{ij} y_{jt}$represents the endogenous interaction effects of the dependent variable, y_{it}. The Spatial Durbin Error Model includes interaction effects among the error terms and it is assumed that the spatial interaction effects are caused by omitted variables that affect both the local and neighbouring regions. The SDEM model is presented below:

$$y_{it} = X_{it}\beta_1 + \beta_2 \sum_{j=1}^{N} W_{jt} X_{jt} + \mu_i + \phi_{it} \tag{1.29}$$

where, $\phi_{it} = \lambda \sum_{j=1}^{N} W_{ij}\, \phi_{jt} + \varepsilon_{it}$ (1.30),

where, $\phi_{it}$is spatially auto-correlated error term, λ is the spatial autocorrelation coefficient of the error term.

Due to the presence of multicollinearity of the explanatory variables, I have formulated different models. In successive chapters, these two models help us to capture both direct and indirect effects of space across the states(districts).

1.6 Organization of the Chapters

On the basis of the overall background and following my major research objective, I have developed six chapters to carry out my research. Chapter 1 consists of overall introduction with background, major literature review, scope of the study, research questions along with data and methodologies. Human capital index (HCI) is comprised of education and health index. Therefore, before going to examine the presence of convergence as well as trap in terms of human capital, I have examined the presence of convergence both in education and health. This is why in Chapter 2, I have examined the education convergence and educational trap whereas in Chapter 3, I have examined the presence of health convergence and health trap across 26 Indian states. Using these education and health index obtained from chapter 2 and 3, I have examined the convergence as well as trap in Human Capital Index in chapter 4. In Chapter 5, I have examined the same for sub state-level where unit of analysis is district. Chapter-6, consists of overall conclusions as well as policy implications.

Notes

[1.1]There are different kind of kernel function (Guassian kernel function, Triangular kernel function, etc). Choice of kernel function is not very sensitive.

[1.2]Optimum Bandwidth: h is the smoothing parameter (Silverman 1986, Kar Jha Kateja 2011)

$$MISE(h) = E[\int (\hat{f}_h(x) - f(x))^2 dx] \Rightarrow AMISE(h) = \frac{R(K)}{nh} + \frac{1}{4} m_2(K)^2 h^4 R(f'')$$

$$\frac{\partial}{\partial h} AMISE(h) = -\frac{R(K)}{nh^2} + m_2(K)^2 h^3 R(f'') = 0$$

$$h_{AMISE} = \frac{R(K)^{\frac{1}{5}}}{m_2(K)^{\frac{2}{5}} R(f'')^{\frac{1}{5}} n^{\frac{1}{5}}}$$

[1.3]The spatial weight matrix can be defined in many ways. For example, Rook contiguity, queen contiguity, Bishop contiguity, linear contiguity, double linear contiguity, double rook contiguity and distance matrix.

Queen Contiguity: For entities that share a common side or vertex with region of interest define $w_{ij} = 1$ and zero otherwise.

Appendix

Appendix 1A.1: Property of indices

1. Pure Number: The indices value is a pure number lies between 0 and 1 or 0 to 100.
2. Transitivity: Suppose you have three different numbers for different individual states, i.e. A, B and C.

If $A > B$

And $B > C$

Then $A > C$

This condition is known as transitivity. The index also satisfies this property.

3. Homogeneity:

$$EI = \sqrt{GERI * YSI * LRI}$$

$$\Longrightarrow \lambda EI = \sqrt{\lambda GERI * \lambda YSI * \lambda LRI}$$

$$\Longrightarrow EI^* = \sqrt{\lambda^3 (GERI * YSI * LRI)}$$

$$\Longrightarrow EI^* = \lambda * \sqrt{GERI * YSI * LRI}$$

$$\Longrightarrow EI^* = \lambda * EI$$

So, the index is homogenous of degree 1.

4. Convexity:

$$EI = \sqrt{GERI * YSI * LRI}$$

$$\Rightarrow EI = GERI^{\frac{1}{3}} * YSI^{\frac{1}{3}} * LRI^{\frac{1}{3}}$$

$$\Rightarrow \frac{EI}{GERI^{\frac{1}{3}}} = YSI^{\frac{1}{3}} * LRI^{\frac{1}{3}}$$

$$\Rightarrow A = B * C$$

This proves that the index is convex to the origin with respect to two sub-dimensions.

5. Substitutability:

$$EI = \sqrt{GERI * YSI * LRI}$$

$$\Rightarrow EI = GERI^{\frac{1}{3}} * YSI^{\frac{1}{3}} * LRI^{\frac{1}{3}}$$

$$\frac{\partial EI}{\partial GERI} = \frac{1}{3} * GERI^{-\frac{2}{3}} * YSI^{\frac{1}{3}} * LRI^{\frac{1}{3}}$$

$$\frac{\partial EI}{\partial YSI} = \frac{1}{3} * GERI^{\frac{1}{3}} * YSI^{-\frac{2}{3}} * LRI^{\frac{1}{3}}$$

$$\frac{\frac{\partial EI}{\partial GERI}}{\frac{\partial EI}{\partial YSI}} = \frac{\frac{1}{3} * GERI^{-\frac{2}{3}} * YSI^{\frac{1}{3}} * LRI^{\frac{1}{3}}}{\frac{1}{3} * GERI^{\frac{1}{3}} * YSI^{-\frac{2}{3}} * LRI^{\frac{1}{3}}}$$

$$\Rightarrow \frac{\frac{\partial EI}{\partial GERI}}{\frac{\partial EI}{\partial YSI}} = \frac{YSI}{GERI}$$

$$MRS = \frac{\frac{\partial EI}{\partial GERI}}{\frac{\partial EI}{\partial YSI}} = \frac{YSI}{GERI}$$

$$\alpha = \frac{d(\frac{YSI}{GERI}) \Big/ (\frac{YSI}{GERI})}{d(\frac{YSI}{GERI}) \Big/ (\frac{YSI}{GERI})} = 1$$

Appendix 1A.2: Beta convergence is necessary but not sufficient for sigma convergence

Consider the following regression equation

$$ln(y_{it}) = \alpha + (1-\beta)ln(y_{it-1}) + u_{it}$$

$$ln(y_{it}) = \alpha + ln(y_{it-1}) - \beta ln(y_{it-1}) + u_{it}$$

$$ln(y_{it}) - ln(y_{it-1}) = \alpha - \beta ln(y_{it-1}) + u_{it}$$

$$ln\left(\frac{y_{it}}{y_{it-1}}\right) = \alpha - \beta ln(y_{it-1}) + u_{it}$$

The beta lies between 0 and 1, beta shows the inverse relation between growth and initial level.

$$\sigma_t^2 = \frac{1}{N} * \sum_{i=1}^{N} [ln(y_{it}) - \mu_t]^2$$

$$\sigma_t^2 \cong (1-\beta)^2 \sigma_{t-1}^2 + \sigma_u^2$$

If beta lies between 0 and 1, if beta negative, the variance increases over time. if beta equal to 1, the variance is constant and if beta is positive then variance decreases.

Appendix 1A.3 Generalized Entropy Measures of Inequality:

$$GE(\alpha) = \frac{1}{n(\alpha^2 - \alpha)} \sum_{i=1}^{n} [(\frac{y_i}{\bar{y}})^\alpha - 1]$$

αmeasures the sensitivity towards different parts of the distribution. For different value of α we will get different equation of the entropy measures of inequality.

GE(0)=Mean Log Deviation=$\frac{\sum ln\left(\frac{\bar{Y}}{Y_i}\right)}{n}$, (9.1)

GE(1)=Theil Index=$\frac{\sum \frac{Y_i}{\bar{Y}} ln\left(\frac{Y_i}{\bar{Y}}\right)}{n}$ (10.1)

GE(2)=$\frac{1}{2} \cdot \frac{\frac{1}{n}\sum(Y_i - \bar{Y})^2}{(\bar{Y})^2} = 0.5.CV^2$

Consider $\alpha = 0$

$$GE(\alpha) = \frac{1}{n(\alpha^2 - \alpha)} \sum_{i=1}^{n} [(\frac{y_i}{\bar{y}})^\alpha - 1]$$

If we put $\alpha = 0$ directly in this equation then the equation will not exist. So, here to get the equation I have used L'hospital Rule.

Let $Z_1(\alpha) = \sum_{i=1}^{n}[(\frac{y_i}{\bar{y}})^\alpha - 1]$ and $Z_2(\alpha) = n(\alpha^2 - \alpha)$

$$\lim_{\alpha \to 0} GE(\alpha) = \lim_{\alpha \to 0} \frac{Z_1{}'(\alpha)}{Z_2{}'(\alpha)}$$

$Z_1' = \sum_{i=1}^{n}[(\frac{y_i}{\bar{y}})^{\alpha}\ln(\frac{y_i}{\bar{y}})]$ and $Z_2' = n(2\alpha - 1)$

$$\therefore \lim_{\alpha \to 0} \frac{Z_1{}'(\alpha)}{Z_2{}'(\alpha)} = \lim_{\alpha \to 0} \frac{\sum_{i=1}^{n}[(\frac{y_i}{\bar{y}})^{\alpha}\ln(\frac{y_i}{\bar{y}})]}{n(2\alpha - 1)}$$

$$= \frac{\sum_{i=1}^{n}[(\frac{y_i}{\bar{y}})^{0}\ln(\frac{y_i}{\bar{y}})]}{n(2 * 0 - 1)}$$

$$= \frac{\sum_{i=1}^{n}\ln(\frac{y_i}{\bar{y}})}{-n}$$

$$= \frac{1}{n}\sum_{i=1}^{n}\ln(\frac{\bar{y}}{y_i})$$

Consider $\alpha = 1$

$$GE(\alpha) = \frac{1}{n(\alpha^2 - \alpha)}\sum_{i=1}^{n}[(\frac{y_i}{\bar{y}})^{\alpha} - 1]$$

If we put $\alpha = 1$ directly in this equation then the equation will not exist. So, here to get the equation I have used L'hospital Rule.

Let $Z_1(\alpha) = \sum_{i=1}^{n}[(\frac{y_i}{\bar{y}})^{\alpha} - 1]$ and $Z_2(\alpha) = n(\alpha^2 - \alpha)$

$$\lim_{\alpha \to 1} GE(\alpha) = \lim_{\alpha \to 1} \frac{Z_1{}'(\alpha)}{Z_2{}'(\alpha)}$$

$Z_1' = \sum_{i=1}^{n}[(\frac{y_i}{\bar{y}})^{\alpha}\ln(\frac{y_i}{\bar{y}})]$ and $Z_2' = n(2\alpha - 1)$

$$\therefore \lim_{\alpha \to 1} \frac{Z_1{}'(\alpha)}{Z_2{}'(\alpha)} = \lim_{\alpha \to 1} \frac{\sum_{i=1}^{n}[(\frac{y_i}{\bar{y}})^{\alpha}\ln(\frac{y_i}{\bar{y}})]}{n(2\alpha - 1)}$$

$$= \frac{\sum_{i=1}^{n}[(\frac{y_i}{\bar{y}})^{1}\ln(\frac{y_i}{\bar{y}})]}{n(2 * 1 - 1)}$$

$$= \frac{\sum_{i=1}^{n}[(\frac{y_i}{\bar{y}})^{1}\ln(\frac{y_i}{\bar{y}})]}{n}$$

Consider $\alpha = 1$

$$GE(\alpha) = \frac{1}{n(\alpha^2 - \alpha)}\sum_{i=1}^{n}[(\frac{y_i}{\bar{y}})^{\alpha} - 1]$$

$$\Rightarrow GE(2) = \frac{1}{n(2^2-2)}\sum_{i=1}^{n}[(\frac{y_i}{\bar{y}})^2 - 1]$$

$$\Rightarrow GE(2) = \frac{1}{n(4-2)}\sum_{i=1}^{n}[(\frac{y_i^2}{\bar{y}^2}) - 1]$$

$$\Rightarrow GE(2) = \frac{1}{2n}\sum_{i=1}^{n}\left[\left(\frac{y_i^2 - \bar{y}^2}{\bar{y}^2}\right)\right]$$

$$\Rightarrow GE(2) = \frac{1}{2n\bar{y}^2}\sum_{i=1}^{n}[(y_i^2 - \bar{y}^2)]$$

$$\Rightarrow GE(2) = \frac{1}{2n\bar{y}^2}[\sum_{i=1}^{n} y_i^2 - \sum_{i=1}^{n} \bar{y}^2]$$

$$\Rightarrow GE(2) = \frac{1}{2n\bar{y}^2}[\sum_{i=1}^{n} y_i^2 - n\bar{y}^2]$$

$$\Rightarrow GE(2) = \frac{1}{2\bar{y}^2}[\frac{1}{n} * \sum_{i=1}^{n} y_i^2 - \frac{1}{n} * n\bar{y}^2]$$

$$\Rightarrow GE(2) = \frac{1}{2\bar{y}^2}[\frac{1}{n} * \sum_{i=1}^{n} y_i^2 - \bar{y}^2]$$

$$\Rightarrow GE(2) = \frac{1}{2\bar{y}^2}V(y)$$

$$\Rightarrow GE(2) = \frac{1}{2} * \frac{V(y)}{\bar{y}^2} = \frac{1}{2} * \frac{(SD_y)^2}{\bar{y}^2} = \frac{1}{2} * (\frac{SD_y}{\bar{y}})^2$$

$$\Rightarrow GE(2) = \frac{1}{2} * CV^2$$

Appendix 1A.4

Derivation of Half-Life Measure

The measure of half-life and its derivation is discussed following the work of Shorrocks (1978). To use the Markov chains for studying the transition dynamics, we divide the observations into a set of m non-overlapping and exhaustive classes or groups. Under the assumption that the Markov chain is an ergodic chain, we can form a transition probability matrix Π from the estimated values of the conditional probability of transition (π_{ij}).

An index of mobility can be defined as a continuous real function X (Π) over the set of transition matrices Π. The assumption of monotonicity requires the index to reflect the higher level of mobility when one of the off-diagonal elements (probability of movement across groups) increases reducing the diagonal component (persistence).

(Monotonicity) $\Pi \succ \Pi' \rightarrow X(\Pi) > X(\Pi')$

The index is restricted to [0, 1]. Minimum value of the index arises under identity matrix with no transitions; perfect mobility occurs when the probability of moving to any group is independent of that initially occupied.

(Immobility) $X(I) = 0$; (Perfect Mobility) $X(\Pi) = 1$ if $\Pi = ux'$ where $u = (111.......1)', x'u = 1$

The following property must be satisfied by the index to avoid the problem of ambiguity of rankings,

(Period Consistency) $X(\Pi) \geq X(\Phi)$ implies $X(\Pi^n) \geq X(\Phi^n)$ *for all integers* $n \geq 1$.

The assumption of period consistency violates the monotonicity and immobility in the stricter sense. Period consistency is replaced by the stricter condition and the time period T which defines Π is introduced.

(Period Invariance) $X(\Pi, T) = X(\Pi^n; nT), n \geq 1$.

Period invariance requires an index to combine the characteristic root of the transition matrix in such way that applying standard decomposition of Π (see Perlis (1952)),

$$\Pi^t = \sum_{i=1}^{n} \lambda_i^t E_i \tag{1.D.1}$$

The matrix E_i is formed by the product of the right column eigenvector (x_i) and left row eigenvector (y_i) corresponding to λ_i, under the normalization $y_i' x_i = 1$.

An index having the property of period invariance is,

$$M_H(P;T) = e^{-ht} \text{where } h = \frac{-\log 2}{\log|\lambda_2|}$$

The expression h indicates the speed of convergence towards the stationary distribution for a Markov chain with probability transition matrix Π. The expression h can be interpreted as the asymptotic half-life. Assume $p(t)$ is the current distribution $p(t-1)$ is the distribution of immediate last time period, and Π is the probability transition matrix.

$$\begin{aligned} p(t) &= p(t-1)\Pi \\ p(t) &= p(t-2)\Pi^2 \\ &\ldots\ldots\ldots\ldots\ldots\ldots \\ p(t) &= p(0)\Pi^t \end{aligned} \tag{1.D.2}$$

The characteristics roots of matrix Π are $\lambda_1, \lambda_2 \ldots \lambda_n$, where, $1 = \lambda_1 > |\lambda_2| > \ldots\ldots > |\lambda_n|$. Under this condition, the distribution has a unique stationary distribution p^* and the deviation from the equilibrium can be written as,

$$d(t) = p(t) - p^* \tag{a}$$

$$d(t) = p(0)\Pi^t - p^* \qquad \text{(b)}$$

From equation (a) and (b), $p(0)\Pi^t = \sum_{i=1}^{n} \lambda_i^t p(0)E_i$ (c)

$$d(t) = \sum_{i=1}^{n} \lambda_i^t p(0)E_i - p^* \Rightarrow d(t) = \lambda_1^t p(0)E_1 + \sum_{i=2}^{n} \lambda_i^t p(0)E_i - p^* \Rightarrow d(t) = \sum_{i=2}^{n} \lambda_i^t p(0)E_i \quad (1.D.3)$$

For a chosen distance metric, the time taken to converge to within half the distance from equilibrium starting from the distribution p(t), is the minimum value h so that

$$\frac{\|d(t+h)\|}{\|d(t)\|} \le \frac{1}{2} \qquad (1.D.4)$$

The "half-life" depends both on the metric and the initial distribution, but for a linear metric (norm) there is a unique asymptotic half-life for allowing $t \to \infty$. Since λ_2 dominates the remaining Eigen values, from equation (c)

$$d(t) = \sum_{i=2}^{n} \lambda_i^t p(0)E_i \Rightarrow d(t) \to |\lambda_2^t| p(0)E_2$$

$$d(t+h) = \sum_{i=2}^{n} \lambda_i^{t+h} p(0)E_i \Rightarrow d(t+h) \to |\lambda_2^{t+h}| p(0)E_2$$

From the above expressions and setting the value equal to $\frac{1}{2}$ corresponding to equation (1.D.3) & (1.D.4),

$$\frac{\|d(t+h)\|}{\|d(t)\|} = \frac{1}{2} \begin{array}{l} \Rightarrow \log\left[\frac{\|d(t+h)\|}{\|d(t)\|}\right] = \log\frac{1}{2} \Rightarrow \log\|d(t+h)\| - \log\|d(t)\| = -\log 2 \\ \Rightarrow \log(|\lambda_2^{t+h}| p(0)E_2) - \log(|\lambda_2^t| p(0)E_2) = -\log 2 \Rightarrow \log|\lambda_2^{t+h}| - \log|\lambda_2^t| = -\log 2 \\ \Rightarrow \log|\lambda_2^h| = -\log 2 \Rightarrow h\log|\lambda_2| = -\log 2 \Rightarrow h = \frac{-\log 2}{\log|\lambda_2|} \end{array}$$

Appendix 1A.5: Statistical testing for GMI and LMI

$Z_{MI} = \frac{MI - E[MI]}{\sqrt{V(MI)}}$ (13), where, $E[MI] = -\frac{1}{N-1}$ and $V(MI) = \frac{NS_4 - S_3 S_5}{(N-1)(N-2)(N-3).W^2} - (E[MI])^2$

$$S_1 = \frac{1}{2}\sum_i \sum_j (w_{ij} + w_{ji})^2, S_2 = \sum_i \left(\sum_j w_{ij} + \sum_j w_{ji}\right)^2, S_3 = \frac{N^{-1}\sum_i (X_i - \bar{X})^4}{\left[N^{-1}\sum_i (X_i - \bar{X})^2\right]^2},$$

$$S_4 = (N^2 - 3N + 3)S_1 - NS_2 + 3W^2 \; S_5 = (N^2 - N)S_1 - 2NS_2 + 6W^2.$$

The z-scores of MI along with the corresponding ‘p-values’ are used for measuring statistical significance whether or not to reject the null hypothesis (of no-spatial auto-correlation); high but positive z-score for a feature indicates that the surrounding features have similar values (either high values or low values). This gives us that the feature is clustered or clubbed geographically (Anselin 1995). Similarly, a low but negative z-score for a feature indicates a statistically significant spatial data outlier which means that the feature values are dispersed spatially. Equation (13) is meant for Global Moran’s Index (GMI), however, a local Moran Index (LMI) is suggested that captures the extent to which points that are “close” to a given point having similar values.

Testing for LMI is very similar to GMI.For a randomization hypothesis, the expected value is:

$E(I_i) = -\dfrac{\sum_{j=1, i\neq j}^{N} w_{ij}}{N-1}$ and the variance of MI_i^L is given as:

$Var(MI_i^L) = \dfrac{(N-B_2)\sum_{j=1, i\neq j}^{N} w_{ij}^2}{N-1} - \dfrac{(2B_2-N)\sum_{k=1,k\neq i}^{N}\sum_{k=1,k\neq i}^{N} w_{ik}w_{ik}}{(N-1)(N-2)} - \left[E(MI_i^L)\right]^2$, where, B_2 is defined as: $B_2 = \dfrac{N\sum_{i=1,i\neq j}^{N}\left(X_i-\overline{X}\right)^4}{\left[\sum_{i=1,i\neq j}^{N}\left(X_i-\overline{X}\right)^2\right]^2}$

CHAPTER-2

Exploring Education Convergence in India: A Sub-National Analysis

2.1 Introduction

India is the largest democratic country in the world but still India has not yet achieved a good rank in respect of education. After 1991, India has experienced a slower growth in literacy rate due asymptotic upper bound of literacy rate. Not only literacy rate, all indicators of education dimension are found to be the same nature. From 1991 to 2001, the growth rate in literacy rate was 12.62% whereas it was decreased to 9.21% in next decade (viz., 2001-2011 (Census 2001, 2011)). In 2017-18, the literacy rate has recorded as 77.7%. The national programme like Right of Children to Free and Compulsory Education Act (2009) and the National Early Childhood Care and Education Policy (2013) have been trying to boost up the outcome of education over time. India has made some improvement in elementary enrolment. However, challenges do remains. According to the SRI-IMRB Surveys, 2009 and 2014, the number of dropout children has decreased from 13.46 million in 2006 to 6.1 million in 2013. Millennium Development Goal Report stated that over time India has significantly improved in primary education but there exists a doubt about the progress of higher education as higher education plays a crucial role towards economic growth (Romer 1990, Mankiw et al 1992, Barro and Sala-i-Martin 1995). The Millennium Development Goal highlights the uneven distribution of education between rural and urban region. As education is an important component of human capital and we all know that human capital follows the property of increasing returns to scale, quality of education is much more important than quantity. Because of this reason Sustainable Development Goals (2015) suggest to provide quality education along with education attainment. So, in India we have the unequal distribution of education both in terms of quantity as well as quality. Initially, Education was considered as major component of human capital. All development indices consist of education dimension as the measurement of economic development. There is an endogenous relationship between human capital (education) and economic growth (Lucas 1988). In order to reap the benefit of maximum working force it is important to focus on quality of education along with progress in literacy rate. Quality education converted in increased in labour productivity by accumulating knowledge and skill by facilitating the technological progress and innovation (Haltiwanger et al 1999, Moretti 2004, Susanto 2014,). No country can achieve the sustainable economic growth without focusing on sustainable growth in education (Hussaini 2019).

A large number of studies have focused on income convergence; however, a very few studies are available at cross country level focusing on education convergence. Initially, the existing literature focused on the causal relationship between education and economic growth. Barro (2002, 2013) has found a significant impact of education on economic growth as Endogenous growth model begins with the introduction of human capital and initially education was the major component of human capital (Lucas 1988, Mankiw (1992)).

Majority of the studies have focused on the input of education on economic growth and have studied income convergence. In cross country level literatures like Bnhabib 1994, Petrakis 2002, 2005, Pelinescu 2015, Agiomirgianakis et al 2002, Kui 2006 etc. have examined the relationship between education and economic growth. In Indian context also most of the studies either focus on the causal relationship between education and economic growth or try to measure the impact of education on economic growth. Self and Grabowski 2004, Viswanath & Pandit 2009, Pradhan 2009, Patowary 2020 have examined the impact of education on economic growth. Studies like Krishnankutty and Chakraborty (2012), Hembram et al 2019, have examined the impact between expenditure on education and economic growth.

2.2 Research Gap and My Contribution

Studies on education convergence are available at cross country level. It is clear that all existing studies in India focused on the contribution of education on economic growth. In India, no studies available on education convergence. Endogenous growth model clearly shows that human capital (Education) is the only path of achieving the peak of economic growth. None of the studies has focused on this path as subject of analysis. At the same time, earlier studies could not focus on trap in respect of low-level of educational attainment. Given the backdrop, in this study I have considered education as human capital and try to examine the education human capital convergence. My study is different from existing literature in several aspects.

Most of the cross-country studies either considered only one or two indicators for convergence analysis. But, I have tried to cover the entire dimension at disaggregate level to capture the actual progress in educational outcome.

None of the study has constructed any index of education based on entire dimension. I have constructed a new education index and explore the presence of convergence based on the education index.

The earlier studies are based on parametric approach. The studies could not use non-parametric approach to examine the presence of convergence.

In this study I have used non-parametric approach along with parametric approach to explore the club convergence as well as chronic low-level trap across the states.

Finally, I have used spatial analysis to observe spatial dependency across the states in respect terms of education index. States located at similar region generally are generally expected to have same types of outcomes. Does it always hold? It may imply that states located in same region may form a cluster or clubs. That is why I have applied spatial analysis to check how does space matter towards formation of spatial clubs.

2.3 Objectives of the study

I have five major research objectives as mentioned below:

- Construct the Education Human Capital Index (Education Index) for four time points corresponding to four rounds of NFHS (NFHS-I,II,III and IV) across 26 Indian states using some selective indicators from education dimension.
- Examine the presence of convergence in Education Index for four time points across 26 Indian states using regression and dispersion-based approaches.
- Examine the presence of regional inequality across the states over time using generalized entropy measures of inequality.
- Explore the presence of club convergence as well as chronic low-level trap in education index across 26 Indian states using distributional dynamics approaches (i.e., Kernel Density Estimation and Markov Process).
- Explore the role of space toward formation of chronic low-level trap across states using Spatial Econometrics Analysis.

2.4 Data and Methodology

2.4.1 Data

Keeping in mind the limitations of the earlier studies, I have considered three sub dimensions of education. First one is the enrolment ratio, second one is complete years of schooling and finally the literacy rate. Under enrolment ratio, I have considered Gross Enrolment Ratio to primary, upper primary, higher secondary and higher education whereas under complete years of schooling I have considered data on the education level less than primary, complete only primary school, complete only middle school, complete high school and complete years of schooling above high school. These data are drawn from four rounds of NFHS data, SRC and Annual Report 1993 and 1999.

To examine the presence of conditional convergence I have used per capita education and health expenditure of lag 5-year, Social Infrastructure Index and Physical Infrastructure index. The same conditional variables are also used to examine the conditional beta convergence for health and human capital index in respective chapters. Following table (Table-2.1) shows the data definitions with their abbreviation and sources.

Table-2.1: Data Description and Sources

Definitions	Abbreviation	Sources
Gross Enrolment ratio to primary education	GER_P	SRC and Annual Report 1993 and 1999, DISE
Gross Enrolment to upper primary School	GER_UP	SRC and Annual Report 1993 and 1999, DISE
Gross Enrolment to higher secondary school	GER_HS	SRC and Annual Report 1993 and 1999, DISE
Gross Enrolment Ratio to higher education	GER_HE	SRC and Annual Report 1993 and 1999, DISE
Schooling Less than Primary School	YS_<P	NFHS I, II, III & IV
Complete Years to primary school	YS_P	NFHS I, II, III & IV
Complete Years to Upper Primary school	YS_UP	NFHS I, II, III & IV
Complete years to high school	YS_HS	NFHS I, II, III & IV
Complete Years to above high school	YS_>HS	NFHS I, II, III & IV
Literacy Rate	LR	Census, DISE
Per Capita Education Expenditure	PCEE	RBI, Government of India, NITI Aayog.
Per Capita Health Expenditure	PCHE	RBI, Government of India, NITI Aayog.
No. Of Primary School	No. of PS	SRC and Annual Report 1993 and 1999,
Number of Middle School	No. of UP	SRC and Annual Report 1993 and 1999,
Number of Secondary School	No. of HS	SRC and Annual Report 1993 and 1999,
Number of Sub Centre	SC	RBI, Government of India, NITI Aayog.
Number of PHC	PHC	RBI, Government of India, NITI Aayog.
Number of Community Health Centre	CHC	RBI, Government of India, NITI Aayog.
Road Length	Road	RBI, Government of India, NITI Aayog.
Railway Length	Rail	RBI, Government of India, NITI Aayog.

2.4.2 Methodologies

All the measures of well-being considered education as an important component. Most of the measures focused on literacy rate or enrolment ratio to define education level. Some of the measures considered expected years of schooling also. Literacy rate or expected years of schooling are average in nature. To reap the actual benefit from education human capital it is important to focus on disaggregate level of education. Both MDG as well as SDG have focused on specific level of education according to the need.

Criticizing arbitrary weights of Human Development Index (HDI) and human poverty index (HPI), some have suggested Principal Component Analysis (PCA) method through which one can estimate weights endogenously from the data matrix (Tatlidil 1992; Noorkbakhsh 1998; Ogwang and Abdou 2003; Roy and Haldar 2010, Haldar et al 2020). Interestingly, using PCA, Tatlidil (1992), Noorkbakhsh (1998) have empirically proved that identical (equal) weights are justified in HDI. I have used the PCA from panel data matrix and found that the factor loadings of indicators from gross enrolment ratio and years of schooling dimensions. The weights are time and space invariant since the correlation matrix is estimated from panel data. I have used the factor specific weights to construct enrolment and years of complete index. These two sub-indices are used to construct the education index across states.

Before going to run the principal component analysis, I have normalised all the data to get unit free measurement. The methodology of normalisation has already discussed in chapter 1. In each dimension I have normalised the indicators in following ways;

$$E_{ijt} = \frac{ActualE_{ijt} - \underset{i,t}{Min}E_{ijt}}{\underset{i,t}{Max}E_{ijt} - \underset{i,t}{Min}E_{ijt}} \tag{2.1}$$

Where, i=1, 2…26; j is the indicators to respective dimension; t=NFHS 1, NFHS 2, NFHS 3 and NFHS 4. The same is to be applied for next chapters also.

Now the next step is to run the PCA for finding out the significant indicators along with their weights. I have three sub dimensions under education dimension. Among these three sub dimensions, two dimensions consist more than one variable. That's why I have used the PCA[2.1] for those two sub dimensions. It will help me to get significant indicators with a weight and construct the index for sub dimensions with significant indicators. Principal component analysis provides the weights for each respective indicator. Using student's t-test, I have chosen the significant indicators as well as weights (Nunnally and Bernstein 1994)

$$t = \frac{r*\sqrt{n-2}}{\sqrt{1-r^2}} \tag{2.2}$$

Where, r is the factor loadings, and n is the number of observations. After obtaining the results of PCA now I am able to construct the index for those two dimensions. Instead of using arithmetic mean I have constructed the weighted arithmetic mean to construct the sub dimensional index.

The first index is known as Gross Enrolment Index (GERI) and the second index is called Years of Schooling Index (YSI). Literacy rate consists only one indicator itself. I have constructed the literacy rate index with literacy rate across 26 Indian states for four time points.

$$LRI_{ij} = \frac{Actual\,LR_{ij} - \underset{i,j}{Min}\,LR_{ij}}{\underset{i,j}{Max}\,LR_{ij} - \underset{i,j}{Min}\,LR_{ij}} \tag{2.3}$$

$$GERI_{ij} = \frac{w_{11}\cdot G_{1ij} + w_{12}\cdot G_{2ij} + w_{3}\cdot G_{13ij} + w_{14}\cdot G_{4ij}}{w_{11} + w_{12} + w_{13} + w_{14}} \tag{2.4}$$

$$YSI_{ij} = \frac{v_{11}\cdot Y_{1ij} + v_{12}\cdot Y_{2ij} + v_{13}\cdot Y_{3ij} + v_{14}\cdot Y_{4ij} + v_{15}\cdot Y_{5ij}}{v_{11} + v_{12} + v_{13} + v_{14} + v_{15}} \tag{2.5}$$

In equation(2.4) and (2.5), $G_{rij}$and $Y_{rij}$are the indicators from gross enrolment ratio and years of schooling dimensions respectively. w_{ij} and $v_{ij}$are the weights for respective indicators. All the weights for respective indices are given in the following table.

Table-2.2: Result of Principal Component Analysis of Education indicators

Gross Enrolment Ratio		Years of Schooling	
Variables	Factor Loadings	Variables	Factor Loadings
GER_Primary (G1ij)	0.012	Less than Primary (Y1ij)	-0.808
GER_Upper Primary(G2ij)	0.788***	Only Primary (Y2ij)	-0.067
GER_Higher Secondary (G3ij)	0.936***	Upper Primary (Y3ij)	0.238
GER_Higher Education (G4ij)	0.909***	High school (Y4ij)	0.824***
		Greater than High School(Y5ij)	0.836***

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

Above table shows the result of Principal Component Analysis (PCA). Since the first objective is to construct education human capital index or education index across the states using some selective indicators from the education dimension. I have applied PCA to obtain the significant indicators to construct the education index. Table-2.2suggest that from gross enrolment sub-dimensions, gross enrolment to higher secondary and higher educations are appeared as significant. Similarly, from years of schooling dimension only two variables (High school and greater than high school) appear as significant. Now using the weights (factor loadings) coefficient of these significant indicators, I have constructed sub-dimension indices which is the weighted arithmetic mean of all these significant indicators (Equation (2.6) and (2.7)).

$$GERI_{ij} = \frac{0.788*G_{2ij}+0.936*G_{3ij}+0.909*G_{4ij}}{0.788+0.936+0.909} \qquad (2.6)$$

$$YSI_{ij} = \frac{0.824*Y_{4ij}+0.836*Y_{5ij}}{0.824+0.836} \qquad (2.7)$$

Finally, using these two sub-indices along with literacy rate index (equation 2.3), I have constructed the Education Index. The education index which is a geometric mean of LRI, GERI and YSI. The construction of Education index is followed from the methodology of Human Development Index developed by UNDP in 2010.

$$EI_{ij} = [LRI * GERI_{ij} * YSI_{ij}]^{0.333} \qquad (2.8)$$

Before 2010, UNDP considered arithmetic mean of three sub dimensions to construct the Human Development Index. But arithmetic mean has some limitations. It fails to capture the dimension specific achievement as well as interdependency across the sub-dimensions. In arithmetic mean the dimensions are perfectly substitutes whereas in geometric mean the substitution across the dimensions is constant. Because of these advantage in my studies, I have used the geometric mean to construct the Education Index. Subsequently in next three chapters also I have used same methodology to construct health and human capital index.

The **EI** is best seen as a measure of state's status of human capital; the progress of education human capital can easily be measured by observing the difference of EI over time. This Education Index satisfy the important properties of an ideal index like transitivity, substitutability, homogeneity, convexity and sub-group decomposability. The proof is already given in the appendix section of chapter 1.

2.5 Empirical Findings

The following table shows the value of education index across 26 Indian states for four time points (NFHS I,II,III &IV). The number in parenthesis represents the rank of each state over time. The index value lies between 0 and 1. Value nearer to 1 represents the higher education status whereas nearer to 0 represents the lower education status. Some of the states are improve their positions whereas some of the states could not.

Table-2.3: Education Index (EI) across 26 Indian states for four time points (NFHS 1 to NFHS 4)

States	EI_NFHS 1 1992-93	EI_NFHS 2 1998-99	EI_NFHS 3 2005-06	EI_NFHS 4 2015-16
Andhra Pradesh	0.140(19)	0.199(20)	0.359(14)	0.525(16)
Arunachal Pradesh	0.079(23)	0.183(22)	0.226(25)	0.514(17)
Assam	0.174(17)	0.233(13)	0.240(23)	0.430(24)
Bihar	0.011(26)	0.132(26)	0.129(26)	0.384(26)
Delhi	0.521(02)	0.649(01)	0.733(01)	0.839(01)
Goa	0.571(01)	0.572(02)	0.527(04)	0.778(03)
Gujarat	0.305(09)	0.318(11)	0.351(15)	0.545(14)
Haryana	0.262(12)	0.320(10)	0.369(12)	0.628(11)
Himachal Pradesh	0.342(07)	0.457(04)	0.705(02)	0.777(04)
Jammu & Kashmir	0.221(15)	0.2116(16)	0.369(11)	0.501(19)
Karnataka	0.250(14)	0.306(12)	0.391(10)	0.609(12)
Kerala	0.458(03)	0.567(03)	0.598(03)	0.835(02)
Madhya Pradesh	0.126(20)	0.211(17)	0.278(20)	0.428(25)
Maharashtra	0.342(06)	0.367(07)	0.497(06)	0.663(10)
Manipur	0.360(04)	0.418(05)	0.444(08)	0.698(07)
Meghalaya	0.117(21)	0.160(25)	0.278(19)	0.531(15)
Mizoram	0.348(05)	0.358(09)	0.447(07)	0.670(09)
Nagaland	0.269(11)	0.218(14)	0.303(17)	0.503(18)
Odisha	0.157(18)	0.214(15)	0.259(21)	0.477(21)
Punjab	0.300(10)	0.365(08)	0.420(09)	0.671(08)
Rajasthan	0.023(25)	0.175(23)	0.229(24)	0.437(23)
Sikkim	0.052(24)	0.206(18)	0.366(13)	0.701(06)
Tamil Nadu	0.323(08)	0.371(06)	0.514(05)	0.735(05)
Tripura	0.215(16)	0.185(21)	0.328(16)	0.560(13)
Uttar Pradesh	0.112(22)	0.169(24)	0.244(22)	0.461(22)
West Bengal	0.259(13)	0.1995(19)	0.299(18)	0.492(20)

Sources: Author's estimation, Note: Values in parentheses represent rank.

From the above table it can be observed that Delhi, Goa, Kerala, Himachal Pradesh and Tamil Nadu are in good position whereas Uttar Pradesh, Bihar, Madhya Pradesh and Rajasthan are in bad position during the periods. Rest of the states are having moderate position but all states are experiencing an increasing trend in education index. To get some preliminary idea about the distribution of education index over time, I have used the descriptive statistics of education index. The descriptive statistics for each indicator is given in Appendix 2.A.1.

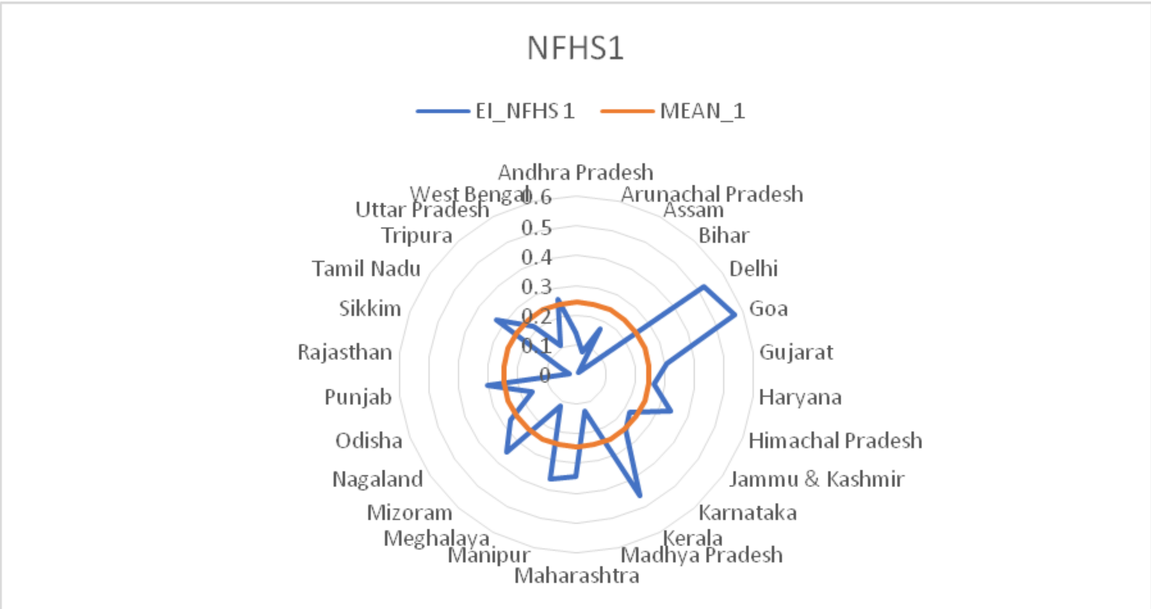
Table-2.4: Descriptive statistics of Education Index over time

Years	Max	Min	Range	Mean	SD	CV
NFHS_1	0.571	0.011	0.560	0.244	0.145	0.594
NFHS_2	0.649	0.132	0.517	0.299	0.140	0.470
NFHS_3	0.733	0.129	0.603	0.381	0.147	0.385
NFHS_4	0.839	0.384	0.455	0.592	0.133	0.225

Sources: Author's estimation

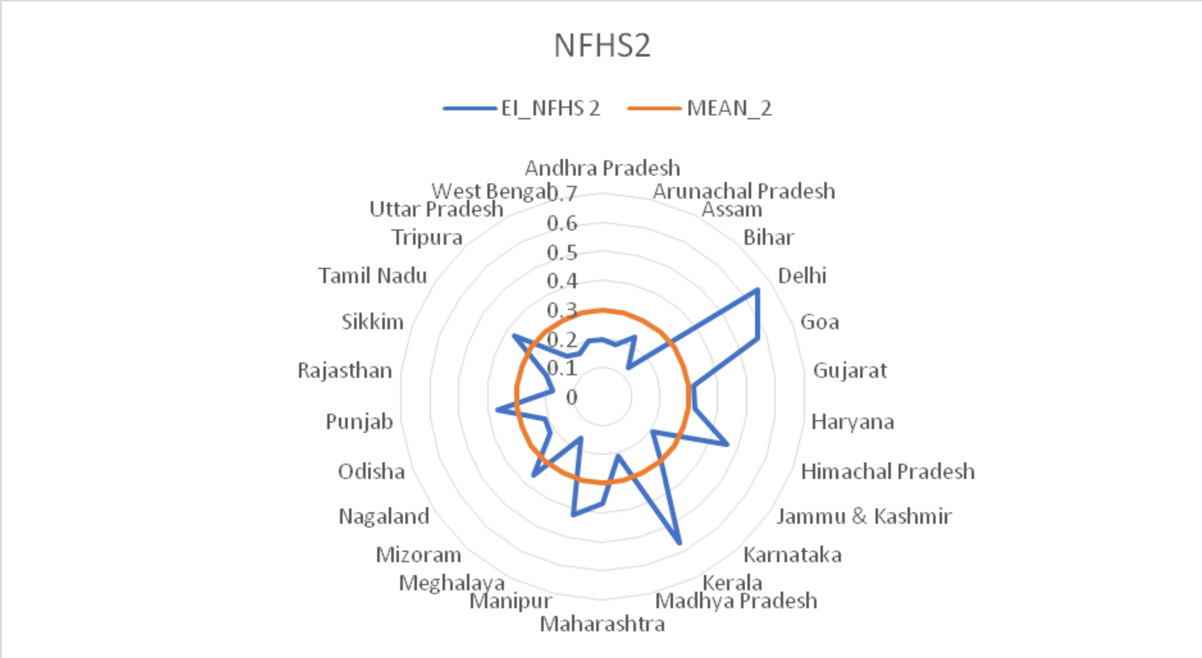
Using the table (Table-2.4) of descriptive statistics one can easily guess the pattern of distribution of educational status across the states. The trend of maximum value has increased but the minimum value is found to be fluctuating over time. As a result, the dispersion among the states in respect of educational attainment fluctuate (as shown by range and standard deviation). But the coefficient of variation has decreased and the mean of education status increased over time. The table of descriptive statistics shows a mixed result about the distribution as well as transitions of states over time. The same can be observed from the graphical representation of transition of states in terms of education over time. Here, I have used Radar diagram for four time points. Each diagram shows the relative position of each state over mean value.

Figure-2.1(A): Relative position of states in respect of Education Index over mean in NFHS 1



Source: Author's estimation

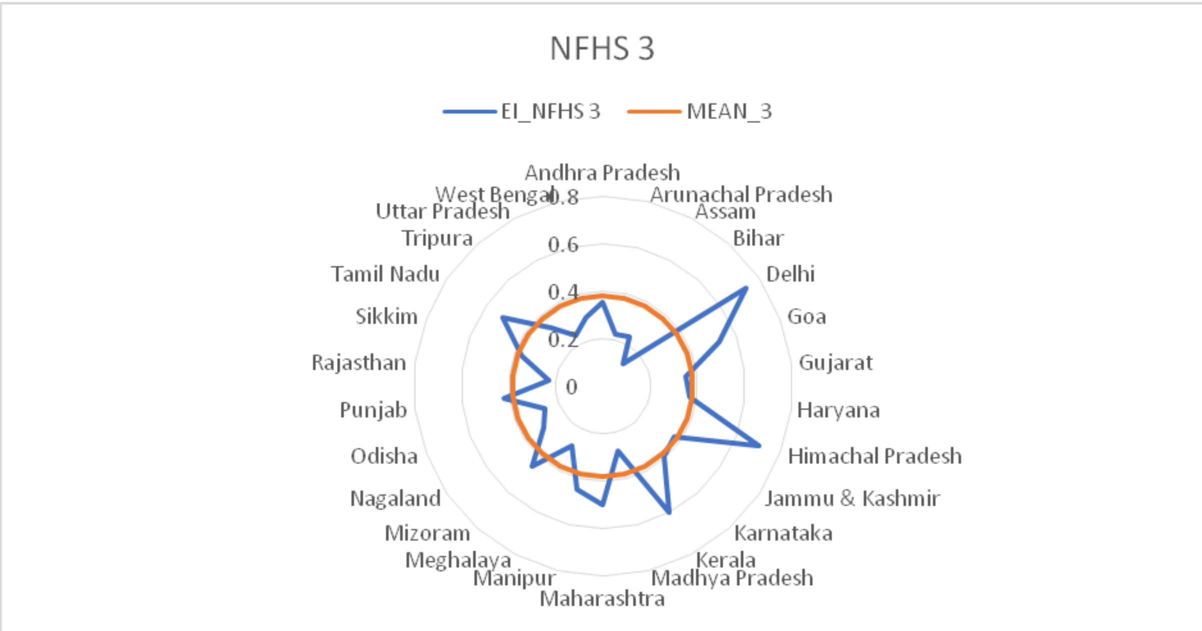
Figure-2.1(B):Relative position of states in respect of Education Index over mean in NFHS 2



Source: Author's estimation

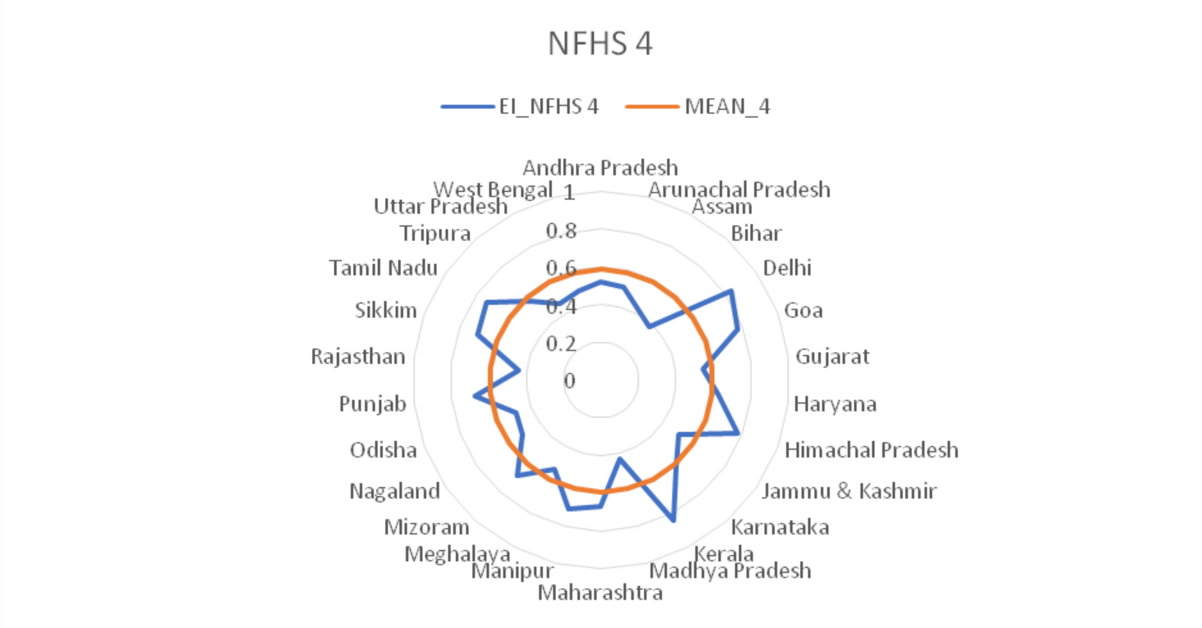
From these diagrams some important results can be observed. First, the mean value has increased over time. Second, the educational status of each state has increased. Third, since they are improving in educational status, it roughly indicates a process of convergence as the value of CV is found to declining over time.

Figure-2.1(C):Relative position of states in respect of Education Index over mean in NFHS 3



Source: Author's estimation

Figure-2.1(D):Relative position of states in respect of Education Index over mean in NFHS 4



Source: Author's estimation

These diagrams also suggest that though the states are improving but few states are found to have a lower rank over the period. For example, Bihar, Assam, Orissa, Madhya Pradesh, Rajasthan are having lower rank in respect of educational outcome consistently. Similarly, Kerala, Goa and Delhi have higher rank consistently over time. Thus, the descriptive statistics give some hints of the presence of different clubs.

Table-2.5 shows the rank correlation coefficient of all states over time in terms of education index. The result shows that the value of rank correlation coefficient is very high and statistically significant. This implies, on aggregate level current position of states is highly related to previous position. One important observation is that, outcome of one time point is highly correlated with the previous time point. If check carefully, we find that the correlation gets decreased over time. So, we can say that most of the states are found to be stable to their relative positions.

Table-2.5: Rank Correlation Coefficient of Education Index

	EI_NFHS_1	EI_NFHS_2	EI_NFHS_3	EI_NFHS_4
EI_NFHS_1	1.000			
EI_NFHS_2	0.926***	1.000		
EI_NFHS_3	0.865***	0.875***	1.000	
EI_NFHS_4	0.755***	0.786***	0.907***	1.000

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

Following the absolute and relative movements across the states over time, I need to examine the presence of convergence in terms of Education Index as follows:

2.5.1 Convergence based on Neoclassical Approach

Initially I have used the parametric approach to examine the presence of convergence. The following table shows the result of absolute beta (β) convergence, since my second objective is to examine the presence of convergence in terms of education index using parametric approach. Here, I have checked the presence of absolute beta (β) convergence along with conditional convergence. The result shows an evidence of absolute beta convergence. Here the fixed effects model is appropriate than random effects model as the value of Hausman test statistics is significant.

Table-2.6: Result of Absolute Beta (β) Convergence of Education Index

Absolute Beta Convergence of EI			
Explanatory variables	Coefficients	t	P>|t|
Initial EI	-0.0983***(0.0109)	-9.00	0.000
Constant	-0.0354***(0.0066)	-5.34	0.000
Within R squared	0.6136		
Between R squared	0.7405		
Overall R squared	0.6285		
F(1,51)	80.99***		
Hausman Test	7.00***		
No. of observations	78		

Source: Authors' estimation. *** implies significance at 1 percent level.** implies significant at 5 percent level

To examine the presence of conditional beta (β) convergence, here, I have used several indicators from social and physical infrastructure along with lagged per capita health and education expenditure. Because of the multicollinearity among these variables, I have constructed four different models. At the same time using principal component analysis, I have constructed social and physical infrastructure index. Each model supports the existence of conditional beta (β) convergence. In first model, I have used 5 years lagged per capita education expenditure which is assumed to be optimum lag (Haldar 2009). It can be observed that lagged per capita education expenditure has a positive and significant impact on growth of education index. Similarly, in second model lagged per capita health expenditure shows a positive and significant impact on growth of education.

Table-2.7: Result of Conditional Beta (β) Convergence of Education Index

Explanatory variables	Model 1	Model 2	Model 3	Model 4
Constatnt	-0.131***(0.013)	-0.097***(0.013)	-0.349***(0.021)	-0.428***(0.064)
$\ln(EI)\_{t-j}$	-0.1363***(0.01)	-0.149***(0.017)	-0.158***(0.010)	-0.117***(0.018)
lnPCEE_5	0.0627***(0.006)			
lnPCHE_5		0.0462***(0.0058)		
lnSII			0.155***(0.010)	
lnPII				0.117***(0.018)
R^2 overall	0.4400	0.3306	0.2849	0.0133
R^2 –within	0.7240	0.6207	0.8518	0.5267
R^2-between	0.4378	0.3241	0.2778	0.0383
F(2,50)	65.58***	40.91***	43.67***	27.82***
Huasman Test	46.65***	33.28***	36.41***	49.72***
Number of observations	78	78	78	78

Source: Authors' estimation. *** implies significance at 1 percent level.** implies significant at 5 percent level

In third and fourth model, I have used social and physical infrastructure index as two conditional variables respectively. Initially, I had number of primary, upper primary, secondary and higher secondary school, number of higher education (college and university) and number of sub centre, primary health centre and community health centre as the indicators of social infrastructure whereas under physical infrastructure, I have used road length and rail route length. Out of those social infrastructure indicators, only the number of primary schools, number of middle schools, number of secondary schools, number of sub centre and number of community health centre are appearing as significant[2.2].

Hence, I have used them towards contribution of the social infrastructure index (SII) and for physical infrastructure index (PII). The regression results suggest that both social and physical infrastructure significantly affect educational growth.

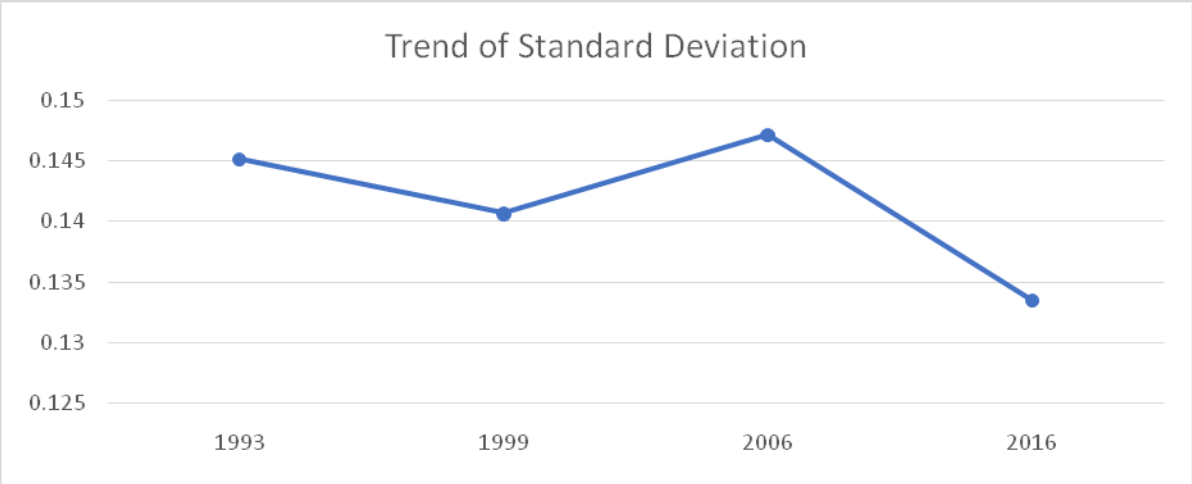
From the descriptive statistics I have already found that over time the dispersion is found to be fluctuating trend over time. If we compare the value of dispersion from NFHS 1 to NFHS 4, then the dispersion has decreased. As a result, we have the result of both absolute and conditional beta (β) convergence along with sigma divergence (in long term there exists sigma convergence).

Table-2.8: Result of Sigma (σ) Convergence/Divergence of EI

SD	NFHS_1	NFHS_2	NFHS_3	NFHS_4
EI	0.145	0.140	0.147	0.133

Source: author's estimation

Figure-2.2: Trend of Standard Deviation(σ) of EI over time



Source: Author's estimation

It is clear that the trend is fluctuating over time whereas for the long run comparison there exists sigma convergence. But in the short run there exists sigma divergence.

2.5.2 Convergence based on Inequality Approach

In this chapter, I have also used inequality-based approach (of convergence) along with β and σ convergence. As inequality falls over time, one can expect the presence of convergence across the states over time. I have already mentioned the limitation of Gini coefficient as well as advantage of GE measures of inequality in the methodology section in Chapter 1. Both the table and the graphs show that inequality has decreased. The graph shows that GE (2) is higher than GE (0) and GE (1). Inequality sensitive to the upper part of the distribution is higher than lower and middle class. Why is it happening? It is because there may exit few numbers of states having a very high value of education level at the upper part of the distribution compared to middle and lower or there may exist a large number of states towards upper part of the distribution. As a result, inequality sensitive to upper portion of the distribution compared to other parts. From the value of GE (0), GE (1) and GE (2) we can find a wide gap between lower and higher class.

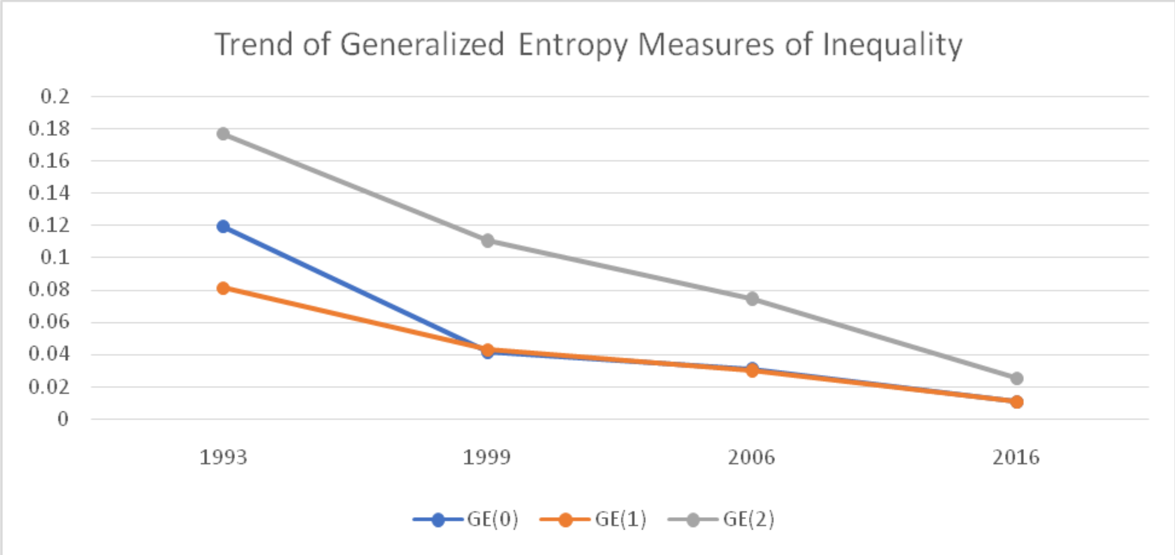
Table-2.9: Result of Generalized Entropy Measures of Inequality of EI

GE	EI_NFHS1	EI_NFHS2	EI_NFHS3	EI_NFHS4
GE(0)	0.118	0.041	0.030	0.010
GE(1)	0.081	0.042	0.029	0.010
GE(2)	0.176	0.110	0.074	0.025

Source: Author's estimation

Initially GE(0) was higher than GE(1), but from second time point both GE(0) and GE(1) coincides with each other. But, at the terminal time points all the inequality values are small and getting closer. This may be due to lower dispersion of education level at that time point.

Figure-2.3: Trend of Generalized Entropy Measures of Inequality of EI from NFHS 1 to NFHS 4



Source: Author's estimation

Inequality sensitive to higher part of the distribution is found to be higher than inequality to lower and middle groups; since GE(2) is higher than GE(1) and GE(0). Therefore, distribution sensitive inequality approach also supports the presence of convergence.

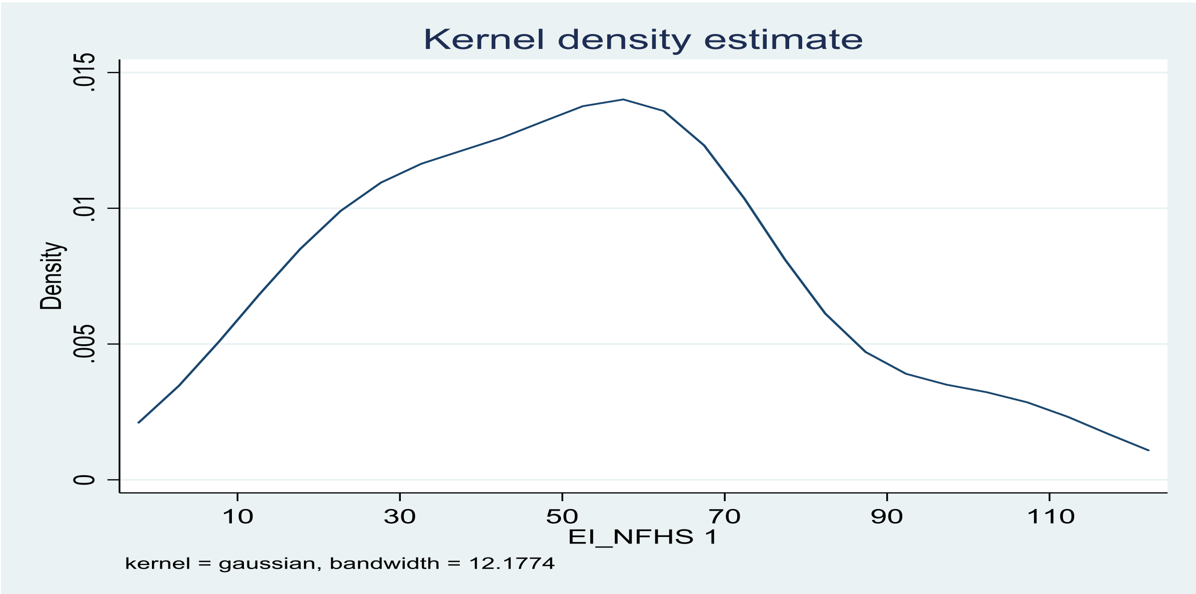
2.5.3 Convergence based on Non-Parametric Approach

The radar diagrams represent dispersion of states around mean EI; it also gives sufficient hint about club formation. In NFHS 1, out of 26 states 12 states are having lower educational status whereas rest of the states have higher value. In next two time points the percentage of states having lower educational status has increased (46.2% to 53.8% and then 61.5%).Radar diagram for NFHS 4, also shows that number of states below the mean value is higher than states above the mean EI. Over time the mean value of EI has increased. So, we can argue that states are improving in respect of overall EI but most of the states are found to be concentrating towards lower level of educational status.

If we compare the states in respect to mean then we will have only two classes. Lower class (below the mean) and upper class or higher class (above the mean). Presence of polarisation can be observed in each time point. But in reality, there may be more than two classes in a distribution; that cannot be captured by the radar diagrams. Following the result of polarization obtained from the radar diagram in non-parametric analysis, I have arbitrarily constructed five non overlapping classes. The classes are defined as follows: Extreme lower class: 10-30, Lower class:30-50, Lower Middle Class:50-70, Upper Middle Class: 70-90 and higher class: 90-110. The range is based on the relative value. Under non-parametric approach, I have Kernel density estimation and Transitional Probability Matrix (TPM). The TPM is used to capture the dynamics of the distribution and transition of individual states over time.

2.5.3.1 Non-Parametric Approach: Kernel Density Estimation

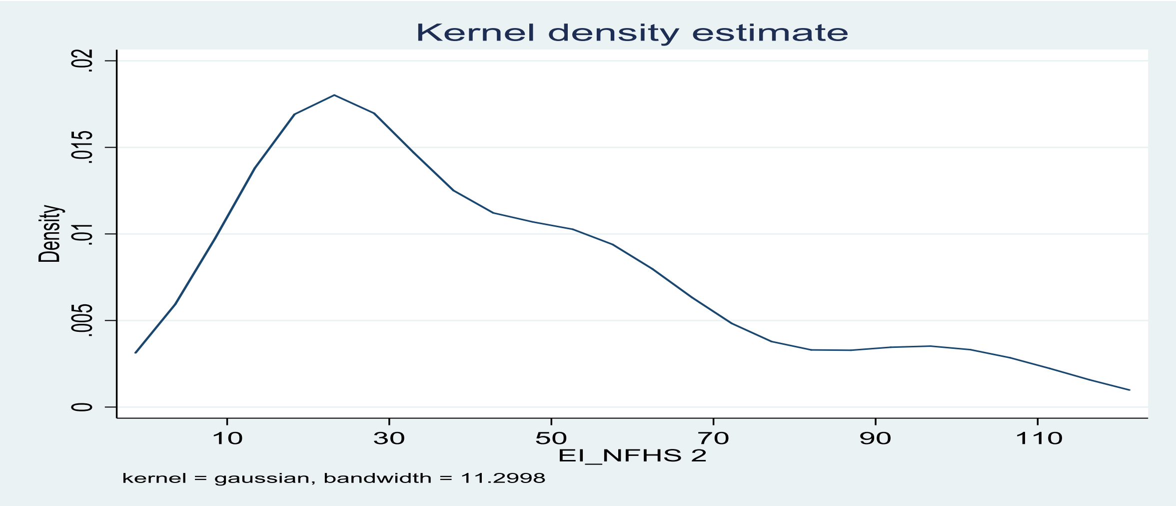
Figure-2.4(A): Kernel density estimation of Education Index in NFHS 1



Source: Author's Estimation

The above plot shows the non-parametric distribution of Education Index (EI) across 26 Indian states for the first time point (NFHS 1). The distribution has two peaks but first peak captures major portion of the distribution whereas a few states are there in the second peak. First peak covers first four arbitrary classes whereas second peak covers only the higher class (90-110). Presence of two peaks implies presence of two clubs or classes. In the next time point (NFHS 2), the distribution has changed from polarisation to stratification, showing multiple peaks.

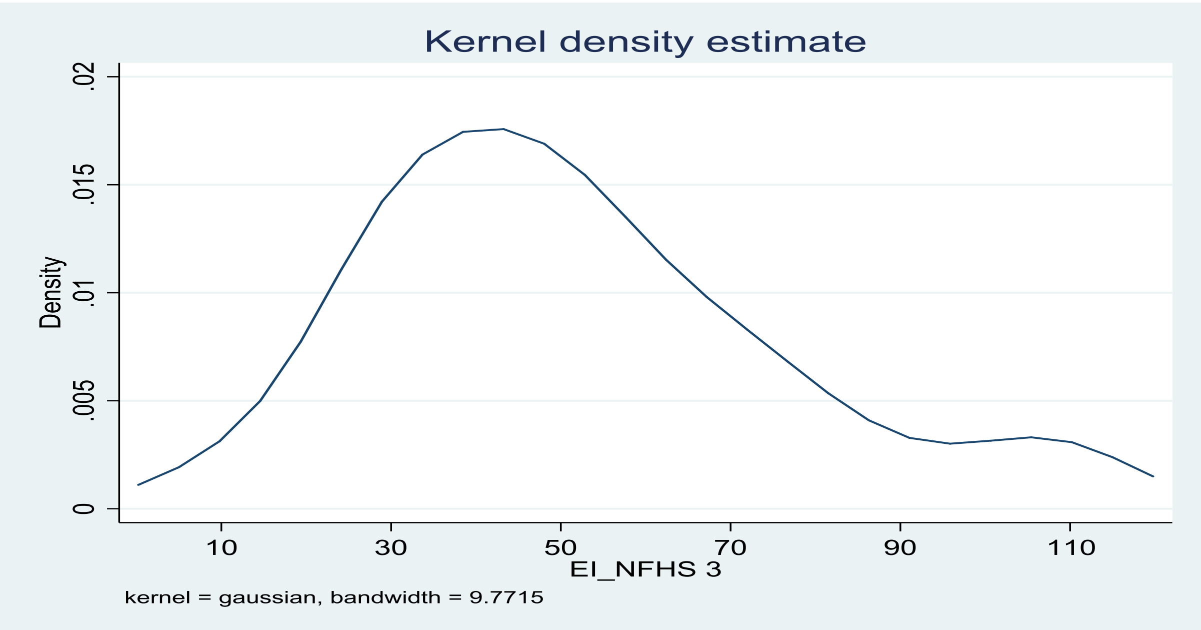
Figure-2.4(B): Kernel density estimation of Education Index in NFHS 2



Source: Author's Estimation

The distribution of NFHS 2 shows that states are forming three clubs or classes. Number of states in lower class is higher than that of middle or higher class. Here, first peak covers extreme low class, third peak covers low and lower middle class whereas the last peak covers upper middle and high classes. As states are improving in terms of education status, in next time point (NFHS 3) again I have found a polarized distribution with more states towards lower class and few states in higher class.

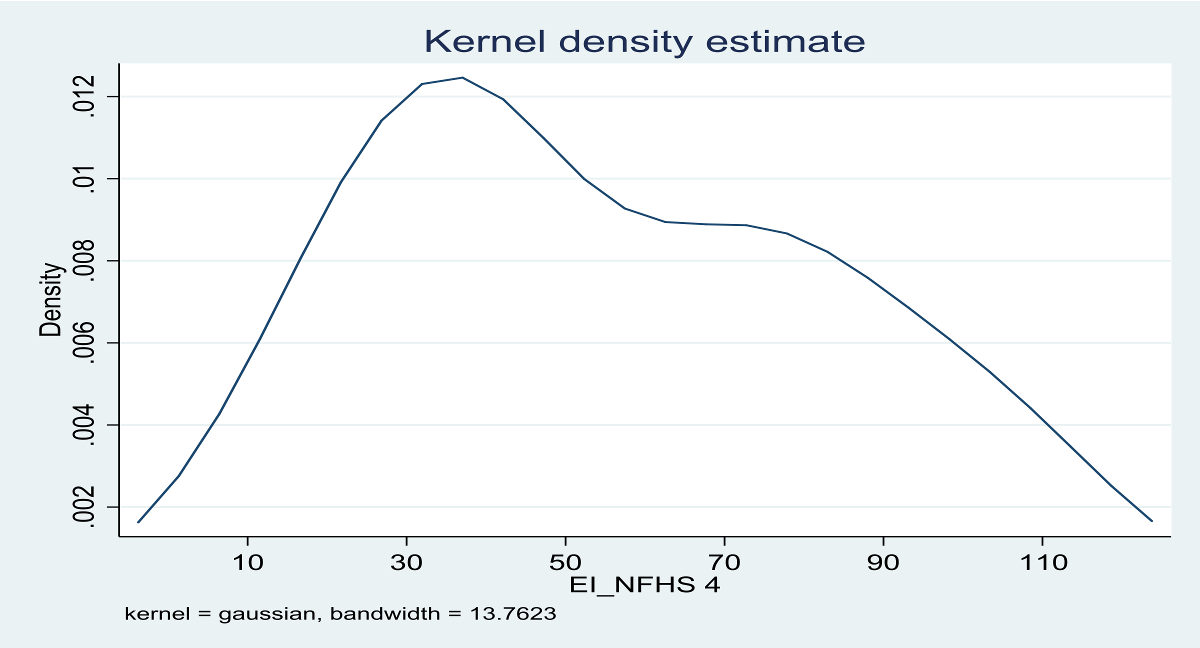
Figure-2.4(C): Kernel density estimation of Education Index in NFHS 3



Source: Author's Estimation

Transition from stratification to polarization implies that the states in middle class are unstable in nature and they are mobile to lower class. In terminal time point (NFHS 4), we have a polarized distribution but here the density of the second peak has increased compared to earlier distributions. Two classes are formed from the lower middle class.

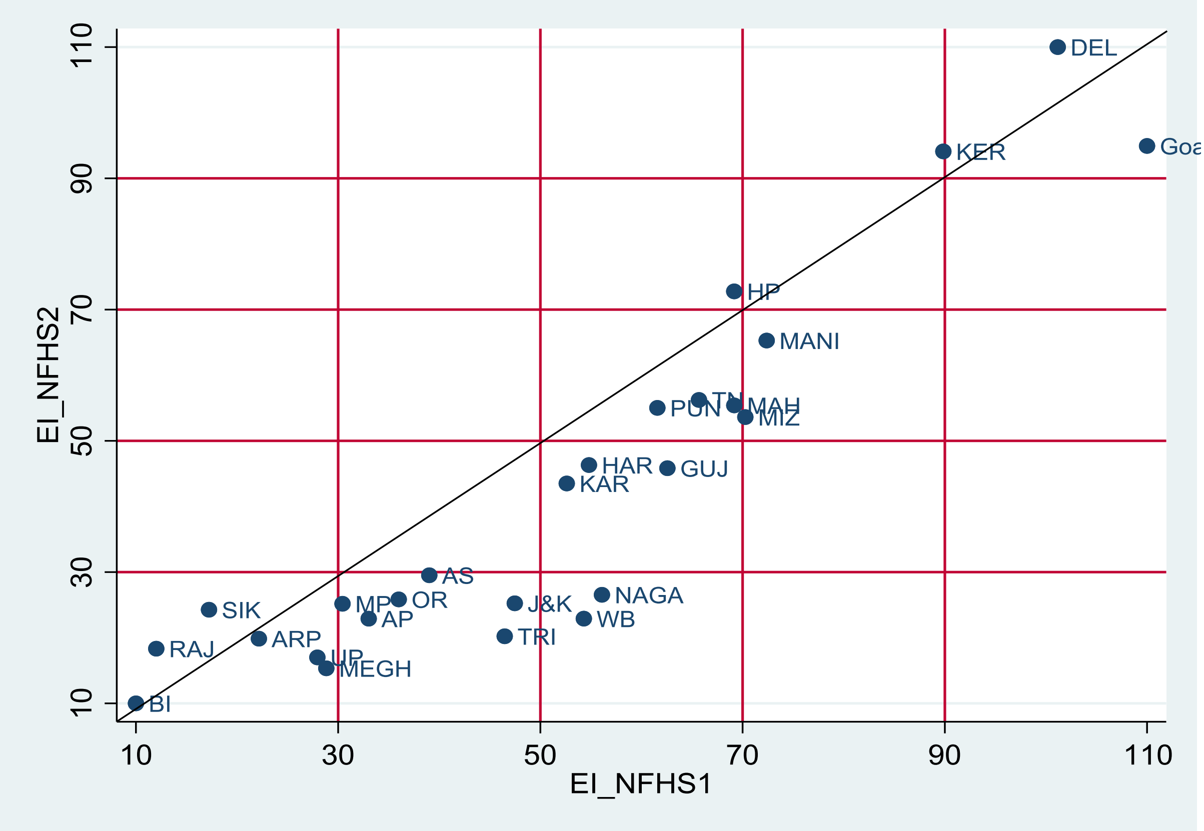
Figure-2.4(D): Kernel density estimation of Education Index in NFHS 4



Source: Author's Estimation

Therefore, the kernel density estimation of the terminal time point, shows that in the long run states are forming two clubs or classes. Kernel density estimation is a visual inspection of presence of clubs or club convergence. The intra distributional dynamics of transition cannot be captured by the kernel density. How can we capture the intra-distributional transition of states over time? To answer that here, I have used the scatter plots showing the relation between education status of states for two different time points. From the Radar Diagram it can be observed that all states are improving in absolute sense. The pace of improvement is different for different states. Some of the states improve at a higher rate whereas other states deteriorate over time. These transitions are not captured by Kernel density estimation. In order to capture that I have used the graphical representation of transition of states over time and to capture the probability of the transition, I have used Transitional Probability Matrix (TPM). Dynamics of the distribution is the result of transitions of states over time.

Figure-2.5(A): Scatter Box-Plot of transition of states in respect of EI from NFHS 1to NFHS 2.

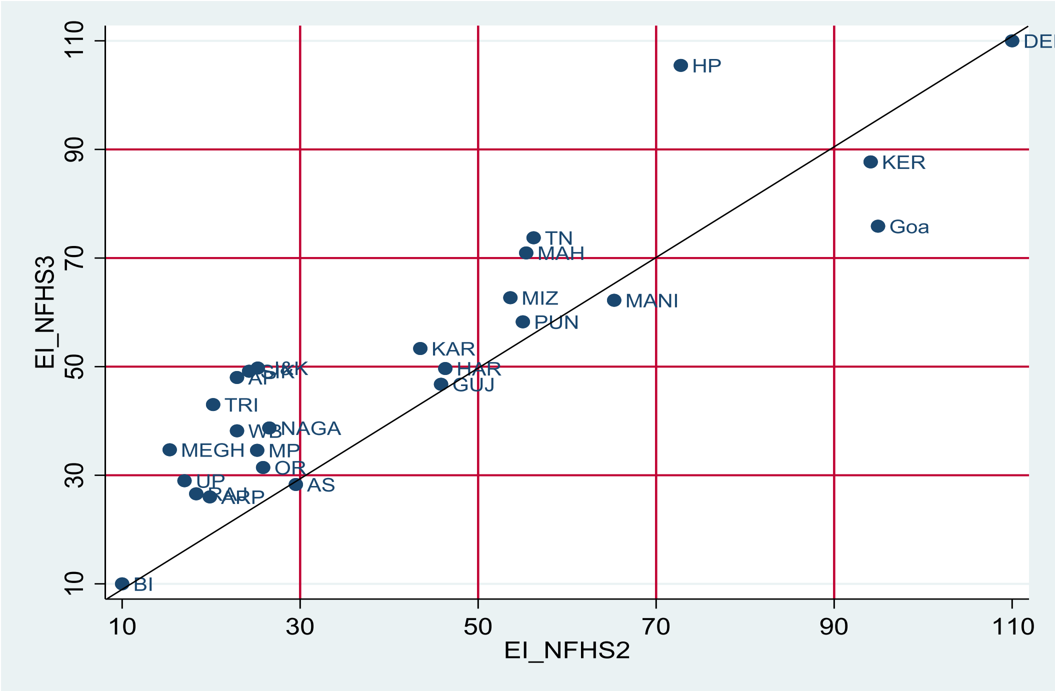


Source: Author's estimation

The above diagram represents the scatter distribution of states in respect of education index for NFHS-1 and NFHS-2. The 45^{o} degree line defines the same relative position of states over time. For example, Bihar is on the 45^{o} degree line. That means in both the time points Bihar has same relative position. Any point below or above the line represents the deterioration or improvement of states over time respectively. This transition of states was not captured by Kernel density estimation. Most of the states are fall below the 45^{o}line, that means they have deteriorated from their earlier positions. The States are found to be concentrating towards lower class.

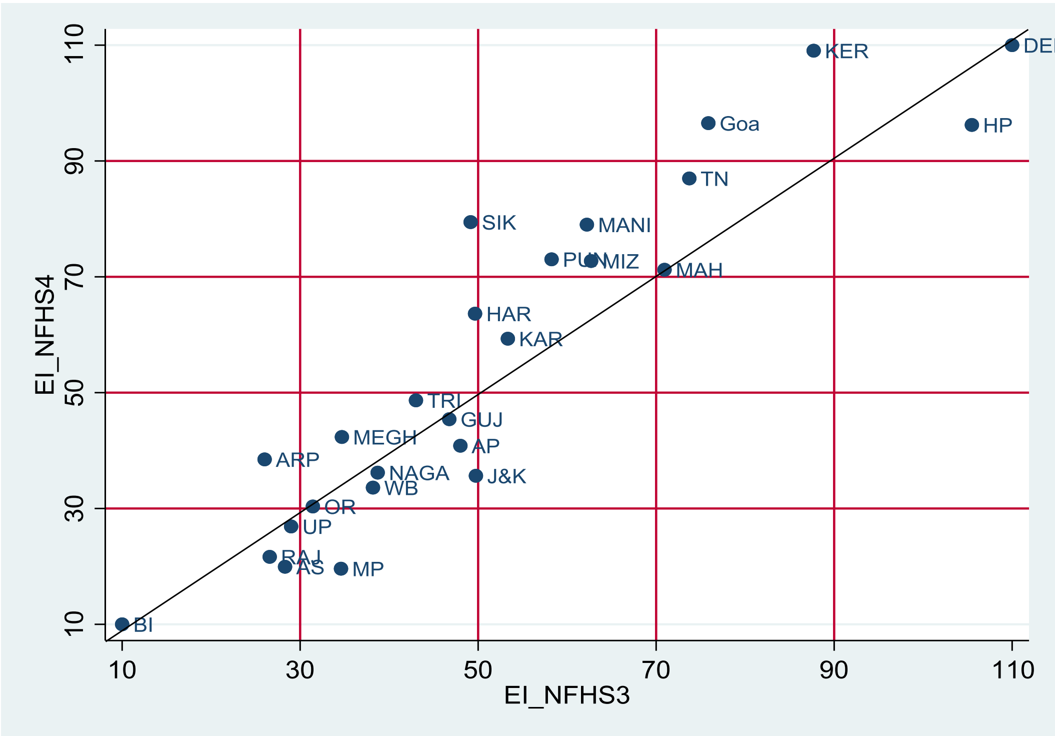
An opposite result can be observed in case of NFHS 2 and NFHS 3. During this time period, the states are found to be improving, only few states fall below the equality line. In the next time period (NFHS 3 to NFHS 4), states belong to middle class are found to be improving much higher than the states belong to lower class.

Figure-2.5(B): Scatter Box-Plot of transition of states in respect of EI from NFHS 2 to NFHS 3.



Source: Author’s estimation

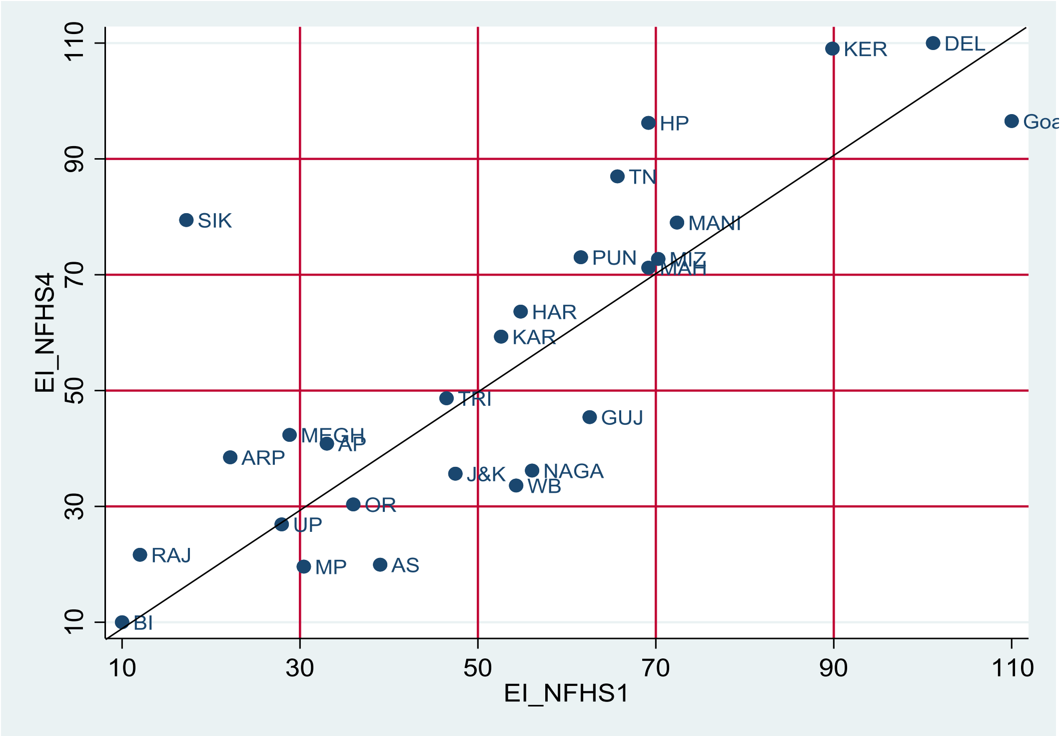
Figure-2.5(C): Scatter Box-Plot of transition of states in respect of EI from NFHS 3 to NFHS 4.



Source: Author’s estimation

The following diagram shows the long run transitions of states (NFHS1 to NFHS 4) in respect of education index. In all classes we have both upward as well as downward transitions.

Figure-2.5(D): Scatter Box-Plot of transition of states in respect of EI from NFHS 1to NFHS 4.



Source: Author's estimation

In all the diagrams, Bihar always stays on the 45^{o} degree line. It means even though Bihar improves in absolute sense but it remains at same in relative position. These scatter plots also show the concentration of states over time. Now, based on these transitions, I have estimated the probability of the transition over time. The dynamics of the distribution is captured by the Transitional Probability Matrix based on Markov Process. Using this matrix one can capture both short run as well as long run transitional pattern of states. These matrixes are the reflection of each kernel plots.

2.5.3.2 Non-Parametric Approach: Transitional Probability Matrix

The first transitional probability matrix (TPM) shows the transitional patterns from NFHS 1 to NFHS 2. During this short run time period, the overall mobility is found to be higher than the stability index. Mobility index consists of both upper and lower mobility; elements above diagonal represent the upper mobility whereas elements below the diagonal are used to define the lower mobility. Here, lower mobility is found to be higher than the upper mobility. Because of this higher mobility, the speed of convergence is very high. The initial distribution needs only 0.959 year to complete the half distance. Interestingly, the scatter plots of transition show the same result.

Table-2.10(A): Transitional Probability Matrix (TPM) of states in respect of EI from NFHS-1 to NFHS-2

		NFHS 2				
		10-30	30-50	50-70	70-90	90-110
NFHS1	10-30	1	0	0	0	0
	30-50	1	0	0	0	0
	50-70	0.2222	0.3333	0.3333	0.1111	0
	70-90	0	0	0.6667	0	0.3333
	90-110	0	0	0	0	1
	Stability Index(SI)=0.4667 Mobility Index(MI)=0.6667			Half-Life=0.959		

Source: Author's estimation

Similar to the earlier short run transitional probability matrix the next short transitional matrix captures the transitional pattern of states from NFHS 2 to NFHS 3. This matrix corresponds to the second scatter plot. During this time period mobility index has increased compared to earlier time period. Here the upper mobility is higher than lower mobility. The overall mobility index is 76%. It leads to higher speed of convergence towards stationary distribution (half-life = 1.71).

Table-2.10(B): Transitional Probability Matrix (TPM) of states in respect of EI from NFHS 2 to NFHS 3

		NFHS 3				
		10-30	30-50	50-70	70-90	90-110
NFHS2	10-30	0.357	0.643	0	0	0
	30-50	0	0.667	0.333	0	0
	50-70	0	0	0.6	0.4	0
	70-90	0	0	0	0	1
	90-110	0	0	0	0.667	0.333
	Stability Index(SI)=0.39 Mobility Index(MI)=0.76			Half-Life=1.71		

Source: Author's estimation

Next transitional probability matrix (TPM) shows higher overall stability index. This implies that states are holding their relative position in respective class. As a result, during this time period, the speed of convergence becomes very low. It needs 5.98 years to cover the half of the distance between initial distribution and stationary distribution given the total time span is 10 years.

Table-2.10(C): Transitional Probability Matrix (TPM) of states in respect of EI from NFHS 3 to NFHS 4

		NFHS 4				
		10-30	30-50	50-70	70-90	90-110
NFHS3	10-30	0.8	0.2	0	0	0
	30-50	0.09	0.73	0	0.18	0
	50-70	0	0	0.25	0.75	0
	70-90	0	0	0	0.5	0.5
	90-110	0	0	0	0	1
	Stability Index(SI)=0.655 Mobility Index(MI)=0.43			Half-Life=6.79		

Source: Author's estimation

The long run transitional probability matrix (TPM) is also similar to the short run matrix. During this long period of time (NFHS 1 to NFHS 4), both upward and downward mobility is observed. The value of half-life index is 9.14, which is very short compared to total time span. Probability of stability is little higher than mobility index. It is also clear that the distribution has separated from middle class and formed two classes.

Table-2.10(D): Transitional Probability Matrix (TPM) of states in respect of EI from NFHS 1 to NFHS 4

		NFHS 4				
		10-30	30-50	50-70	70-90	90-110
NFHS1	10-30	0.5	0.333	0	0.1667	0
	30-50	0.333	0.667	0	0	0
	50-70	0	0.333	0.111	0.444	0.111
	70-90	0	0	0	0.667	0.333
	90-110	0	0	0	0	1
	Stability Index(SI)=0.59 Mobility Index(MI)=0.51			Half-Life=9.14		

Source: Author's estimation

From the above table (2.10D), we can see the transitions of individual states over time (NFHS 1 to NFHS 4). This table also helps us to identify the presence of chronic low-level education trap. If I consider only extremely low-level class to define the low-level trap then out of 26 states only three states (viz., Bihar, Uttar Pradesh and Madhya Pradesh) belong to this class (or group).

Table-2.11: Transition of states in respect of EI over time

Clubs	NFHS_1	NFHS_2	NFHS_3	NFHS_4
10-30 (Extreme Low)	BI,RAJ, SIK, UP ARP, MEGH	BI, MEGH, UP,RAJ, ARP, TRI, AP, WB, SIK, MP, J&K, OR, NAGA, AS	BI, ARP, RAJ, AS, UP	BI, MP, AS, RAJ, UP
30-50 (Low)	MP, AP, OR, AS, TRI, J&K	KAR, GUJ, HAR	OR, MP, MEGH, WB, NAGA, TRI, GUJ, AP, SIK, HAR, J&K	OR, WB, J&K, NAGA, ARP, AP, MEGH, GUJ, TRI
50-70 (Lower Middle)	KAR, WB, HAR, NAGA, PUN, HP, GUJ, TN, MAH	MIZ, PUN, MAH, TN, MANI	KAR, PUN, MANI, MIZ	KAR
70-90 (Upper Middle)	MIZ, MANI, KE	HP	MAH, TN, GOA, KE	HAR, MAH, MIZ, PUN, MANI, SIK, TN
90-110 (High)	DEL, GOA	KE, GOA, DEL	HP, DEL	HP, GOA, KE, DEL

Source: Author's estimation

Among the five arbitrary classes extreme lower class is representing the worst position in terms of educational status, since the range of extreme lower class is 10-30. The upper range of this class is far from the mean value. Thus, to explore the presence of chronic trap, here, I have considered this class only. After considering this class, we have found that Bihar, Uttar Pradesh and Madhya Pradesh are found to be stable in extremely low-level class in four time points. In addition, I have considered low class along with extreme low class to explore the trap (viz. combining the range 10-50). After extending the range the number of states falling in trap has increased from 3 to 11.

2.5.3.2.1 Analysis of Variance

Since, I have considered five arbitrary classes to examine the presence of club convergence, here I used another parametric approach (Analysis of Variance) to test the significance mean difference of these classes. Here the null hypothesis is that there is no significance of mean difference across the groups with the alternative hypothesis that is there exists a difference of means across the classes.

$$H_0 = \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5 = \mu_0$$

$$H_0 = \mu_1 \neq \mu_2 \neq \mu_3 \neq \mu_4 \neq \mu_5 \neq \mu_0$$

The F-statistics shows an evidence of significance mean difference across the groups. This is true for all time points. Groups are different from each other. However, both the between and within group variations are found to be fluctuating over time.

Table-2.12: Mean difference across groups over time [NFHS 1 to NFHS 4]

EI	NFHS_1	NFHS_2	NFHS_3	NFHS_4
Between variation	0.490	0.478	0.506	0.429
Df	4	4	4	4
Within variation	0.036	0.016	0.034	0.016
Df	21	21	21	21
MSB	0.122	0.119	0.126	0.107
MSE	0.001	0.0007	0.0016	0.0007
F-statistics	70.53***	155.62***	76.51***	139.20***

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

NFHS 1 and 3 have higher within and between variation compared to NFHS 2 and 4. As a result, mobility index obtained from NFHS 2 to 3 is higher than other two short run transitional probability matrix; lower variation occurs due to higher mobility of states. This implies that the classes are closer to each other.

Now, the result of specific group mean difference shows that out of five groups, mean difference among all groups is significant. This result support that the arbitrary groups are not inconsistent.

Table-2.13: Group Specific Mean difference across groups over time

NFHS 1	Group 1	Group 2	Group 3	Group 4
Group 2	0.106**			
Group 3	0.229**	0.122**		
Group 4	0.323**	0.216**	0.094**	
Group 5	0.480**	0.373**	0.251**	0.157**
NFHS 2	Group 1	Group 2	Group 3	Group 4
Group 2	0.121**			
Group 3	0.183**	0.061**		
Group 4	0.264**	0.142**	0.080**	
Group 5	0.403**	0.281**	0.220**	0.139**
NFHS 3	Group 1	Group 2	Group 3	Group 4
Group 2	0.109**			
Group 3	0.212**	0.102**		
Group 4	0.320**	0.210**	0.108**	
Group 5	0.505**	0.395**	0.293**	0.185**
NFHS 4	Group 1	Group 2	Group 3	Group 4
Group 2	0.088**			
Group 3	0.190**	0.102**		
Group 4	0.261**	0.172**	0.070**	
Group 5	0.379**	0.290**	0.188**	0.117**

Source: Author's Estimation. Note: *** define 1% sig. level, ** define 5% sig. level and * define 10% sig. level

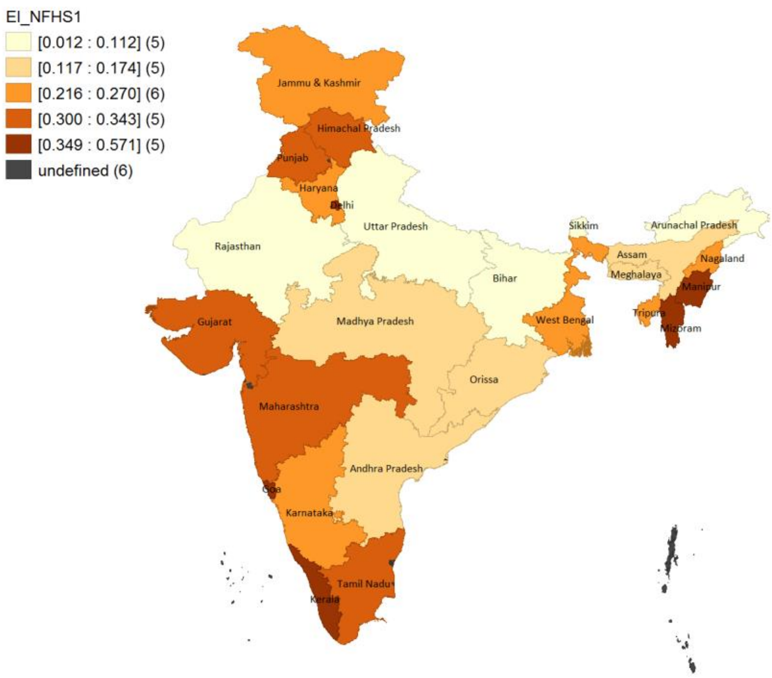
I have started convergence analysis using non parametric method and finally I have used parametric Method (ANOVA) to strengthen the analysis wherein groups are statistically significant or not!

2.5.4 Convergence based on Spatial Analysis

2.5.4.1 Spatial Analysis: Global and Local Moran's Index

Following Quah (1997), I have checked the role of space towards formation of clubs over time. Club convergence states that the geographical unit (state) may converge with the homogenous geographical units. Obviously one can expect that states located in the same region are homogeneous. In this section, I have examined the hypotheses of spatial autocorrelation across the states using some tools and techniques (viz., Global Moran's Index, Local Moran's Index, Spatial Auto regressive model etc.) from spatial econometrics. First, I have checked the geographical distribution of states in respect of education index.

Map-2.1(A): Map Distribution of states in respect of Education Index in NFHS 1(1992-93)

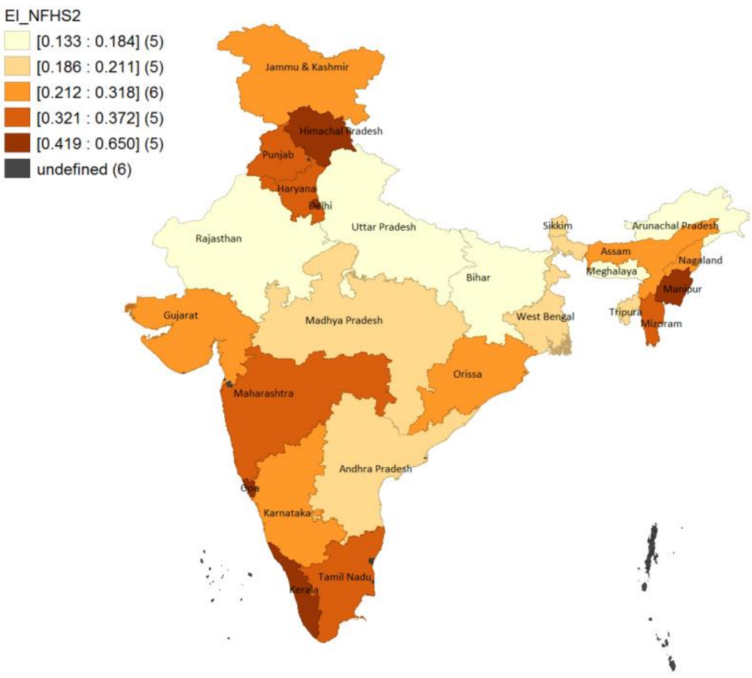


Source: Author's estimation

In the above map (Map-2.1A), we can observe the geographical distribution of states in respect of education index for the first time point (NFHS 1). Here, I have chosen five arbitrary classes based on absolute value of education index. In each class, I have few numbers of states. From the map it can be observed that similar location has a role for club formation. Rajasthan and Uttar Pradesh and Bihar and Uttar Pradesh have common border and the states belong to same classes. Similarly, Gujarat and Maharashtra share common border and the states belong to same class.

In next time point (NFHS 2), we can observe the geographical distribution of education index across 26 Indian states. In NFHS 2, the states belonging to Central part of India, the EI values still have lower value whereas Southern and Northern states are manifesting higher EI values. The two maps indicate the presence of positive spatial relationship across states. One important observation is that Gujarat has dark colour in NFHS 1, but in NFHS 2, the colour become lighter. Here, we can suspect some influence from Madhya Pradesh and Rajasthan on Gujarat. Similarly, West Bengal is influenced by its neighbour during this period.

Map-2.1(B): Map Distribution of states in respect of Education Index in NFHS 2



Source: Author's estimation

So, both the maps help us to identify the presence of club in terms of education index. Now, we can take the help of scatter diagram of states with respect to the average neighbour's value; four possible spatial dependency can be observed. States with higher value of EI are surrounded and influenced by its neighbouring states with higher values. This is known as high-high clustering. Conversely, lower EI states may be surrounded and influenced by the states with lower EI. This is known as low-low clustering. These two clustering are known as homogeneous clustering. Similarly, states may be surrounded as well as influenced by states with opposite EI value. High-low and low-high clustering are the examples of this specific clustering. From these two clustering, one can observe the presence of outlier. Therefore, on the basis of spatial dependency, states can form four different clusters; the maps fail to identify these four clustering. Following these clustering, spatial autocorrelation can be observed between similar states as well as between dissimilar states also. In the scatter diagram, we have four quadrants. Top right is used to define High-High clustering, top left is Low-High clustering, whereas bottom left and right represent Low-Low and High-Low clustering respectively. High-High and Low-Low clustering define the clustering of those homogenous states which are located in the same region. In NFHS 1, Tamil Nadu, Goa, Haryana, Karnataka, Manipur, Mizoram, Kerala and Maharashtra are in High-High cluster (30.8%). These states show a higher EI compared to mean value of EI. States like, Punjab, West Bengal, Gujarat, Himachal Pradesh, Nagaland and Delhi also have higher EI value but they are located in High-Low cluster (23.1%). In NFHS 1, the map shows that Delhi and Goa have the higher values of EI and both of them are surrounded by states with higher and lower values of EI. As a result, Goa remains at High-High cluster whereas Delhi remains at High-Low cluster (average neighbour's value is dominated by lower value). States likeBihar, Madhya Pradesh, Andhra Pradesh, Arunachal Pradesh, Assam, Rajasthan, Orissa, Meghalaya and Uttar Pradesh are found in Low-Low cluster (34.6%), and the map in NFHS 1 also shows that these states are either belonging to lower or extreme lower class and they are located in the same region also. This result shows a clear indication of spatial dependency across the states. States like Sikkim, Jammu & Kashmir and Tripura have lower value but the scatter plots define them under Low-High cluster. This is because their average neighbour's value is dominated by higher value. Now, in NFHS 2, Tamil Nadu, Goa, Haryana, Karnataka, Kerala and Maharashtra are in High-High Cluster (23.1%);so, in NFHS 2, two new states like Manipur and Mizoram have left the cluster. In earlier time point, these two states were in High-High cluster but now they have moved to high-low cluster. In NFHS 2, the number of states in Low-Low cluster has increased. About 46.2% states are there in Low-Low cluster which was 34.6% in earlier time point. States like Sikkim, Tripura, West Bengal, and Nagaland are the new states in this Low-Low cluster. They were in the cluster with dissimilar states. States like Sikkim and Tripura were in Low-High cluster, they fail to restore their position because of domination of a neighbour with lower value. Due to the same reason other two states from same region have moved from High-High cluster to High-Low cluster. States like West Bengal and Nagaland were in dissimilar cluster too. They were surrounded by lower states, as a result in NFHS 2, they move to Low-Low cluster. But, states like Uttar

Pradesh they is having lower value but it was surrounded by higher EI states. All the higher EI states dominated the average value for these two states. Other states in High-Low clustering are found to be stable in their respective class.

Figure-2.6(A):Spatial Autocorrelation of EI in NFHS 1

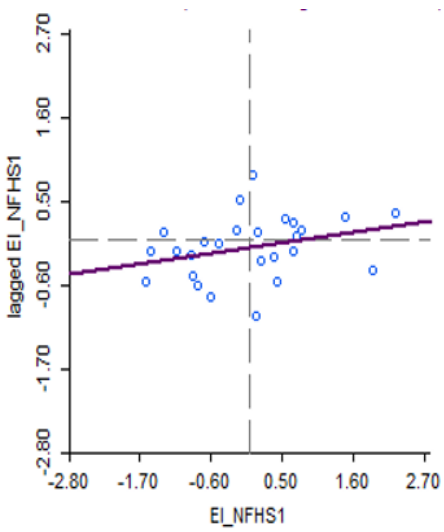
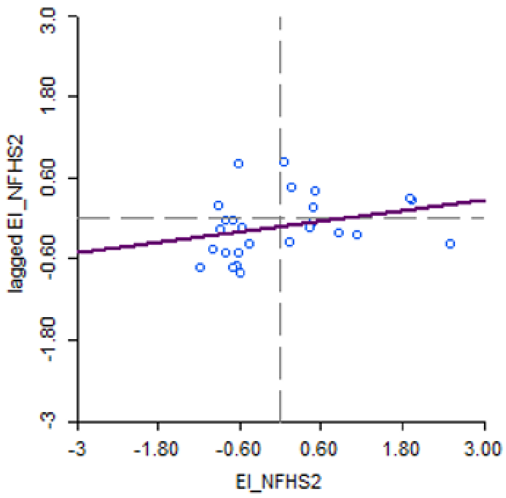


Figure-2.6(B): Spatial Autocorrelation of EI in NFHS 2



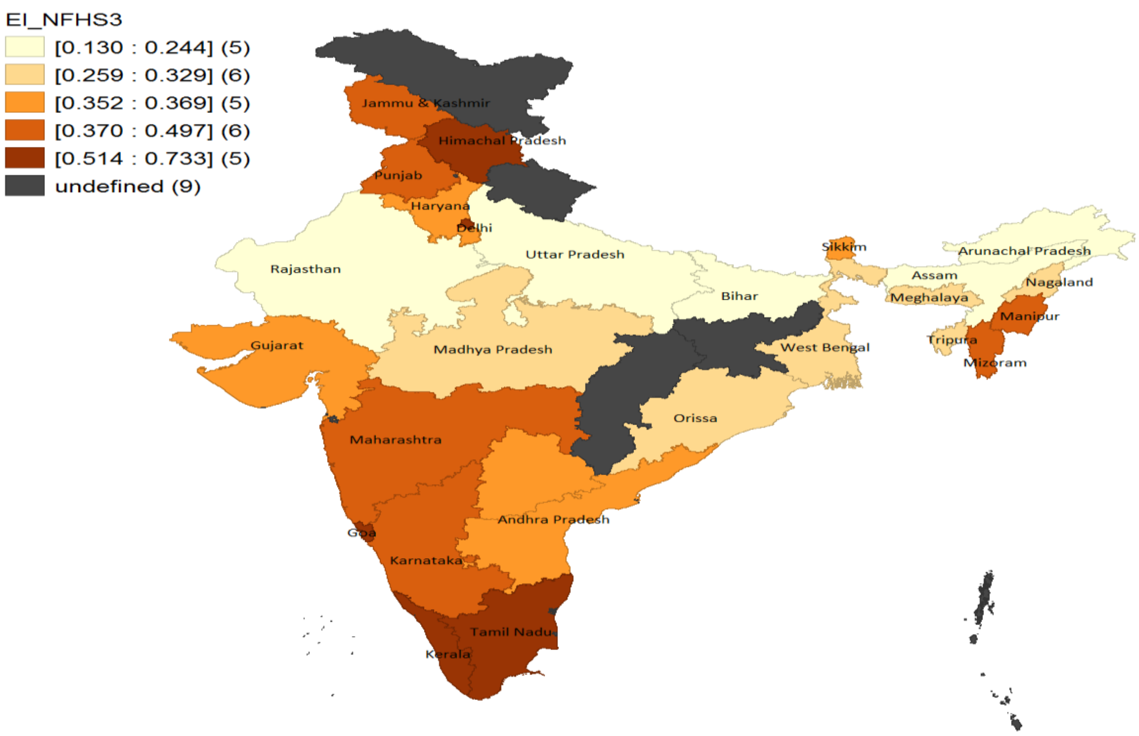
Source: Author’s estimation

The above scatter plots reveal the importance of space for different clusters as well as the aggregate relationship across the states in respect of EI. The fitted line shows that there exists a positive spatial autocorrelation across the states for EI for two time points (NFHS 1 & 2). In both the time points, states with similar EI values form homogenous clusters. In NFHS 2, the fitted line is flatter compared to earlier one, indicating the decreases in spatial dependency.

Similarly, I have examined the transition of states from NFHS 2 to NFHS 3 and NFHS 4. Analysis of NFHS 3 and 4 is slightly different from earlier analysis because here, I have some undefined states (they are present in the map, but not considered in my analysis like, Chhattisgarh, Jharkhand, Ladakh, Telangana etc). In NFHS 3,clustering of lower states is clear. States like Manipur, Mizoram, Himachal Pradesh and Delhi show a higher value of EI. In NFHS 3, they were in High-Low cluster. Due to strong influence of lower value, Gujarat moves from high-low cluster to low-low cluster. States like Delhi and Himachal Pradesh are located in the same region but they are not sharing any common border. They are surrounded by states with both higher and lower values of EI. Here, we find that their average neighbour’s value is dominated by lower value. Manipur and Mizoram are sharing a common border, at the same time, they are surrounded by the states with lower value. As a result, they hold their positions in this respective cluster. States like Bihar, Rajasthan, Assam, Arunachal

Pradesh, Orissa, Nagaland, Sikkim, Tripura, Gujarat, West Bengal, Andhra Pradesh, Meghalaya and Madhya Pradesh are in low-low trap (50%). These states are either located in the Central part or Eastern part of India. Compared to NFHS 2, Southern states are found to be stable in their positions. Surprisingly, Haryana moves to low-high cluster and Punjab moves from high-low cluster to high-high cluster. Following the transition of states, we can identify the spatial impact across the states. Since, these states were in high-high cluster and the value of GMI is positive, this implies positive neighbouring impact. Spatial impact can be observed both in homogeneous as well as heterogenous states in respect of EI values.

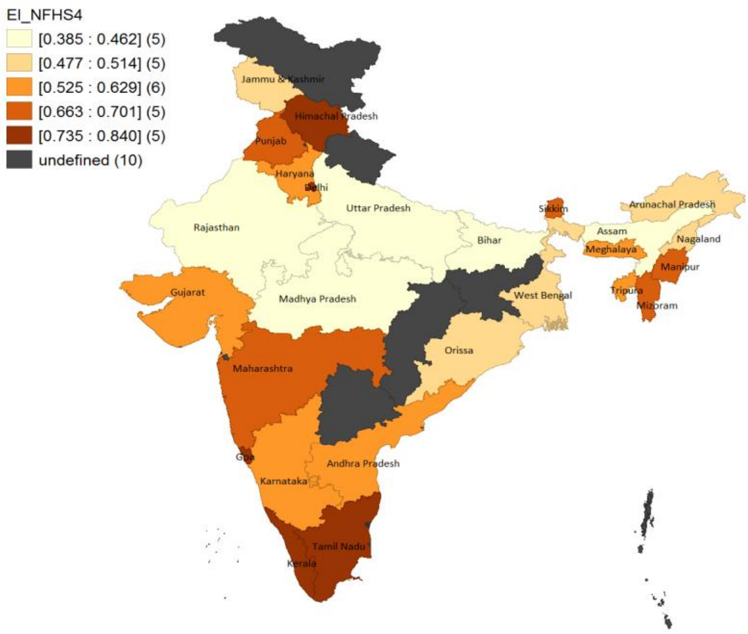
Map-2.1(C): Map distribution of states in respect of Education Index in NFHS 3



Source: Author's estimation

In NFHS 4, Southern states are forming a separate cluster from Central states. In earlier time points, Southern states improve and the process is continued till NFHS 4. The scatter plots of states for NFHS 3 and 4 show that states are found to be more scattered than earlier time points (NFHS 1& 2).

Map-2.1(D): Map Distribution of states in respect of Education Index in NFHS 4



Source: Author's estimation

In NFHS 4, there are only 5 states who form High-High cluster. Among these five states, Karnataka, Kerala, Goa and Tamil Nadu were in the same cluster in the earlier time points, but now Haryana again moves from low-high cluster to high-high cluster and Maharashtra moves from high-high cluster to high-low cluster. About 46.2% of states are in low-low cluster. Earlier time point it was 53.8%. There are two states who move to different clusters in this time point. For example, Andhra Pradesh moves to low-high clustering whereas Sikkim moves to High-Low cluster. So, from these four maps, it can be observed that space plays an important role for both similar and dissimilar clustering. Similar to NFHS 1 and NFHS 2, the scatter plots show the presence of positive spatial autocorrelation across states in respect of EI.

Figure-2.6(C):Spatial Autocorrelation of EI in NFHS 3

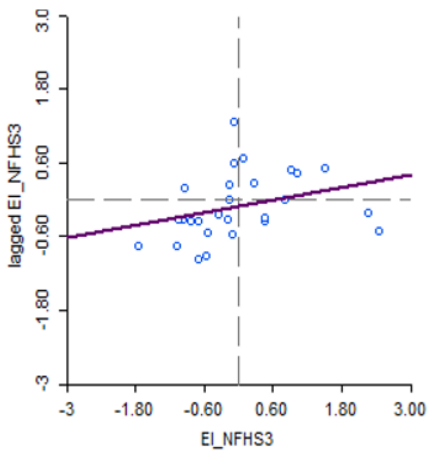
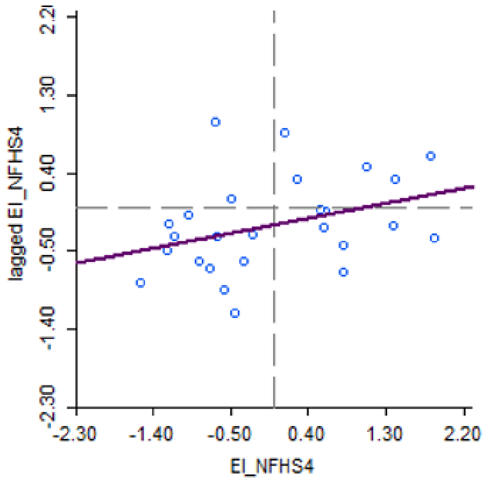


Figure-2.6(D): Spatial Autocorrelation of EI in NFHS 4



Source: Author's estimation

Following the graphical distribution of states in respect of EI, I have constructed the Global Moran's Index (GMI) for four time points. Here, the values of GMI are found to be positive but the values of GMI are statistically insignificant.

Table-2.14: Result of Global Moran's Index of EI for four time points

GMI	NFHS_1	NFHS_2	NFHS_3	NFHS_4
EI	0.123	0.129	0.170	0.192

Source: Author's estimation

Therefore, based on the values of GMI for four time points, we can expect a random distribution of EI across states. Thus, we have a counter intuitive result of random distribution and positive spatial distribution. For an in-depth analysis, I have used the Local Moran's Index. In this analysis, I can get state specific index value showing the relationship with its neighbours. Following table (Table-2.14) shows the Local Moran's Index across 26 Indian states for four time points. Positive LMI indicates positive relationship with its neighbours and a negative LMI implies inverse relationship with its neighbour. From the value of GMI, one cannot identify individual specific auto-correlation. In order to capture the individual specific dependency, I have used the result of Local Moran's Index along with the GMI.

Table-2.15: Result of Local Moran's Index of EI across states for four time points

States	NFHS1	NFHS2	NFHS3	NFHS4
Andhra Pradesh	0.021	0.024	0.0004	-0.055
Arunachal Pradesh	0.174	0.425	0.805	0.550
Assam	0.027	0.174	0.321	0.228
Bihar	0.886	0.844**(2)	1.304	1.346
Delhi	0.749	-0.962	-1.249	-0.655
Goa	0.810	0.5199	0.449	0.457
Gujarat	-0.237	-0.045	0.063	0.215
Haryana	0.013	0.069	-0.047	0.092
Himachal Pradesh	-0.094	0.259	-0.461	-0.275
Jammu & Kashmir	-0.083	-0.496	-0.095	-0.673
Karnataka	0.0347**(1)	0.040**(1)	0.049	0.107**(1)
Kerala	0.4320	0.541	0.756	1.085
Madhya Pradesh	0.492**(2)	0.327**(2)	0.244	0.600
Maharashtra	0.161	0.077	0.005	-0.007
Manipur	0.110	-0.174	-0.154	-0.344
Meghalaya	0.422	0.458	0.682	0.551
Mizoram	0.029	-0.059	-0.137	-0.127
Nagaland	-0.047	0.083	0.285	0.222
Odisha	0.452**(2)	0.483**(2)	0.297	0.541
Punjab	0.084	-0.026	0.073	0.027
Rajasthan	0.239	0.138	0.345	0.392
Sikkim	0.140	0.465	0.056	-0.609
Tamil Nadu	0.145	0.215	0.443	0.512
Tripura	-0.023	0.017	0.090	0.075
Uttar Pradesh	0.185	-0.167	-0.177	0.070
West Bengal	0.106**(4)	0.513**(2)	0.510**(2)	0.530

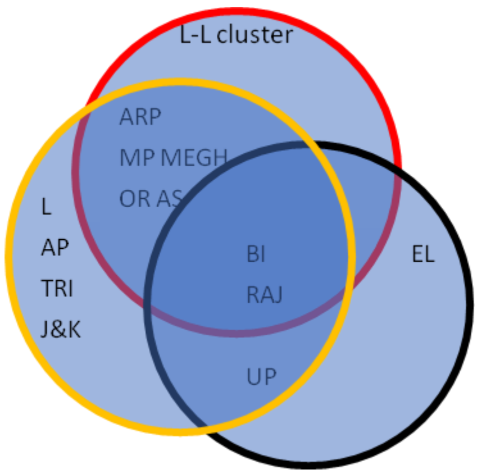
Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level, within parenthesis 1 represents H-H cluster, 2 represents L-L cluster, 3 represents L-H cluster and 4 represents H-L cluster.

In NFHS 1, out of 26 states, 21 states are positively related with their neighbours whereas rest of the states are inversely related with their neighbours EI. We find West Bengal is a significant outlier. It can be observed that even though 80.8% states have positive LMI, but most of them are found to be insignificant.

All the negative LMI also appear as insignificant. As a result, the overall GMI is positive but insignificant. Out of 26 states only four states (Karnataka, Madhya Pradesh, Orissa and West Bengal) have significant LMI. Among these four states, Karnataka belongs to High-High cluster and Madhya Pradesh and Orissa belons to Low-Low cluster and West Bengal belongs to High-Low cluster. Similarly, in NFHS 2, out of 26 states, 19 states have positive LMI and only 7 states have negative LMI. Here, most of the states are found to be insignificant. As a result, the overall GMI is positive but insignificant. Among 26 Indian states, only five states are significant, they are Bihar, Karnataka, Madhya Pradesh, Orissa and West Bengal. Among these, only Karnataka belongs to high-high cluster and rest of the states form low-low cluster. States like Madhya Pradesh and Orissa were in low-low cluster. Due to spatial influence, Bihar and West Bengal move to low-low cluster. In NFHS 3 and 4, 18 states are having positive LMI and only 8 states have negative LMI. In each time point, except one state all the states are found to be insignificant. So, the value of GMI in each time point is positive but insignificant. In NFHS 3, West Bengal is in low-low trap whereas in NFHS 4, Karnataka is in high-high cluster. Both of them are positively related with their neighbours.

Now, we can compare this result of clustering with the result obtained from non-parametric analysis (Transitional Probability Matrix). From both the long run and short run transitional probability matrix, we find that Uttar Pradesh, Rajasthan and Bihar are in extreme low-level trap in EI. Now, if we compare the stability of the low-low clustering, then out of 26 states only 7 states are stable in low-low cluster. These seven states are either belonging to extreme low- or low-level class in the analysis of transitional probability matrix. Among these, Bihar and Rajasthan are the common states in extremely low-level trap.

Figure-2.7: Venn diagram exploring Chronic low-level trap in terms of EI



Source: Author’s estimation

The above venn diagram helps us to identify the states which are in extreme low-level trap as well as trap found on spatial analysis. The circle with yellow border represents the states having education status in between 10 to 50 (L & EL). The circle with black border consists of states with range 10-30 (EL only). The circle with red border defines the L-L cluster that shows the states which form low-low cluster. The diagram shows that Bihar and Rajasthan are in extremely low-level trap and they also belong to L-L cluster.

It can be observed that states in each group are located in similar region in India. They may have same structural characteristics and other features due to this common location. We can argue that space plays an important role towards the formulation of clubs or cluster.

2.5.4.2 Spatial Analysis: Spatial Autoregressive are Error Model (SDAR and SDEM)

Global Moran's Index and Local Moran's Index are used to estimate the presence of aggregate and individual specific spatial dependency respectively. Aggregate index shows the presence of spatial autocorrelation based on average neighbor's value. Analysis of spatial dependency using regression analysis is a complementary methodology to Global Moran's Index or Local Moran's Index. Here,I have considered two different models for the analysis. First one is Spatial Durbin Autoregressive (SDAR) model whereas the second one is Spatial Durbin Error Model (SDEM). Under these two models, I have examined the presence of spatial dependency using four different sub models based on explanatory variables. In both the models the coefficients of lagged dependent variable and residual term are used to examine the presence of spatial dependency across the states. This is true for both SDAR model and SDEM model. To capture the spatial dependency of both dependent and independent variables in the single regression equation, I have used Spatial Durbin Autoregressive model and Spatial Durbin Error Model. The following table shows that all the lagged coefficients of dependent and residual are positive and statistically significant. In regression approach, I have considered the impact of neighbors of neighbors. Due to this reason, the result of regression appears as significant. Moreover, my regression analysis is panel data wherein, GMI considers only a single time point.

Table-2.16: Result of Spatial Durbin Autoregressive Model and Spatial Durbin Error Model

Explanatory Variables	Spatial Durbin Autoregressive Model				Spatial Durbin Error Model			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Constant	0.087***	0.273***		-0.033	0.122***	0.341***	-1.00***	0.001
(ρ)	0.35***	0.251**	0.372***	0.755***				
(λ)					0.375**	0.359***	0.445***	0.777***
lnPCEE	0.306***				0.304***			
WlnPCEE	-0.825				0.034			
LnPCHE		0.191***				0.193***		
WlnPCHE		0.022				0.085***		
Ln.SII			0.798***				0.783***	
WlnSII			-0.170				0.068	
LnPII				0.164***				0.147***
WlnPII				-0.1222***				-0.021
Log likelihood Ratio	103.0688	93.58	104.85	80.681	102.51	94.18	87.79	79.63
Wald Chi-square	440.41***	330.34***	439.79***	256.31***	226.01***	173.78***	124.55	44.41***
R-Square	0.4257	0.3851	0.0744	0.2787	0.4371	0.4209	0.0911	0.2715
No. of Observation	104	104	104	104	104	104	104	104

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level, WlnPCEE defines weighted lag per capita education expenditure, WlnPCHE is weighted lag per capita health expenditure, WlnSII is weighted lag social infrastructure index, WlnPII defines weighted lag physical infrastructure index.

In the above table, ρ represents the impact of lag dependent variable whereas λ defines the impact of lag residual factor on outcome variable. Spatial Durbin Autoregressive model shows that in each model, there exists a positive spill over effect across states. At the same, time the explanatory variables reveal a positive impact on the outcome (EI). But the lagged explanatory variables do not show any significant impact on the outcome (EI). Only lagged of physical infrastructure index has an inverse significant impact on outcome, as the connectivity increases in the neighbour's state that reduces the outcome. The Spatial Durbin Error model shows that based on the residual there exist a positive spatial impact on outcome (EI) across states. Here, also the explanatory variables have positive impact whereas most of the lagged explanatory variables have insignificant impact. In error model, lagged expenditure on health has a positive impact; as the health expenditure increases in the neighbours states the health services will increase as a result, individual state will indirectly receive the health benefit as well as education benefits.

Table-2.17: Impact of explanatory variables under SDAR and SDEM

	Spatial Durbin Autoregressive Model				Spatial Durbin Error Model			
Impact	PCEE	PCHE	SII	PII	PCEE	PCHE	SII	PII
Direct Impact	0.308***	0.195***	0.810***	0.165***	0.304***	0.193***	0.783***	0.147***
Indirect Impact	0.027	0.069***	0.145	0.004	0.027	0.067***	0.054	-0.0167
Total Impact	0.335***	0.263***	0.955***	0.169***	0.331***	0.259***	0.836***	0.131***

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

Since, both SDAR and SDEM considered impact of neighbours of neighbour via dependent and intendent variables, the above table shows the total impact of independent variables obtained from each model and sub models.

From both models one can estimate the direct and indirect impact of explanatory variable on outcome. In each model, all the explanatory variables have positive and significant direct impact whereas most of the lagged explanatory variables are found to have insignificant impact. Only lagged per capita health expenditure have significant impact on outcome in spatial autoregressive and error model. The above table shows that under spatial autoregressive model, in overall PCEE and PCHE have 33.5% and 26.3% impact on education index respectively whereas social infrastructure and physical infrastructure have 95.5 and 16.9% respectively. Similarly, under error model, in overall PCEE and PCHE have 33.1% and 25.9% impact whereas social infrastructure and physical infrastructure have 83.6% and 13.1% impact on education respectively.

So, both the GMI and regression-based approach support the presence of spill over effect of EI across the states. Scatter plots of LMI shows that states form clusters with the states having similar values. From the maps, it can be observed that states in similar region form clusters (both low-low and high-high). Now, I can compare these results with the results obtained from TPM for checking consistency of clubs.

Both the short run and long run transitional probability matrix reveal that Bihar, Uttar Pradesh and Rajasthan remain at extreme low-level trap whereas if we consider both extreme low and low classes (less than mean value) then Meghalaya, Arunachal Pradesh, Rajasthan, Bihar, Madhya Pradesh, Orissa, Assam, Uttar Pradesh, Tripura, Andhra Pradesh and Jammu & Kashmir are found to be stable in extreme low and low-level trap. Spatial analysis reveals that Bihar, Madhya Pradesh, Arunachal Pradesh, Assam, Rajasthan, Orissa, and Meghalaya are in low-low cluster whereas Tamil Nadu, Goa and Kerala are in high-high cluster. Comparing the result with TPM, it can be observed that all the states belong to L-L cluster (the also belong to extremely low and low-level trap). Similarly states from high education index also reflect the H-H cluster, though the result of low-low clustering could not appear significant. Therefore, the impact of spatial autocorrelation is not clear here.

2.6 Major Findings

The present study examines the presence of convergence of education index (EI) across 26 Indian states for four time points. All the states do experience an upward trend of education capital index. The study finds the result of both absolute and conditional beta (β) convergence but there exists Sigma (σ) divergence. Conditioning variables have the positive impact on growth. The Inequality based approach suggests that the of EI are inequalities sensitive to lower, middle and upper tail of the distribution; however inequality of EI is found to be decreasing over time. All inequality values approach towards same value. Keeping in mind the limitations of neoclassical approach of convergence, I have explored the presence of club convergence using distributional dynamics approach. The results of club convergence based on Kernel density and Markov process (based on transitional probability matrix) support the existence of polarisation in respect of education index. From the distributional dynamics approach, I have found both extreme low-level trap of EI as well as high level EI. Since, my objective is to explore the states belonging to the extremely low-level trap of EI that is why, I ignore the other classes of EI. The transitional pattern of distribution reveals that out of 26 states only three states remain stable in the chronic low -level trap (range of extreme low-level class is 10-30) in respect of education index (EI) for the four consecutive time points. The number of states in chronic low-level trap may increase if I extend the range from 10-30 to 10-50. The results of spatial autocorrelation supports that EI does vary across geographical locations. The result shows that Bihar, Rajasthan, Arunachal Pradesh, Madhya Pradesh, Meghalaya, Orissa and Assam (26.9%) are in Low-Low cluster.

Both the distributional dynamics approach and spatial approach suggest that Bihar, Rajasthan are falling both in extreme low-level trap as well as in low-low cluster. If we consider the extended range of low-level trap (10-50) then Bihar, Rajasthan, Arunachal Pradesh, Madhya Pradesh, Meghalaya, Assam and Orissa are found to be in low-level trap; at the same time, they fall in the Low-Low clusters also. The result of spatial autoregressive and spatial error model suggests that there exist both direct as well as indirect spill over impact of education across the states.

Notes

[2.1]Principal Component Analysis is used to reduce the data dimension based on the variance within the data matrix. It will generate a synthesis variable based on the correlation across all the variables within the data matrix. Number of synthesis variable is equivalent to number of variables in the data set. These synthesis variables are known as Principal Component. The equation of principal component can be written as follows;

$$PC_1 = a_{11}.P_1 + a_{12}.P_2 + \ldots\ldots\ldots + a_{1n}.P_n$$

$$PC_2 = a_{21}.P_1 + a_{22}.P_2 + \ldots\ldots\ldots a_{2n}.P_n$$

$$PC_n = a_{n1}.P_1 + a_{n2}.P_2 + \cdots\ldots\ldots a_{n3}.P_n$$

a_{ij} 's are the correlation coefficient between factors and the component. Based on the eigen value one can select the components. If first eigen value is very high and capture the maximum variance then there is no need to move to second or third component (Nunnally and Bernstein 1994).

[2.2]A principal component analysis using the seven social infrastructure variables and two physical infrastructure variables has been done to identify the dimensions of infrastructure. Out of seven social infrastructure variables only five variables are appearing as significant whereas all indicators from physical infrastructure are significant. So the equation for social and physical infrastructure index can be written as:

$$SII_{ij} = 0.803 * No.of\ PS_{ij} + 0.844 * No.of\ MS_{ij} + 0.821 * No.of\ SS_{ij} + 0.656 * No.of\ SC_{ij} + 0.655 * No.of\ CHC_{ij} \quad (a)$$

$$PII_{ij} = 0.917 * Road_{ij} + 0.917 * Rail_{ij} \quad (b)$$

Appendix 2A.1

Table-2A.1: Descriptive statistics of Education indicators over time

NFHS 1	**Max**	**Min**	**Range**	**Mean**	**SD**	**CV**
Literacy Rate	89.81	38.48	51.33	57.44	13.05	0.23
Complete High School	20	3.55	16.45	11.10	3.97	0.36
Complete Above HS	14.3	2.1	12.2	4.55	2.51	0.55
GER to UP	110.8	37.1	73.7	71.02	20.17	0.28
GER to HS	91.32	16.37	74.94	33.15	14.35	0.43
GER to Higher Education	13.98	1.75	12.23	5.62	3.22	0.57
NFHS 2						
Literacy Rate	90.9	47	43.9	68.38	10.37	0.15
Complete High School	19.85	4.15	15.7	9.13	4.08	0.45
Complete Above HS	24.65	3.85	20.8	8.97	4.29	0.48
GER to UP	95.4	34.8	60.6	65.12	15.15	0.23
GER to HS	85.42	18.68	66.73	33.11	16.37	0.49
GER to Higher Education	18.96	0.89	18.07	6.96	4.28	0.61
NFHS 3						
Literacy Rate	92.4	55.4	37	73.01	9.07	0.12
Complete High School	18.95	4.2	14.75	9.69	4.01	0.41
Complete Above HS	29.6	6.45	23.15	11.78	5.07	0.43
GER to UP	109.27	30.42	78.85	65.89	20.76	0.32
GER to HS	131.51	16.02	115.49	46.45	20.95	0.45
GER to Higher Education	46.86	5.69	41.16	12.46	7.65	0.61
NFHS 4						
Literacy Rate	93.9	63.8	30.1	77.63	7.99	0.10
Complete High School	19.9	7.7	12.2	12.45	3.59	0.29
Complete Above HS	30.15	10.2	16.95	17.80	5.62	0.32
GER to UP	150.61	70.2	80.41	104.75	20.19	0.19
GER to HS	101.31	54.03	47.28	74.31	13.11	0.18
GER to Higher Education	45.4	14.3	31.1	25.94	8.31	0.32

Source: Author's Estimation

CHAPTER-3

Exploring Health Convergence in India:

A Sub-National Analysis

3.1 Introduction

India roughly accounts for 17% of the world's population, but it contributes to one-fifth of the world's share of diseases; a major health challenge posed by the specific phase of the demographic transition that India is going through is related to infant mortality, child malnutrition, mothers suffering from anaemia and poor reproductive health of the mothers (The Lancet 2019; IHME 2018). The national level performance of millennium development goals (MDG) which was ended in 2015 for health indicators is not so disappointing, but the sub-national level performance is not so encouraging. Three out of eight goals (of MDGs) are related to health; these are (a) reduction in child mortality; (b) to improve maternal health and (c) to control HIV/AIDS, malaria and other communicable diseases. India at the national level could not manage to achieve the target of maternal health and marginally fell below the target in reducing child mortality but could manage to achieve the target (c) as mentioned above. The most alarming fact is the interstate disparity in respect of health outcomes; the national family health survey- 4 (NFHS-4) data released in 2015–16 which show that the under-five mortality rate (U5MR, per thousand) of Kerala was 7, whereas it was 78 in Uttar Pradesh; the maternal mortality rate (MMR) was recorded as 289.8 (per lakh) in Assam, whereas it was 50.21 in Kerala. But, if we consider the life expectancy at birth (LEB), the discrepancy is quite low; the maximum value is 75.1 in Kerala, whereas the lowest value is accorded as 64.8 in Uttar Pradesh. Therefore, only one indicator like LEB fails to arrest the true health scenario of the states in India. Instead of targeting life expectancy, the United Nations' millennium development goals (MDG) as well as sustainable development goals (SDGs) has given emphasis on health issues related to the reproductive and child health parameters including water and sanitation, gender equality, climate change, peace and stability. India at the aggregate level is expected to enjoy the benefit of demographic dividend roughly after 2025, but only the numbers of working age cohort cannot guarantee to generate sufficient income if the health status of the future working population remains poor (Bloom et al. 2003; James 2008; Bhattacharya and Haldar 2015). Thus, in order to get the real benefit of demographic dividend in near future, we must know about the present health status of the mothers and children so that appropriate measures can be undertaken at the disaggregate level. Keeping in mind this emerging issue in Indian backdrop, I have incorporated three dimensions of health based on age–sex composition of the population like child, reproductive and general health toward construction of a health index (HI) across states over time.

Numerous studies have already been conducted in respect of income convergence across countries in the world as well as different regions within a country; but convergence studies based on social indicators of development like human development and its component are few in numbers. The main focus of my research is to study the progress, inequality and convergence of health at sub-national level in India; therefore, I first review the literature of health convergence and explore the scope of my study.

A robust cross-country convergence study on standard of living indicators like daily calorie supply, daily protein supply, infant mortality rate and life expectancy at birth is undertaken by Hobijn and Franses (2001); they have used **β** convergence, club convergence based on distribution dynamic approach and cluster analysis and have found that convergence in real GDP per capita does not imply convergence of social indicators as mentioned above. The study has used different sample of countries for examining club convergence in terms of above variables. The study found the presence of club convergence across countries rather than the catch-up process.

Mayer-Foulkes (2010) observes that life expectancy dynamics appear to generate a number of 'convergence clubs', each club is having similar life expectancy. The study has analyzed the convergence of components of human capital (of HDI) like life expectancy, literacy and gross enrolment ratio across 111 countries over 1970-2005; he has concluded that the components of human capital initially diverge and then converges. The analysis show that life expectancy divergence replaces convergence in the late 1980's because of adult mortality differences.

Edwards and Tuljapurkar (2005) have examined the difference in the age pattern of mortality across seven industrialized countries overtime and have found that there is no **σ** convergence in mortality in industrialized countries.

Using 192 countries at 5 years interval over the period 1950–2005, Bloom and Canning (2007) have rejected the convergence hypotheses of life expectancy, rather their empirical findings support club convergence with twin peaks of countries– countries with high mortality and countries with low mortality.

Glei et al. (2010) find that there is no **σ** convergence for life expectancy at older ages in higher-income countries.

Drawing from estimates covering 195 countries over a longtime span (1955–2005), Clark (2011) has found convergence of life expectancy but divergent of infant mortality rate; he has concluded that health outcomes follow 'Welfare Kuznets Curve' as economic development proceeds. He has found that reduction in infant mortality is greater in high income countries.

Edwards (2011) points out that there is **β** convergence but not **σ** convergence in life expectancy at birth across countries. He has found that reduction in infant mortality is greater in high income countries but the study could not find the result of **β** convergence. The study has focused on 180 countries including both rich and poor for the period 1970-2000.

Wilson (2011) has studied the world distribution of life expectancy and found a decrease in its dispersion (**σ** convergence).

D'Albis et al. (2012) have not found **β** and **σ** convergence across countries when they consider the entire sample of industrialized countries, but they find some evidence of **σ** convergence among a subset of countries.

Maynou et al. (2015) have worked on health inequality and convergence in the countries of EU; they have found **β** convergence in respect of life expectancy but **σ** divergent in respect of mortality during 1995–2009 across 27 European Union.

The same result is found by Goli et al. (2019) who have considered 193 countries over a long span of time (1950–2015); however, their nonparametric results support regional (club) convergence, rather than global convergence of health (measured in terms of IMR and LEB).

Duncan and Toledo 2019 have found club convergence in respect of body mass index (BMI) among the 172 countries; they argue that existence of different clubs of BMI is due to globalization, human capital, income and urbanization.

Indian Study:

There is evidence of convergence in mortality decline across the states in India.

Saikia and Ram (2010) have examined the factors that influence trend of adult mortality across 26 Indian states using NFHS 1998-99 data. The study has found a strong relationship between mortality and the mortality influencing factors like lifestyle factors (standard of living, literacy, household type etc).

Goli and Arokiasamy (2013) have found divergent result in respect of infant mortality rate (IMR) and total fertility rate (TFR) across 16 states using three rounds of NFHS (NFHS 1, NFHS 2, NFHS 3). The study has found the presence of convergence on average health status measured by IMR and TFR.

Goli et al. (2015) have focused on currently married women in the third round of NFHS (2005-06). The objective was to examine how this factor effects the nutrition level of women. Along with this indicator, the study has considered many other indicators as the determinants of health status of women. The result shows that early marriage has reduced the nutrition level of women. The study also shows a decreasing trend on fertility rate across different states. But some states also had higher fertility rate.

Singh and Ladisingh (2013) have found the presence of convergence of life expectancy in India.

3.2 Research Gap and My Contribution

The majority of the convergence studies have considered life expectancy and infant mortality as health variables; few studies have used nutritional achievement, total fertility rate and BMI. Very few studies have adopted the methodology of distributional dynamic approach of club convergence. Moreover, country-specific studies on health convergence are few in numbers. Previous studies are partial in nature, because health outcomes cannot be assessed by one or two health parameters like life expectancy or infant mortality; the earlier studies, specifically in Indian context, do not attempt toward exploring the existence of club convergence and fail to identify the existence of 'low-level health trap'. All the Indian studies on health convergence are based on parametric approach considering only the 15 major states. They did not focus on the dynamics of the distribution over time, as a result they failed to explore low-level trap in terms of health outcome. The existence of a 'low level health trap' has important policy implications in Indian backdrop as pointed out earlier. Such low-level health trap, if exists in Indian states, justifies the 'big push' theory to health to help states reach and cross the health trap. The present study tries to contribute to the existing literature on health convergence by four ways. First, it attempts to measure an overall health of the states by creating a health index (HI) from a set of interrelated health indicators based on age–sex composition of population which is comparable over time across 26 states; the relative progress of any state can easily be estimated by observing the value of health index

(HI) over time. Second, our study is comprehensive in the context of health convergence since it uses both parametric approach like **β** (and **σ**) convergence in one hand and nonparametric approach like Gaussian kernel (along with Markov's process of transition) on the other hand. The Nonparametric approach of the distributional dynamics of HI is expected to provide a clear picture of the stratification, polarization and club convergence process of HI over time (1992–93 to 2015–16); the parametric approach (viz. regression based) of club convergence cannot be implemented in our analysis, because it requires a time series data; however, we use regression based **β** convergence toward exploring conditional variables determining the growth of HI. We go beyond **σ** convergence, the health inequality of the HI (and its subindices) and original health indicators (used in the construction of HI) are estimated by coefficient of variation and Gini coefficient. Third, the present study explores the existence of 'low level health trap' in respect of HI that persists over time among the states. If a state is caught by 'low level trap' in respect of HI, does it mean that the state remain in low level in respect of sub-dimensions of HI? This is analyzed further by estimating Markov's transition probability matrices of sub-health indices. Fourth, the present study is distinct from earlier studies, because I have estimated the short-run and long-run mobility as well as stability indices of states in respect of HI. This is important for understanding the dynamic process of club convergence. Lastly, I have examined the role of spatial impacts toward formation of class or clubs in respect of health index. I am motivated by the seminal cross-country study done by Bloom and Canning (2007) and Goli et al. (2019) who have argued about the existence of 'mortality trap' that persist in some countries over long period of time.

3.3 Objectives of the study

- Construct the Health Human Capital Index or Health index for four time points across 26 Indian states using some selective indicators from health dimension.
- Examine the presence of convergence in Health Index for four time points across 26 Indian states using regression and dispersion-based approaches.
- Examine the presence of regional inequality across states in terms of health index using generalized entropy measures of inequality.

- Explore the presence of club convergence or presence of chronic low-level health trap across 26 Indian states using distributional dynamics approaches (Kernel Density Estimation and Markov Process).
- Explore the presence of spatial dependency towards club formation across the states for four time points.

3.4 Data and Methodologies

3.4.1 Data

In order to construct the health human capital index, I have used different health indicators. Following table shows the data abbreviation with their definition and sources.

Table:3.1: Data Description and Sources

Definitions	Abbreviation	Sources
Life expectancy at birth	LEB	NITI AAYOG, RBI; available at SRS, RGI
Normal body mass index (%)	BMI	National Family Health Survey (1–4), IIPS, Mumbai
Infant survival rate (per 1000 live birth)	ISR	National Family Health Survey (1–4), IIPS, Mumbai
Not stunted (%)	NS	National Family Health Survey (1–4), IIPS, Mumbai
Not wasted (%)	NW	National Family Health Survey (1–4), IIPS, Mumbai
Not underweight (%)	NUW	National Family Health Survey (1–4), IIPS, Mumbai
Non-anemic (%)	NA	National Family Health Survey (1–4), IIPS, Mumbai
Low TFR (children per woman)	LTFR	National Family Health Survey (1–4), IIPS, Mumbai
Per Capita Education Expenditure	PCEE	RBI, Government of India, NITI Aayog.
Per Capita Health Expenditure	PCHE	RBI, Government of India, NITI Aayog.
No. of Primary School	No. of_ PS	SRC and Annual Report 1993 and 1999,
Number of Middle School	No. of UP	SRC and Annual Report 1993 and 1999,
Number of Secondary School	No, of HS	SRC and Annual Report 1993 and 1999,
Number of Sub Centre	SC	RBI, Government of India, NITI Aayog.
Number of PHC	PHC	RBI, Government of India, NITI Aayog.
Number of Community Health Centre	CHC	RBI, Government of India, NITI Aayog.
Road Length	Road	RBI, Government of India, NITI Aayog.
Railway Length	Rail	RBI, Government of India, NITI Aayog.

3.4.2 Methodologies

Similar to the education index, health index also is a component of human capital index. In this methodology section, I have only discussed the construction of health index or health human capital index. Methodologies for convergence studies are already discussed in Chapter1.

Construction of health index

Life expectancy at birth or infant mortality rate are the most standard indicators of measuring health status across countries in the world (UNDP 1991, 2010), but a single indicator fails to arrest various aspects of health of a transitional economy like India. According to the World Health Organization (2008), health is define das a state of complete physical, mental and social well-being; reproductive and child health must be addressed to evaluate the health status of a country. The millennium development goals (MDGs) were ended in 2015, and a more comprehensive development goal has been proposed by the United Nations (UN) toward achieving sustainable development goals (SDG) of 2030. The reproductive and child health are given priority to address the health issues in Goal-3 of SDG. Sen(1998) has emphasized the importance of mortality data in any assessment of human well-being, because mortality information has intrinsic importance, enabling significance and associative relevance. Therefore, I argue that health is not determined by a single parameter like life expectancy or infant mortality, rather a set of health indicators are needed to assess the aggregate health of a country (or states in a country); thus, I divide the total health dimension into three sub-health dimensions like child health, reproductive health and general health. Linear aggregation over three dimensions implies perfect substitutability, essentially meaning that a state (or country) can compensate for deficiency in one dimension by achievements in another (Sagar and Najam 1998). Following UNDP (2010), my health index (HI) is the geometric mean of three sub-health dimension indices like child health index (CHI), reproductive health index (RHI) and general health index (GHI), and thus the problem of linearization is solved. Concerning the construction of any composite index (in our case, HI), some criticisms pointed outby Saisana et al. (2005) need to be mentioned here. Why is the life expectancy or infant survival rate insufficient to capture the true health scenario in India at sub-national level? Does my proposed HI satisfy the important properties of an ideal index? How far is the equal weights scheme assigned to each health subdimension justified?

At the very outset, I have mentioned about the regional variations of key health indicators across 26 states using NFHS-4 (2015–16). The descriptive statistics of eight health indicators drawn from panel of states over time (1992–93 to 2015–16)as given in Table-3A.1(Appendix 3A)clearly suggest that low TFR is found to be the least variance followed by LEB; the maximum variance is found in respect of ISR followed by nonanemic mothers. Moreover, the rank correlation coefficient between life expectancy and other health indicators clearly shows a positive and significant value except nonwasted children and BMI as shown in "Appendix 3A.2." If the rank correlation appears to be closer to 1 (perfectly correlated), then only life expectancy could be sufficient to capture the health dimension; but it does not happen in our case. Thus, my proposed HI does not reflect the problem of redundancy in the information provided by the composite index (HI). The HI is best seen as a measure of people's ability to live a long and healthy life.

I can measure the health progress over time by observing the difference of HI. Similar to the Education Index my proposed health index does satisfy the following properties of an ideal index (Pure Number, transitivity, convexity, homogenous, sub group decomposable etc.).Determination of weights assigned to each sub-health dimension (viz. CHI, RHI and GHI) is difficult; an equal weight scheme seems to be arbitrary hence not based on social choice or normative arguments.

A composite index of health status is convenient in the sense that it allows for direct comparison of standard of health across states over time. Combining a wide variety of health indicators (which are measured in different units) would make the final index of the health status is easier to grasp if the health indicators are normalized. We take into account all the positive health variables. To construct health index (HI),first I calculate separate dimension indices like child health index (CHI), reproductive health index (RHI) and general health index (GHI). Each dimension is captured by two health indicators as mentioned below; one can incorporate other health indicators in order to capture the dimension indices; but keeping in mind the availability of data at the state level, I have objectively taken two health indicators in each dimension. Before creating the dimensional index, we normalize all the indicators (variables) by using time and space invariant maximum and minimum value. Child health index (CHI) is comprised of following indicators: Infant survival rate (ISR), nutritional status (this is an average of three indicators namely percentage of children who are not stunted, wasted and underweight).The Reproductive health index (RHI) is comprised of the following indicators: Lower fertility rate (LFR) which is the reciprocal of total fertility rate it is assumed that total fertility rate is a bad social indicator; higher fertility is detrimental to the health of reproductive mothers; percentage of women (belonging to age group15–49) who are not suffering from Anemia. The general health index (GHI) consists of the following indicators: Normal BMI (18.5–25) of the adults measured in percentage, life expectancy at birth. I make the indicators scale free by way of relative distance methods. I compute the range for each indicator in each dimension (category). For the *j*th indicator belonging to the *r*th dimension (category),

$$H_{ijt} = \frac{Actual H_{ijt} - \underset{i,t}{Min} H_{ijt}}{\underset{i,t}{Max} H_{ijt} - \underset{i,t}{Min} H_{ijt}} \tag{3.1}$$

Following the methodology of human development index 2010, I have calculated weighted arithmetic mean of sub-indices.

$$CHI_{ij} = \frac{w_{11} * ISR_{ij} + w_{12} Well-Nourishment_{ij}}{w_{11} + w_{12}} \tag{3.2}$$

Where, well-nourishment is the average of not stunned, not wasted and not underweight. It can be defined as follows;

$$Well - Nourishment_{ij} = \frac{NS_{ij} + NW_{ij} + NUW_{ij}}{3} \tag{3.2.1}$$

As, I have mentioned in the earlier section that I have used two health variables from the child health dimensions. Instead of using equal weights to each indicator, I use Principal Component analysis to generate the weights from the data matrix. Here, w_{11} and w_{12} are the weights of corresponding health variables. Similarly, I have calculated the Reproductive and General Health index for 26 Indian states.

$$RHI_{ij} = \frac{v_{11} * LTFR_{ij} + v_{12} * NONANEMIC_{ij}}{v_{11} + v_{12}} \tag{3.3}$$

Under reproductive health dimension, I have two health variables. First one is lower total fertility rate and another one is the percentage of women who are non-anemic. v_{11} and v_{12} are the weights for respective variables.

Similarly, under general health dimension I have life expectancy at birth and normal BMI. Here also I have generated the corresponding weights using Principal Component Analysis.

$$GHI_{ij} = \frac{u_{11}*LE_{ij} + u_{12}*BMI_{ij}}{u_{11}+u_{12}} \tag{3.4}$$

Following table shows the weights of respective indicators obtained from the data matrix;

Table:3.2: Result of Principal Component Analysis of Health indicators

Child Health Dimension		Reproductive Health Dimension		General Health Dimension	
Variables	Factor Loadings	Variables	Factor Loadings	Variables	Factor Loadings
ISR	0.925***	LTFR	0.778***	BMI	0.793***
Well-Nourishment	0.925***	NON-ANNEMIC	0.778***	LE	0.793***

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

From the table, it can be observed that all the factor loadings of the variables from each dimension are statistically significant. I have used those weights to construct sub-indices in following ways;

$$CHI_{ij} = \frac{0.925*ISR_{ij} + 0.925*Well-Nourishment_{ij}}{0.925+0.925} \tag{3.5}$$

$$RHI_{ij} = \frac{0.778*LTFR_{ij} + 0.778*NONANEMIC_{ij}}{0.778+0.778} \tag{3.6}$$

$$GHI_{ij} = \frac{0.793*LE_{ij} + 0.793*BMI_{ij}}{0.793+0.793} \tag{3.7}$$

After getting the weighted arithmetic mean of each dimension, I have constructed the health human capital index. This health human capital index is the geometric mean of those weighted arithmetic mean of sub-indices. Therefore, overall health human capital index can be written as;

$$HI_{ij} = (CHI_{ij} * RHI_{ij} * GHI_{ij})^{0.333} \tag{3.8}$$

Similar to the education index this health index also follows all the properties of a standard index. So, using this index, I can examine the presences of convergence as well as trap across the 26 Indian states for four time points.

3.5 Empirical Findings

Similar to the Education index in Chapter 2, the value of health index lies between 0 to 1; nearer the value to 1 means the state is more developed in terms of health whereas a lower value (approaching to zero) indicates the state is less developed. The progress of any state in respect of social development can be assessed by observing its numerical value of HI over time; in measuring HI, I have used relative distance methodology and the distance is fixed (it is time and space invariant) of any indicator used in measuring sub-dimensions of HI. Following table (Table-3.3) shows the value of health index across 26 Indian states for four time points.

Table: 3.3: Health Index (HI) across 26 Indian States over four time points (NFHS1-NFHS4)

States	HI_NFHS 1 (1992-93)	HI_NFHS 2 (1998-99)	HI_NFHS 3 (2005-06)	HI_NFHS 4 (2015-16)
Andhra Pradesh	0.38094(13)	0.43087(14)	0.42407(16)	0.49219(22)
Arunachal Pradesh	0.31733(17)	0.39847(18)	0.49073(12)	0.68754(06)
Assam	0.12238(26)	0.29314(21)	0.31928(23)	0.53169(19)
Bihar	0.15484(24)	0.24148(24)	0.23569(25)	0.38908(26)
Delhi	0.43654(08)	0.53417(05)	0.57402(07)	0.59281(13)
Goa	0.61463(02)	0.64759(02)	0.65942(03)	0.68567(07)
Gujarat	0.33943(16)	0.41142(15)	0.36069(20)	0.47390(23)
Haryana	0.40471(10)	0.45559(12)	0.41336(17)	0.54195(18)
Himachal Pradesh	0.44523(07)	0.53443(04)	0.55567(09)	0.60102(12)
Jammu & Kashmir	0.40718(09)	0.40047(17)	0.54368(10)	0.65766(08)
Karnataka	0.36738(14)	0.47903(09)	0.44208(15)	0.57230(14)
Kerala	0.72837(01)	0.74168(01)	0.69826(01)	0.78118(01)
Madhya Pradesh	0.16374(23)	0.20984(26)	0.22186(26)	0.43541(24)
Maharashtra	0.40041(11)	0.45398(13)	0.47461(13)	0.56791(16)
Manipur	0.55142(05)	0.57769(03)	0.66034(02)	0.71986(04)
Meghalaya	0.31341(18)	0.22718(25)	0.45667(14)	0.55430(17)
Mizoram	0.58133(04)	0.51631(07)	0.64794(04)	0.72257(03)
Nagaland	0.59057(03)	0.50843(08)	0.60570(06)	0.71073(05)
Odisha	0.15262(25)	0.25775(22)	0.32916(22)	0.52274(20)
Punjab	0.48393(06)	0.52613(06)	0.56124(08)	0.64702(10)
Rajasthan	0.30557(19)	0.30441(19)	0.35271(21)	0.51541(21)
Sikkim	0.34464(15)	0.45705(11)	0.62490(05)	0.77335(02)
Tamil Nadu	0.38653(12)	0.46473(10)	0.52143(11)	0.60832(11)
Tripura	0.24616(21)	0.30389(20)	0.40357(19)	0.65526(09)
Uttar Pradesh	0.16420(22)	0.25714(23)	0.29417(24)	0.43221(25)
West Bengal	0.29897(20)	0.40683(16)	0.41289(18)	0.57070(15)

Source: Author's estimation, Note: Values in parentheses represent rank.

From Table 3.3, it can be observed that some states are performing well compared to other states, but each state experiences a rising trend of HI. Since all the health outcomes have some asymptotic upper bound and all states try to reach that level, but their performance differ in raising HI. The rank of the states in respect of HI over time does not remain fixed; some smaller states like Kerala, Sikkim, Manipur, Mizoram and Nagaland perform better, whereas the bigger states like Bihar, Uttar Pradesh, Madhya Pradesh, Rajasthan and Assam could not perform well in raising HI.

The above table (Table-3.3) can help us to make our mind to guess the possibility of convergence. But that guess may be incorrect. It is because in the above table I have only the information about the performance of states over time, not the growth. As well as the relation between growth and initial value is also missing.

Before going to the analysis of convergence, I have checked the descriptive statistics to get an overall idea about the distribution of health index. The descriptive statistics of each indicator are given in the Appendix 3A.

Table 3.4: Descriptive Statistics of Health Index over time

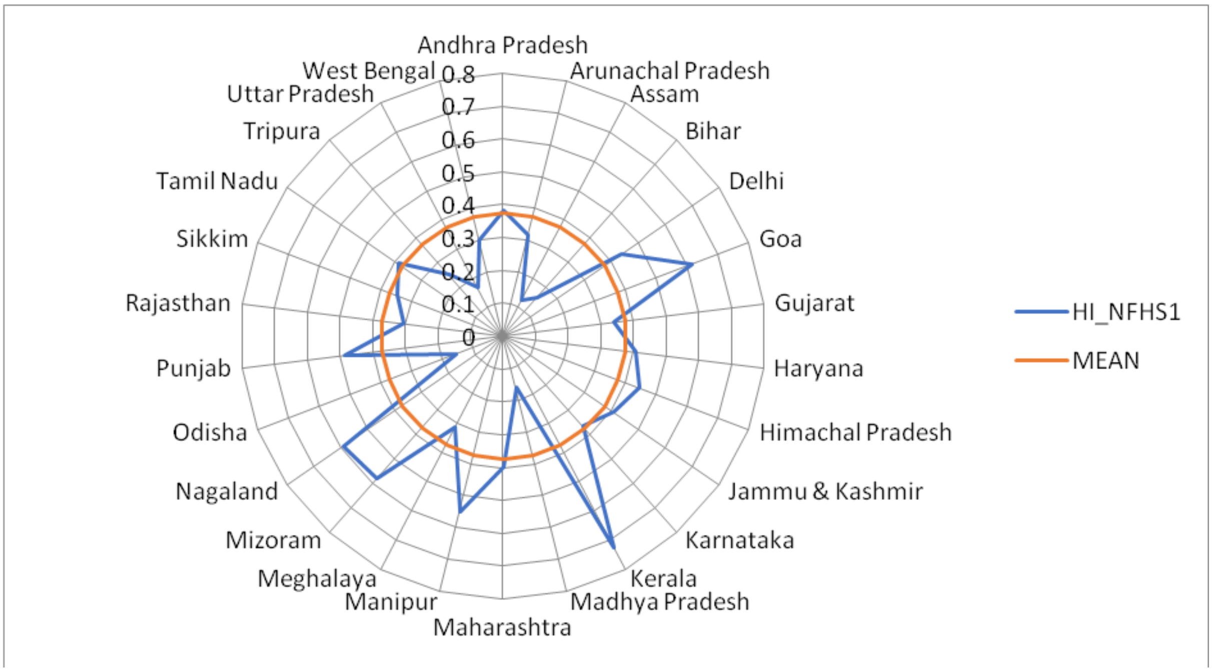
Year	MAX	MIN	RANGE	MEAN	SD	CV
NFHS_1	0.728	0.122	0.606	0.373	0.156	0.419
NFHS_2	0.741	0.209	0.532	0.424	0.134	0.317
NFHS_3	0.698	0.221	0.477	0.472	0.136	0.287
NFHS_4	0.781	0.389	0.392	0.593	0.105	0.178

Source: Author's estimation

Above table (Table-3.4) shows the summary statistics of health index across 26 Indian states for four time points. Similar to the earlier table, this table also helps us to get some idea about the pattern as well as distribution of health index. Maximum range of health index has a fluctuating trend whereas minimum has increased over time. This indicates that states with bad health status are improving. Increasing trend of mean values of HI also indicate an improvement. The table also shows that the dispersion as well as the coefficient of variation has decreased over time. This information indicates the presence of convergence in terms of health index.

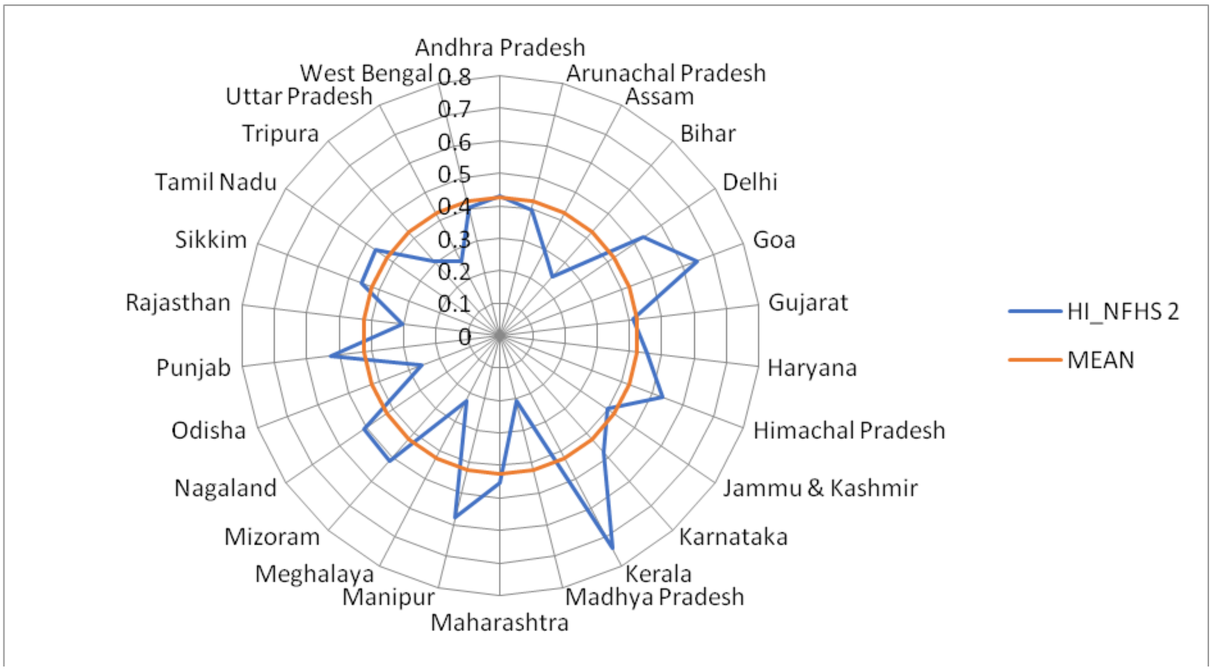
At the same time, I have used graphical descriptive statistics to observe the performance of each state in terms of health outcome.

Figure-3.1(A): Relative position of states in respect of Health Index over mean in NFHS 1



Source: Author's estimation

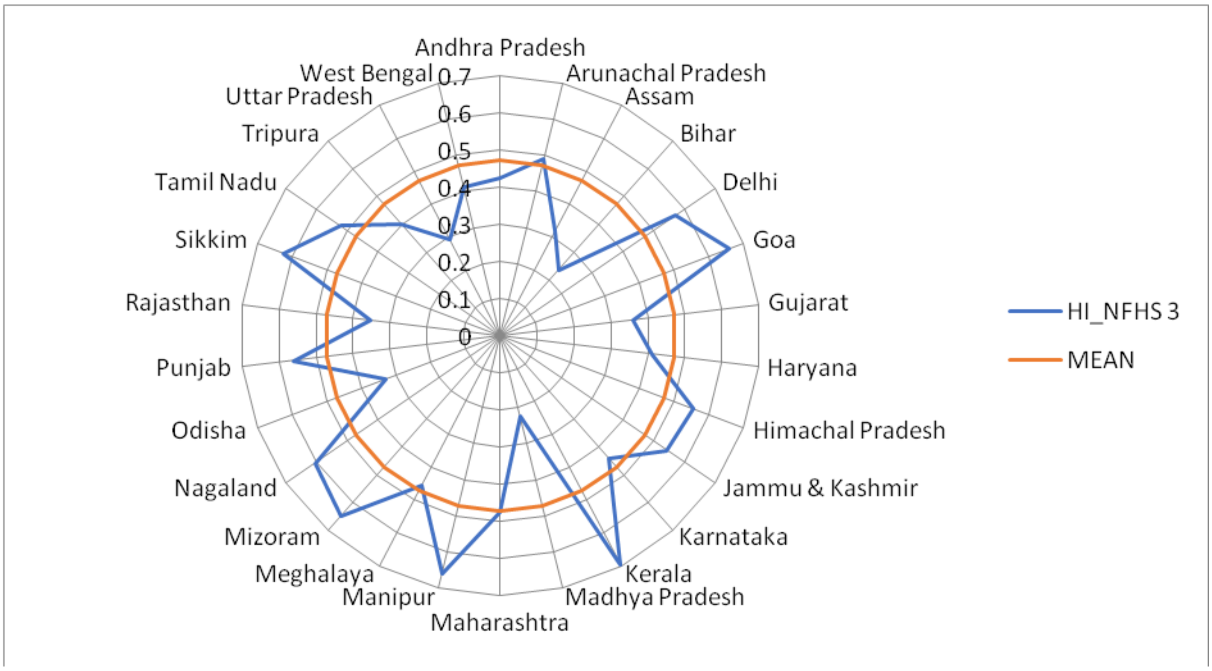
Figure-3.1(B): Relative position of states in respect of Health Index over mean in NFHS 2



Source: Author's estimation

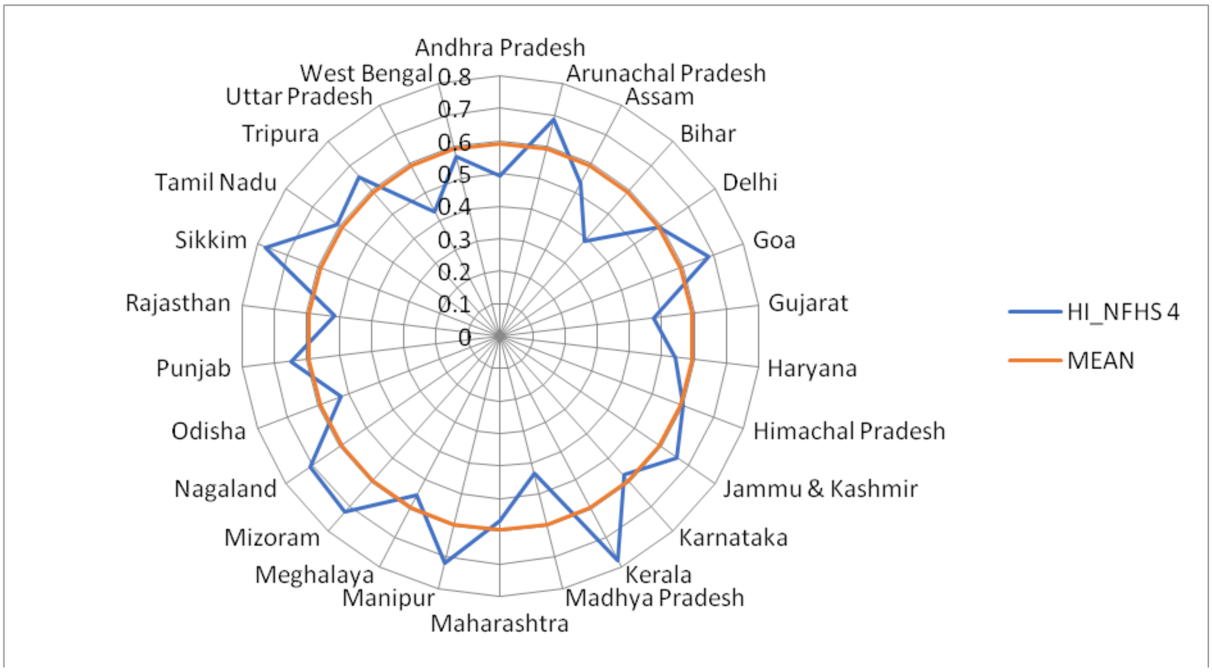
In the first two diagram out of 26 states only 12 states have the health status below the mean value, it has increased to 13 and 14 in next two time points respectively. The figures also show that over time mean health status has increased. But the number of states below the mean value is lower compared to education index. Similar to education index, here, also initially we can observe the presence of two classes (lower mean value and above mean value).

Figure-3.1(C): Relative position of states in respect of Health Index over mean in NFHS 3



Source: Author's estimation

Figure-3.1(D): Relative position of states in respect of Health Index over mean in NFHS 4



Source: Author's estimation

The above diagrams show that over time, the mean health index has increased. All states are improving in respect of health status. This indicates that states are converging. From these four diagrams, the initial presence of health trap can be observed. For example, Assam, Bihar, Uttar Pradesh and Madhya Pradesh consistently belong to the lower class whereas some states (like Goa, Delhi, Kerala) are in higher class. Therefore, we can guess the presence of both health convergence and health trap.

Before going to the analysis of convergence using regression as well as dispersion-based approach, I have examined the rank correlation coefficient to assess the relationship between of health index over time. The result of this bivariate descriptive statistics suggests that relative position of states is highly correlated with the position of earlier time point. If we increase the lag, the correlation gets decreased. So, both the univariate and bivariate descriptive statistics show that states are found to be improving keeping their relative position unchanged.

Table-3.5: Rank Correlation Coefficient Health Index

Year	NFHS_1	NFHS_2	NFHS_3	NFHS_4
NFHS_1	1.000			
NFHS_2	0.902***	1.000		
NFHS_3	0.899***	0.864***	1.000	
NFHS_4	0.702***	0.688***	0.890***	1.000

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

3.5.1 Convergence Based on Neoclassical Approach

Now, I have examined the convergence (absolute and conditional beta convergence) across the states using regression-based approach.

Table-3.6: Result of Absolute Beta (β)Convergence of Health Index

Explanatory variables	Coefficients	t	P>|t|
$\ln(HI)\_{t-j}$	$-0.0799^{***}(0.015)$	-5.06	0.000
Constant	$-0.0223^{***}(0.0063)$	-3.49	0.000
Within R squared	0.3341		
Between R squared	0.6599		
Overall R squared	0.3907		
F(1,51)	25.59^{***}		
Hausman Test	5.59^{***}		
Number of observations	78		

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

From the above Table-3.6,I have found the result of absolute beta convergence as the beta appears as negative. There are many factors that affect the growth of HI. In order to find out the growth determining factors of HI, I have moved to conditional convergence. Here, I have taken lagged PCHE, PCEE and SII and PII as conditional variables. The results are given in the following table (Table-3.7). Keeping in mind the multicollinearity problem, we have formulated three different models.

Table-3.7: Result of Conditional Beta (β) Convergence of Health Index

Explanatory variables	Model 1	Model 2	Model 3	Model 4
Constant	-0.061***(0.010)	-0.047***(0.008)	-0.132***(0.017)	-0.16***(0.03)
$\ln(HI)\_{t-j}$	-0.133***(0.017)	-0.130***(0.018)	-0.140***(0.014)	-0.126***(0.01)
lnPCEE_5	0.0196***(0.004)			
lnPCHE_5		0.013***(0.003)		
LnSII			0.051***(0.007)	
LnPII				0.041***(0.010)
R^2 overall	0.4742	0.4376	0.4088	0.2759
R^2 –within	0.5447	0.5021	0.6521	0.5115
R^2-between	0.7374	0.6959	0.5833	0.4243
F(2,50)	29.91***	25.21***	46.85***	26.18***
Huasman Test	23.69***	20.08***	51.77***	23.78***
Number of observations	78	78	78	78

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

For each model, the presence of conditional beta convergence is observed. Each conditional variable also positively affects the dependent variable. Now,I can go for the measurement of dispersion or the sigma convergence. The result of standard deviation for four time points is given in the following table:

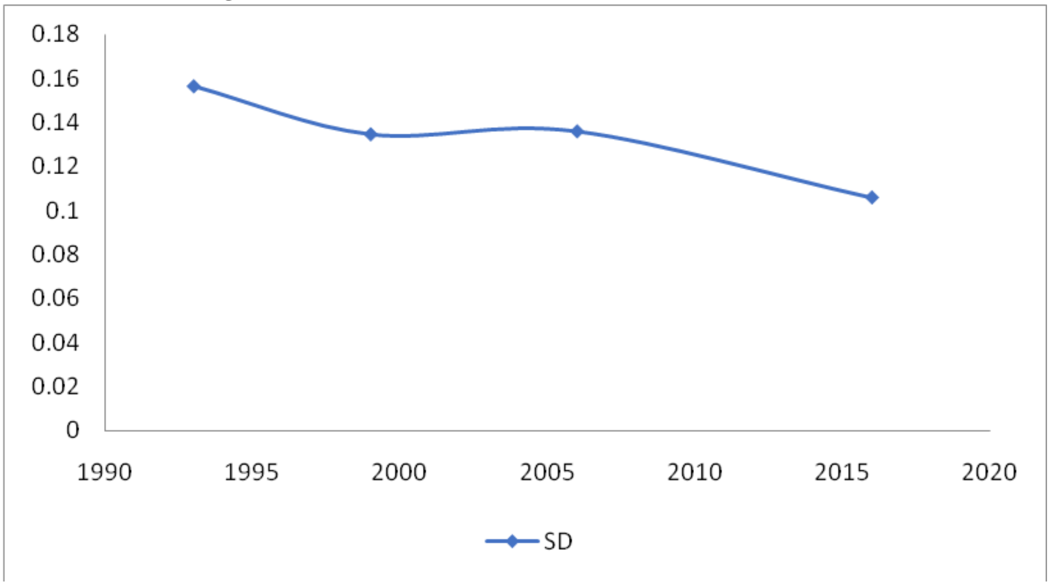
Table-3.8: Result of Sigma (σ) Convergence/Divergence of HI

	NFHS_1	NFHS_2	NFHS_3	NFHS_4
SD_HI	0.156	0.134	0.136	0.105

Source: Author's estimation

From the table (Table-3.8), it is clear that initially the value of SD has decreased (from NFHS 1 to NFHS 2) and then in next time point (NFHS 3, 2005-06) it has increased. In the next time point (NFHS 4, 2015-16),the value of SD has decreased. The overall trend of HI falls over time. That means dispersion of HI across 26 states falls for long run. This implies the presence of sigma convergence. Graphically we can get the trend of SD also. So, in terms of health index, there exists sigma divergence as in the short run the trend is found to be fluctuating over time.

Figure-3.2: Trend of Standard deviation (σ) of HI over time



Source: Author's estimation

3.5.2 Convergence based on Inequality Approach

The SD belongs to dispersion-based approach. So, these measures are used to examine the pattern of dispersion over time. But, decrease in dispersion does not implies the decrease in inequality. So, in this section, I have used inequality-based approach to explore the presence of convergence. As I have mentioned the limitation of GINI in the methodology section of Chapter 1, here, I have reported the result of GE measures of inequality. This measure of inequality is distribution sensitive.

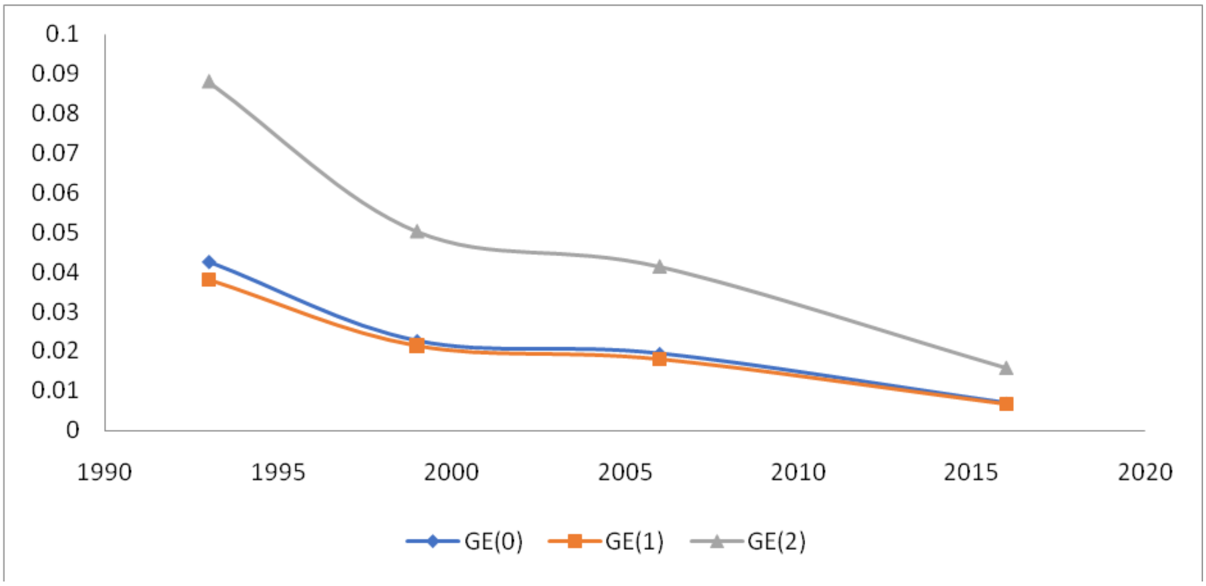
Table-3.9:Result of Generalized Entropy Measures of Inequality of HI

GE	HI_NFHS1	HI_NFHS2	HI_NFHS3	HI_NFHS4
GE(0)	0.042	0.022	0.019	0.006
GE(1)	0.037	0.021	0.018	0.006
GE(2)	0.088	0.050	0.041	0.015

Source: Author's estimation

Above table (Table-3.9) clearly shows that over time the inequality HI has decreased. This is a clear indication of convergence. The GE measures of inequality is distribution sensitive. Inequality sensitive to higher part of the distribution is high compared to inequality sensitive to middle and lower part of the distribution. But all the inequality values are found to be decreasing. Similar to education index, here also all the inequalities values are coming closer. That is also another indication of convergence. So, inequality-based approach also supports the presence of convergence in health index.

Figure-3.3: Trend of Generalized Entropy Measures of Inequality of HI from NFHS 1 to NFHS 4



Source: Author's estimation

The above figure shows the overtime trend of inequality. All are found to be declining but, the rate of decrease in GE(2) is higher than the rate of decrease in GE(0) and GE(1).

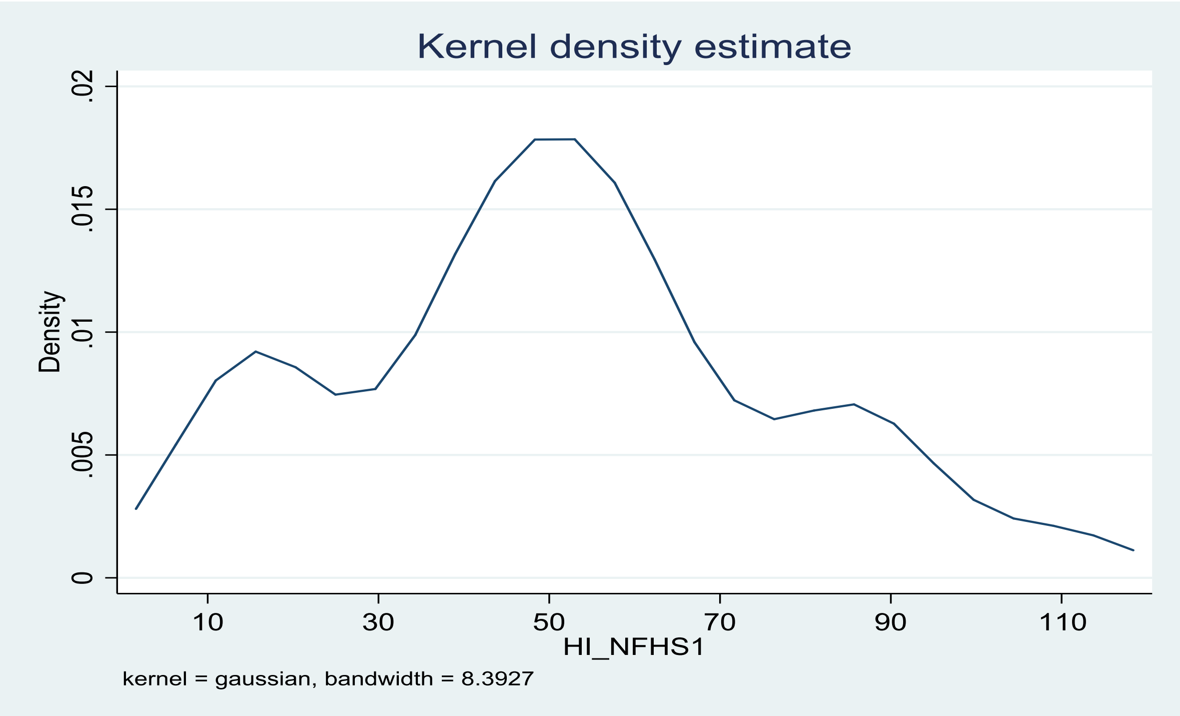
3.5.3 Convergence Based on Non-Parametric Approach

I have drawn the kernel plots of HI for NFHS-1, NFHS-2, NFHS-3 and NFHS-4. Along with kernel plots, I have used the TPM from one time point to next time point (both short run and long run) for measuring the transitional movement of states in respect of HI. From the results of kernel density estimation, visually we can identify the presence of stratification, polarization and club convergence of states in respect of HI. I have already found the dynamics of the distribution over time from the radar diagram for each time point. The diagram also suggests the presence of polarization based on mean value. Following the descriptive analysis about the dynamics of the distribution, in this section, I have used kernel density estimation for identification of club convergence. This analysis is based on relative value not on actual value of health index.

3.5.3.1 Non-Parametric Approach: Kernel Density Estimation

Figure-3.4(A) shows the Kernel density estimation for first time point (NFHS 1). Here the plot shows evidence of stratification. In this study, I have used the Kernel density estimation and Transitional Probability Matrix to explore the presence of club convergence. To begin this analysis, I have arbitrarily chosen five non overlapping classes. I have classified the classes on the basis of relative position. The entire range of health index is 10-110& 10 to 30 is considered as extreme lower class, 10 to 50 used to define the lower class, lower middle class cover the range of 50-70 whereas upper middle class consider the range of 70-90 and the higher class consists of 90-110. First kernel estimation shows that states generate three classes. It shows the presence of stratification in the distribution. First class considers the range 10-30, second class 30-50 and 50-70 whereas the third class covers the range of 70-90 and 90-110. The middle peak consists of higher number of states compared to lower and upper peaks.

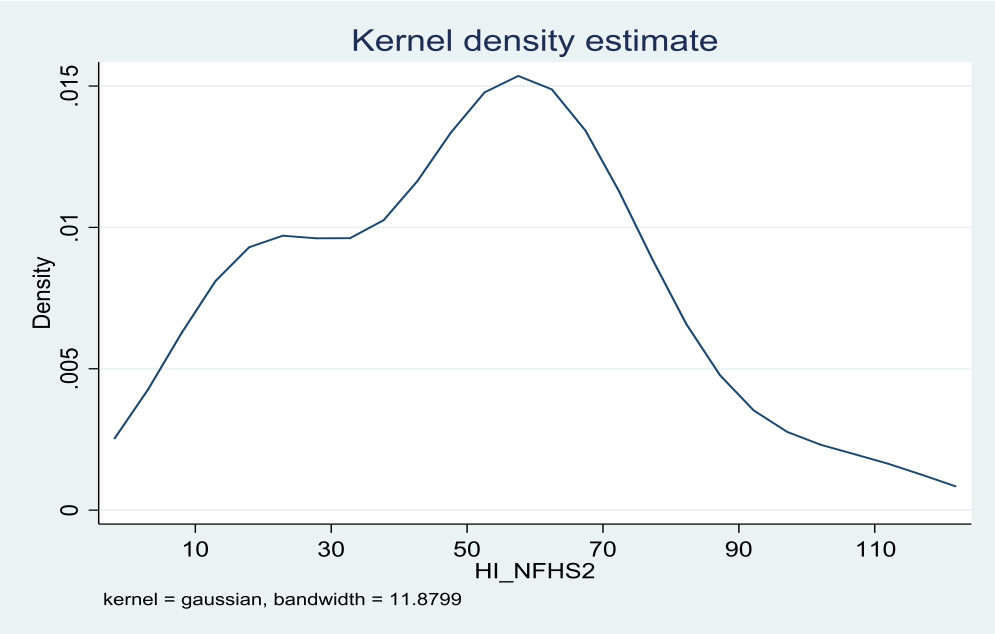
Figure-3.4(A): Kernel density estimation of Health Index in NFHS 1



Source: Author’s estimation

In NFHS 2, the distribution of HI has changed to polarisation. Here, we have the distribution with two peaks. In NFHS 2, density for first class has increased. So, some of the states are moving from lower to extreme lower class. Similarly, mobility between second and third class can be expected.

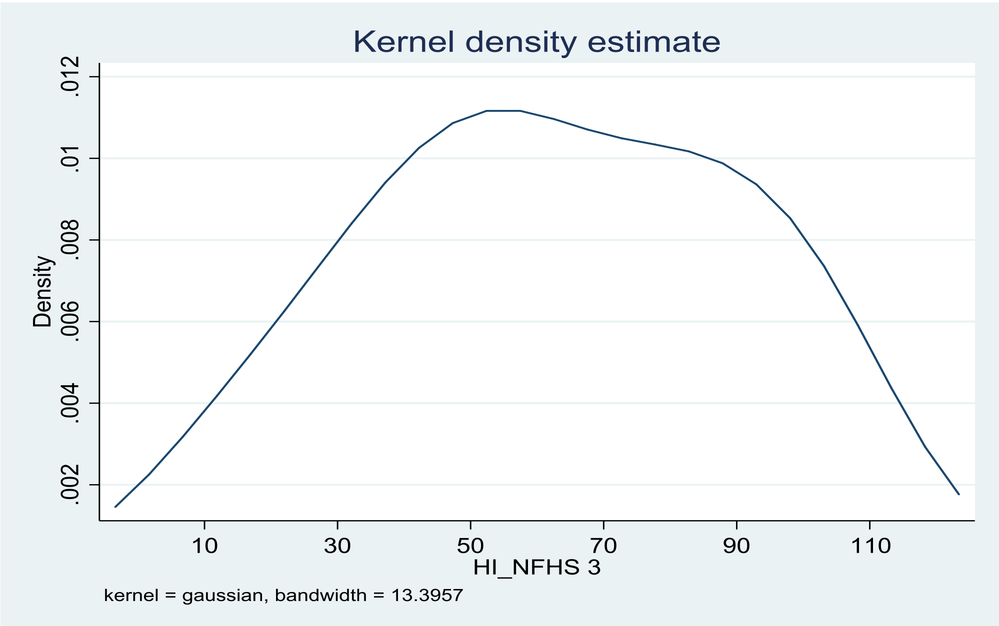
Figure-3.4(B): Kernel density estimation of Health Index in NFHS 2



Source: Author's estimation

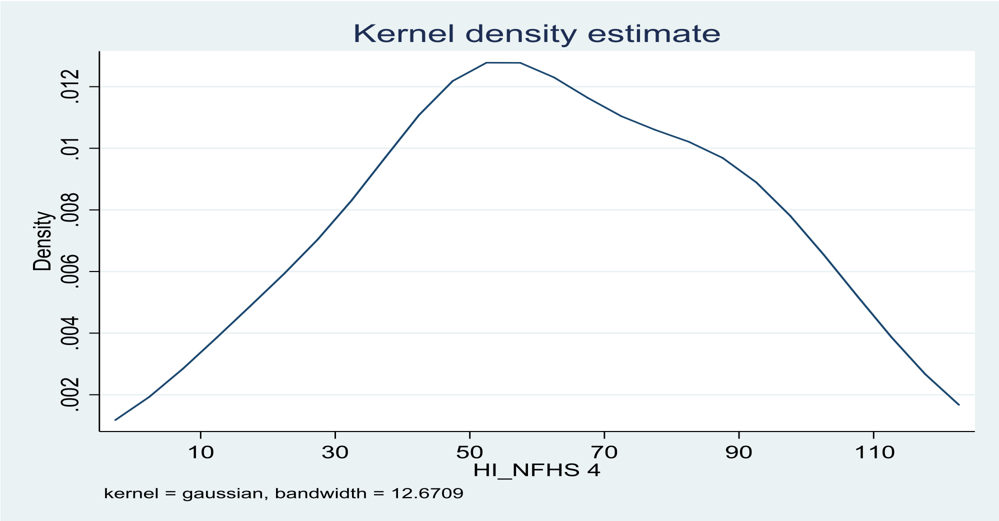
In NFHS 3 and 4, I have different results compared to NFHS 1 and 2. In NFHS-3(2005-06) and NFHS-4(2015–16), the plots of kernel become neither uni-modal nor polarized; however, from the kernel plot of NFHS-4, we see that the states are converging at the middle of the distribution. In NFHS 3, the first class consists of the range of 10-70 and the second class covers the rest of the range. In NFHS 4, I observe the same pattern of distribution. But in the terminal time point, density for the first class has increased compared to the earlier one.

Figure-3.4(C): Kernel density estimation of Health Index in NFHS 3



Source: Author's estimation

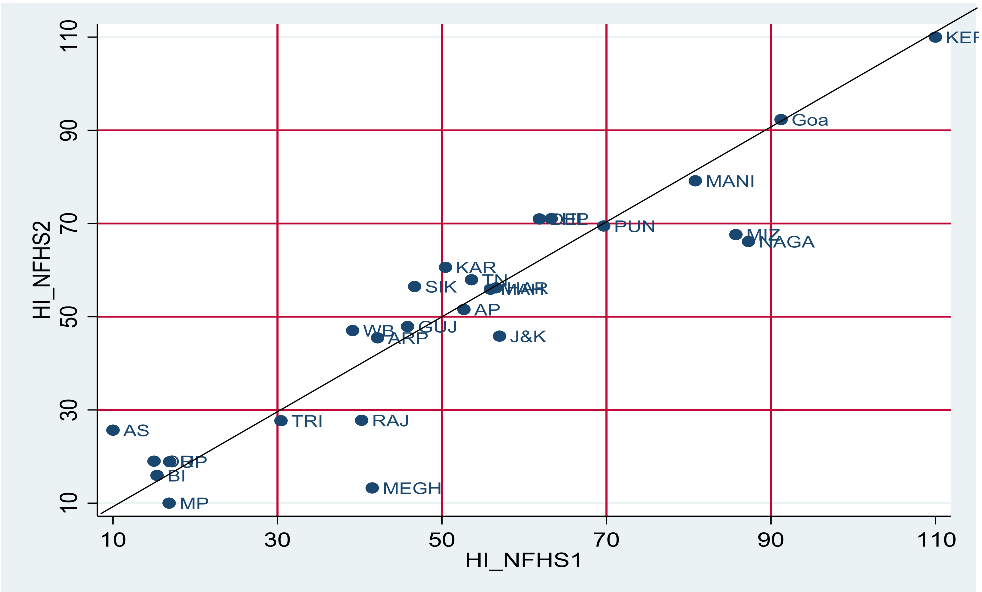
Figure-3.4(D): Kernel density estimation of Health Index in NFHS 4



Source: Author's estimation

Now, if I compare all the density plots for four time points, it can be observed that states are found to be mobile at the same time states are found to be moving from lower to higher class. It is completely a visual inspection of dynamics of the distribution or club convergence. But Kernel density estimation has some limitations as outfit earlier. It fails to identify the individual transition of states within the distribution. At the same time, they fail to identify the probability of mobility or stability or the speed convergence. Using a scatter plot (box-plot), we can identify the presence of within distributional transition over time. It justifies the application of Transitional Probability matrix.

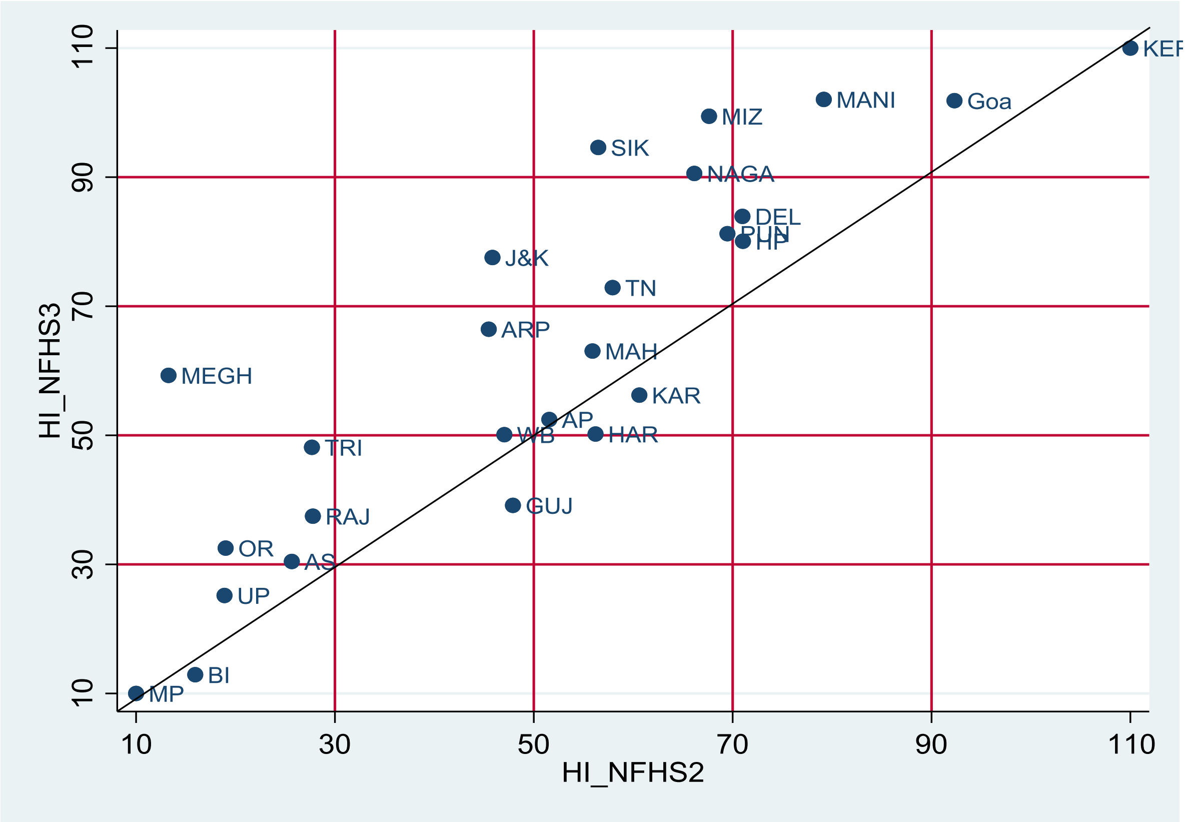
Figure-3.5(A): Scatter Box-Plot of transition of states in respect of HI from NFHS 1to NFHS 2.



Source: Author's estimation

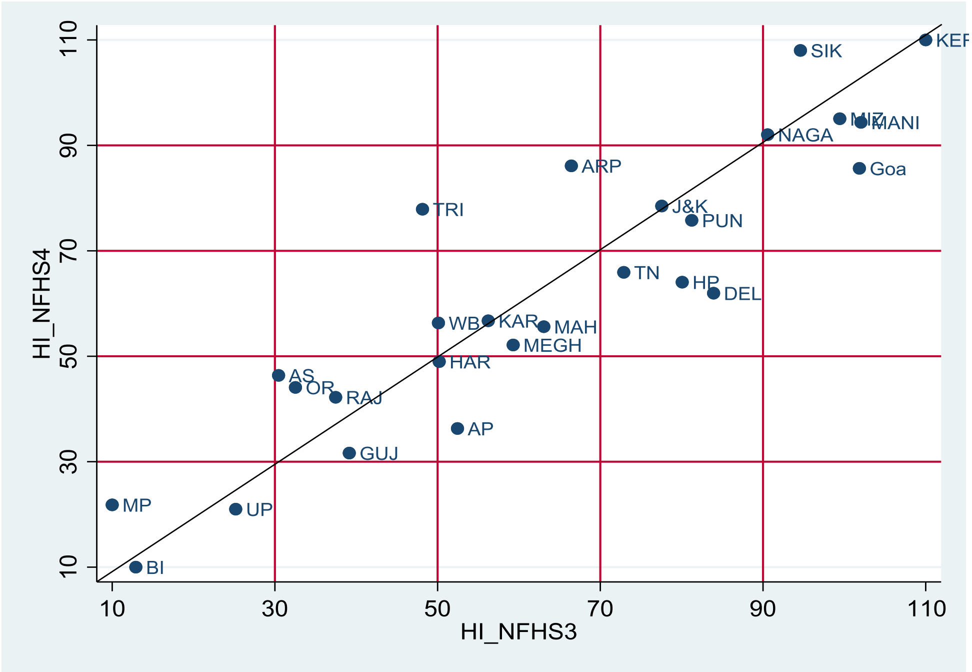
Above diagram captures the transition of states from one class to another during the period NFHS1 to NFHS 2. The 45º degree line shows the stable position of states where any point above or below the line shows the improvement or deterioration of respective state. From this figure it can be observed that states are located in different classes and most of them are nearer to the equality line. The box-plot diagrams reveal that most of the states are improving in health status over time.

Figure-3.5(B): Scatter Box-Plot of transition of states in respect of HI from NFHS 2 to NFHS 3.



Source: Author's estimation

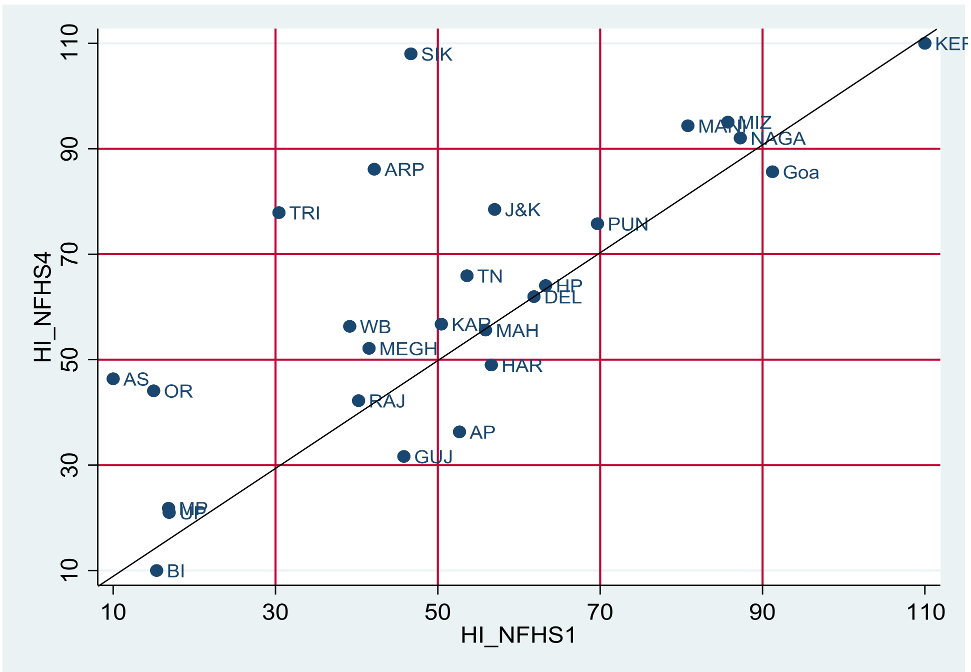
Figure-3.5(C): Scatter Box-Plot of transition of states in respect of HIfrom NFHS 3 to NFHS 4.



Source: Author's estimation

The third figure is capturing the transition pattern across states from NFHS 3 to NFHS 4. The long run transition pattern shows that most of the states are found to be concentrating towards middle class. Both short run as well as long run plots reveal that Bihar, Orissa and Uttar Pradesh are found to be stable in their respective class.

Figure-3.5(D): Scatter Box-Plot of transition of states in respect of HI from NFHS 1to NFHS 4.



Source: Author's estimation

Another important advantage of this box-plot is that one can easily identify both within as well as between transition of states over time.

3.5.3.2 Non-Parametric Approach: Transitional Probability Matrix

Based on this transition of states and to get more prominent result on club convergence, I have used the Transitional Probability Matrix (TPM) based on Markov Process. In this study I have constructed four transitional matrixes, three short run transitional probability matrices and one long run transitional probability matrix.

Table-3.10(A):Transitional Probability Matrix (TPM) of states in respect ofHI from NFHS 1 to NFHS 2

		NFHS 2				
		10-30	30-50	50-70	70-90	90-110
NFHS1	10-30	1	0	0	0	0
	30-50	0.428571	0.428571	0.142857	0	0
	50-70	0	0.111111	0.666667	0.222222	0
	70-90	0	0	0.666667	0.333333	0
	90-110	0	0	0	0	1
	Stability Index(SI)= 0.685714 Mobility Index(MI)= 0.392857			Half-Life=11.45		

Source: Author's estimation

The above matrix (Table-3.10A) is the first short run transitional matrix. It captures the transition of states from NFHS 1 to NFHS 2. This matrix is a reflection of second Kernel density estimation and first scatter plot(figure-3.5A). Based on that transition this first short run transition matrix captures the probability of transition from one class to another. During this short time period the overall stability index is much higher than the mobility index. Because of this lower mobility, the speed of convergence is very low. It will take 11.45 years to cover the half distance between initial distribution and stationary distribution. Similarly, the following matrix shows the transition pattern of states from NFHS 2 to NFHS 3. This is the reflection of third Kernel plot (NFHS 3) and second scatter plot (figure-3.5B). Here, mobility index is found to be higher than stability index, at the same time, no lower mobility is observed.

Table-3.10(B): Transitional Probability Matrix (TPM) of states in respect ofHI from NFHS 2 to NFHS 3

		NFHS 3				
		10-30	30-50	50-70	70-90	90-110
NFHS2	10-30	0.375	0.5	0.125	0	0
	30-50	0	0.25	0.5	0.25	0
	50-70	0	0	0.444444	0.222222	0.333333
	70-90	0	0	0	0.66667	0.333333
	90-110	0	0	0	0	1
	Stability Index(SI)=0.547222 Mobility Index(MI)=0.565972			Half-Life=1.71		

Source: Author's estimation

Following this mobile nature during this short time period (NFHS 2- NFHS 3)the speed of convergence is found to be high compared to earlier period. It needs only 1.71 years to cover the half distance between initial and stationary distribution.

But, in the next period (NFHS 3 to NFHS 4), the states are becoming more stable with a higher overall stability index. As a result, the speed of convergence has decreased.

Table-3.10(C): Transitional Probability Matrix (TPM) of states in respect ofHI from NFHS 3 to NFHS 4

		NFHS 4				
		10-30	30-50	50-70	70-90	90-110
NFHS3	10-30	1	0	0	0	0
	30-50	0	0.8	0	0.2	0
	50-70	0	0.285714	0.571429	0.142857	0
	70-90	0	0	0.6	0.4	0
	90-110	0	0	0	0.166667	0.833333
	Stability Index(SI)=0.720952 Mobility Index(MI)=0.34881			Half-Life= 3.79		

Source: Author's estimation

The above three matrices are non-ergodic in nature. So, I failed to obtain the stationary distribution. Like the short run, the long run transitional probability matrix is also non ergodic in nature. Thus, I fail to obtain the stationary distribution. During this long run time period, the overall mobility index is found to be high compared to stability index. Therefore, we can expect a long run convergence towards stationary distribution with a high speed of convergence.

Table-3.10(D): Transitional Probability Matrix (TPM) of states in respect ofHI from NFHS 1 to NFHS 4

		NFHS 4				
		10-30	30-50	50-70	70-90	90-110
NFHS1	10-30	0.6	0.4	0	0	0
	30-50	0	0.285714	0.285714	0.285714	0.142857
	50-70	0	0.222222	0.555556	0.222222	0
	70-90	0	0	0	0	1
	90-110	0	0	0	0.5	0.5
	Stability Index(SI)=0.388254 Mobility Index(MI)=0.764683			Half-Life= 1.99		

Source: Author's estimation

From these short runs and long run transitional probability matrices, I can identify the chronic low-level health trap over time. If I consider the extreme lower class to identify the presence of low-level trap in terms of health index then only three states will be there (only 11.54% of total states). But if we extend the class limit from extreme lower to lower class (10-50) then the number of states at the chronic lower trap has increased (26.92%). All the classifications are made on the basis of their relative positions. It will help me to implement the policies for poorer states.

Table-3.11: Transition of states in respect of HI over time

Clubs	NFHS_1	NFHS_2	NFHS_3	NFHS_4
10-30	AS, OR, BI, MP, UP	MP, MEGH, BI, UP, OR, AS, TRI, RAJ	MP, BI, UP	BI, UP, MP
30-50	TRI, WB, RAJ, MEGH, ARUNP, GUJ, SIK	ARUNAP, J&K, WB, GUJ	AS, OR, RAJ, GUJ, TRI	GUJ, AP,RAJ,OR, AS, HAR
50-70	KAR, AP, TN, MAH, HAR, J&K, DEL, HP, PUN	AP, MAH, HAR, SIK, TN, KAR, NAG, MIZ, PUN	WB, HAR, AP,KAR, MEGH, MAH, ARUNP	MEGH, MAH, WB, KAR, DEL, HP, TN
70-90	MANI, MIZ, NAG	DEL,HP, MANI	TN, J&K, HP, PUN, DEL	PUN, TRI, J&K, GOA,ARUNP
90-110	GOA,KER	GOA, KER	NAG, SIK, MIZ, GOA, MANI, KER	NAG, MANI, MIZ, SIK, KER

Source: Author's estimation

In the higherclass, the states like Goa and Kerala are found to be stable states at the same time, performance of Manipur, Mizoram and Nagaland are also good. The states like Bihar, Madhya Pradesh and Uttar Pradesh are found to be remaining in the extreme lower trap.

3.5.3.2.1 Analysis of Variance

Before going to further analysis of club convergence, here, I have used a parametric analysis (Analysis of Variance) to check the significance difference of these arbitrary classes. Following table shows the result of Fisher's test for this analysis. It can be observed that there exists a significance mean difference among these arbitrary classes. Initially, the between and within group variations are found to be very high. As a result, in the first short run transitional probability matrix, stability index was higher than the mobility index.

Table-3.12: Mean difference across groups over time [NFHS 1 to NFHS 4]

HI	NFHS_1	NFHS_2	NFHS_3	NFHS_4
Between variation	0.587	0.430	0.443	0.267
Df	4	4	4	4
Within variation	0.025	0.023	0.019	0.012
Df	21	21	21	21
MSB	0.146	0.107	0.110	0.066
MSE	0.001	0.001	0.0009	0.0006
F-statistics	120.89***	96.84***	118.97***	110.70***

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

Following table shows the result of group specific mean difference of HI over time. The following table only captures between group difference and over time the variance is found to vary.

Table-3.13: Group Specific Mean difference across groups over time

NFHS 1	Group 1	Group 2	Group 3	Group 4
Group 2	0.157**			
Group 3	0.260**	0.103**		
Group 4	0.422**	0.265**	0.161**	
Group 5	0.519**	0.362**	0.258**	0.097**
NFHS 2	Group 1	Group 2	Group 3	Group 4
Group 2	0.142**			
Group 3	0.215**	0.072		
Group 4	0.286**	0.144**	0.071**	
Group 5	0.432**	0.290**	0.217**	0.145**
NFHS 3	Group 1	Group 2	Group 3	Group 4
Group 2	0.102**			
Group 3	0.194**	0.091		
Group 4	0.300**	0.198**	0.106**	
Group 5	0.398**	0.296**	0.204**	0.098**
NFHS 4	Group 1	Group 2	Group 3	Group 4
Group 2	0.094**			
Group 3	0.162**	0.068		
Group 4	0.247**	0.153**	0.085**	
Group 5	0.322**	0.228**	0.160**	0.074**

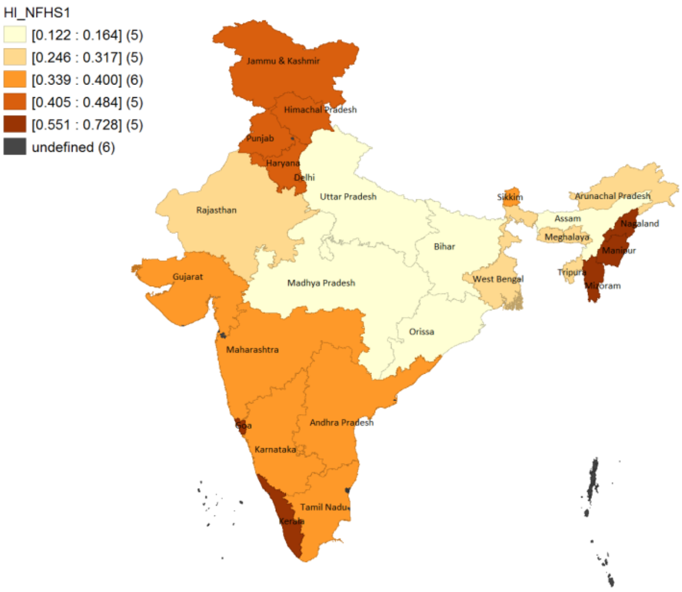
Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

3.5.4 Convergence Based on Spatial Analysis

3.5.4.1 Spatial analysis: Global and Local Moran's Index

Before going to the analysis of spatial dependency across the states in terms of health index, I have used the Indian map to get some preliminary idea about the importance of space towards club formation. Following maps capture the distribution of health index across the states for four time points. Here, I have classified the total range of health index into five quartiles based on absolute value. In these maps, clustering of states can be observed. The Northern and Southern states are having the higher health status comparedCentral and Eastern states.

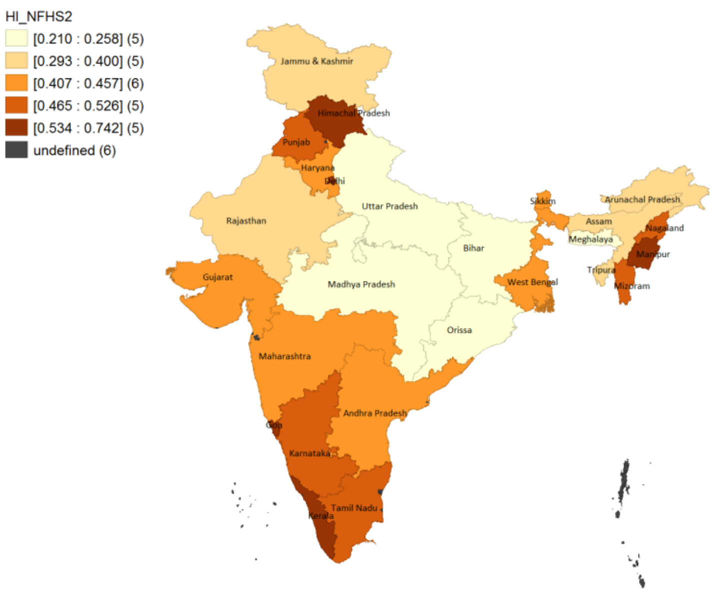
Map-3.1(A): Map Distribution of states in respect of Health Index in NFHS 1



Source: Author's estimation

Two separate clubs can be observed. Southern and Northern states from two clubs, however, Central states form another class with lower health index. This geographical distribution of HI is similar with the initial distribution of first short run TPM (NFHS 1-NFHS 2). Following the transition of states in NFHS 2, Central and Southern states are showing the presence of clustering with neighbouring states whereas distribution among the Northern states has changed. The TPM also shows that out of five states from Northern region, J&K has moved to lower class.

Map-3.1(B): Map Distribution of states in respect of Health Index in NFHS 2



Source: Author's estimation

To support the transition as well as stability over time, I have used the scatter plots of spatial dependency with respect to mean value.

Figure-3.6(A): Spatial Autocorrelation of HI in NFHS 1

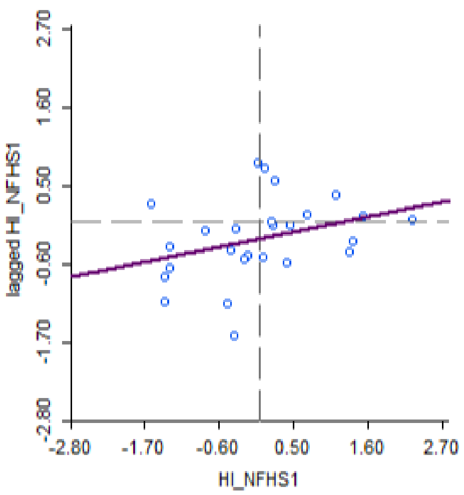
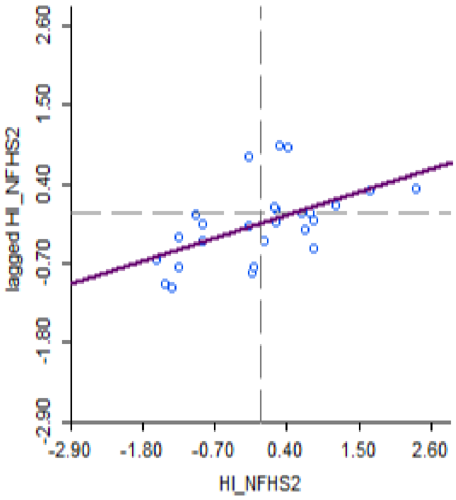


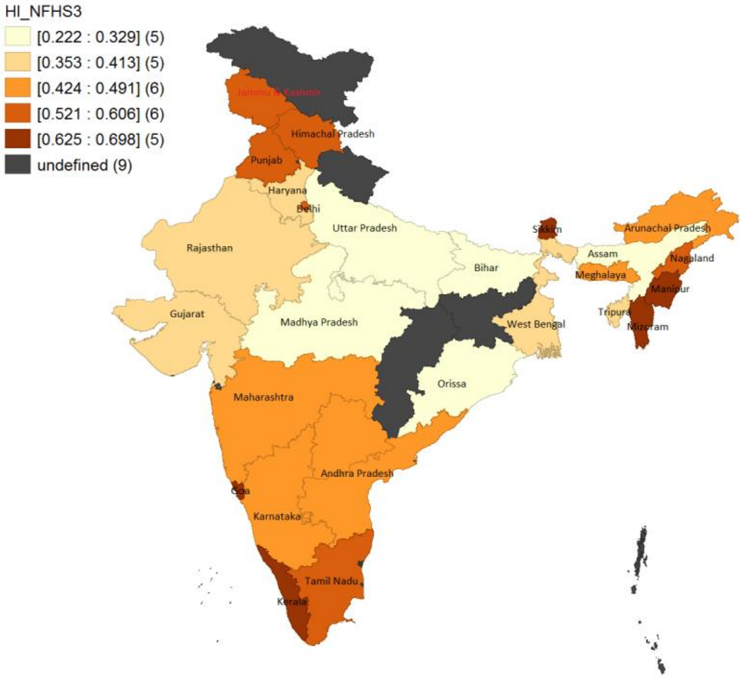
Figure-3.6(B): Spatial Autocorrelation of HI in NFHS 2



Source: Author's estimation

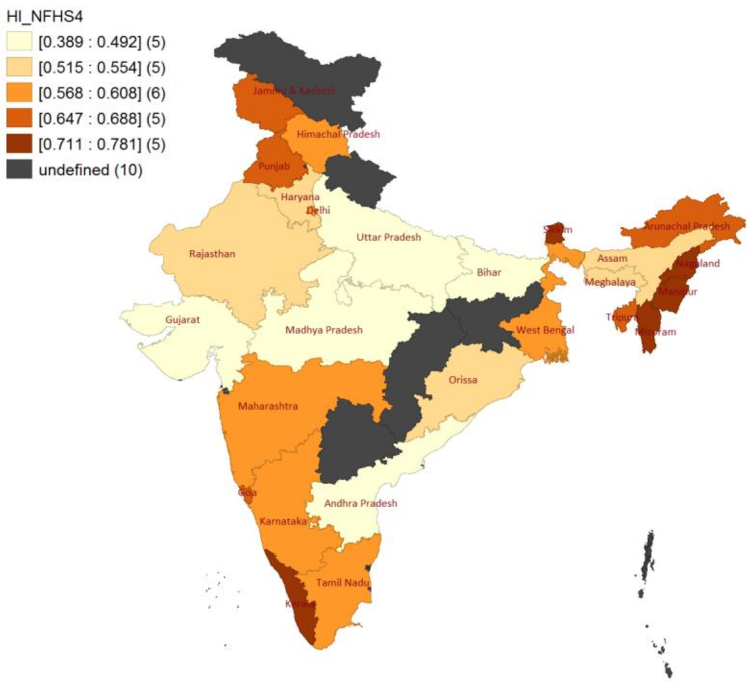
In initial time points, states are found to be more scattered compared to NFHS 2. States like Punjab, Goa, Tamil Nadu, Jammu & Kashmir, Kerala, Maharashtra and Manipur show a higher value and they are surrounded by higher value of HI. This is the high-high cluster. In next time point except J&K, other states are found to be remaining in the high-high cluster. States like Nagaland, Haryana and Karnataka have moved to the high-high cluster. States like Nagaland and Haryana are the richer states, due to improvement of their neighbour's value they move to the high-high cluster. Karnataka was the lower value of HI but not less than the mean value. As a result, it was very easy to move from an outlier cluster to homogeneous cluster. States belonging to low-low cluster are similar with the states under extreme low and lower cluster. In NFHS 3 and 4 states are holding their relative positions, as a result, stability among the cluster is found to be high.

Map-3.1(C): Map Distribution of states in respect of Health Index in NFHS 3



Source: Author's estimation

Map-3.1(D): Map Distribution of states in respect of Health Index in NFHS 4



Source: Author's estimation

Scatter plots also support the stability between the cluster. Here, the points are more scattered. But fitted line shows that there exists a positive relationship between states and its neighbours.

Figure- 3.6(C):Spatial Autocorrelation of HI in NFHS 3

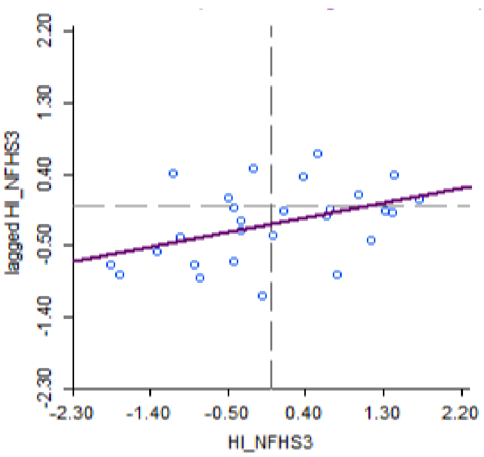
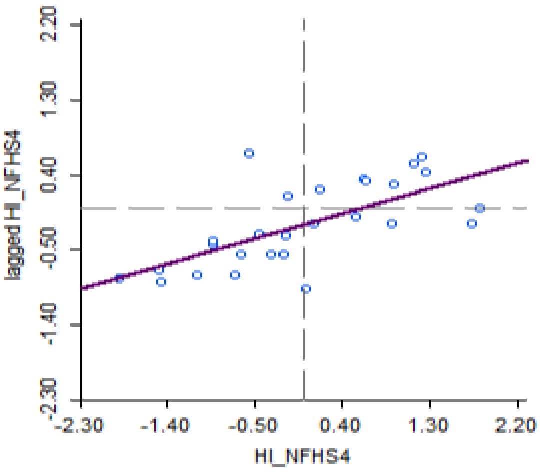


Figure- 3.6(D): Spatial Autocorrelation of HI in NFHS 4



Source: Author's estimation

Above figures show the presence of spatial impact towards club formation across the states. States like Assam, Bihar, Uttar Pradesh, Orissa, Rajasthan, Gujarat and Madhya Pradesh are found to be stable in the extreme low and low class. The above figures show that these states are nearer to each other and they are also stable in the low-low cluster. The transition of states can be observed from these figures. Given these figures, I have estimated Global Moran's Index (GMI) to examine the degree of dependency across the states. Following table shows the result of Global Moran's Index (GMI) which captures the overall spatial dependency across 26 Indian states for four time points in respect of HI. As I have mentioned in the earlier chapter that a positive GMI values refers to positive impact across states whereas for negative value of GMI indicates inverse relationship between states. For health index, I have found a positive GMI value for four time points. The value of GMI has increased over time.

Table-3.14: Result of Global Moran's Index of HI for four time points

GMI	NFHS_1	NFHS_2	NFHS_3	NFHS_4
HI_GMI	0.195	0.290	0.206	0.328

Source: Author's estimation

The fitted line shows that the states are positively correlated with their neighbouring states. Each point within the graph represents the different states. The top right portion represent the space for High-High clustering whereas bottom left space is the area of Low-Low clustering. These two spaces are used to define the homogenous neighbouring states whereas top left and bottom right are the area for heterogenous states or simply capture the presence of outlier across the states.

In NFHS 1, out of 26 states only 6 states (23%) are there in the high-high space, 42.3% states form low-low clustering whereas only 2 states are there in the low-high class (outlier space). 26.9% of states are there in other outlier space. This distribution is the reflection of the first figure.

In next time point, 26.9% and 42.3% of states form high-high cluster and low-low cluster respectively. Number of states in high low outlier space is higher than the low high space. Innext two time points the same pattern of distribution across the different space is observed. So, from TPM and Spatial analysis out of 26 states, 23.1% states are in the chronic low-level trap. Along with the aggregate measurement of spatial dependency, in this study, I have also focused on the individual spatial dependency.

Table-3.15: Result of Local Moran's Index across states for four time points

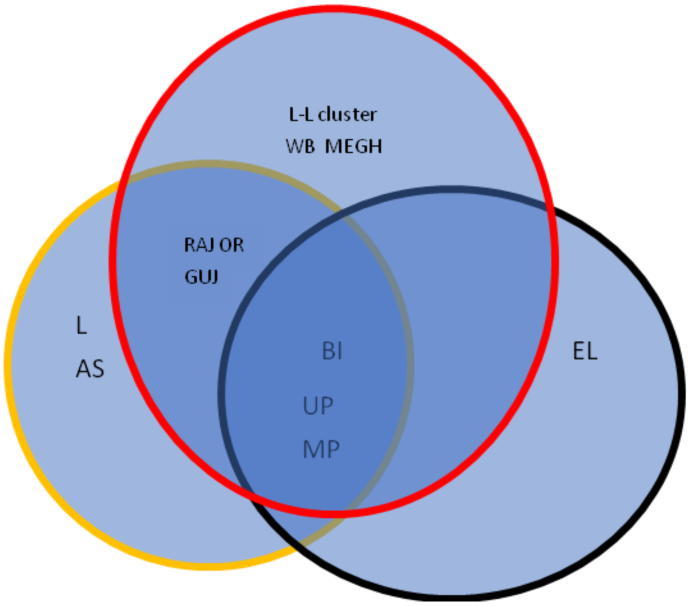
States	NFHS1	NFHS2	NFHS3	NFHS4
Andhra Pradesh	-0.025	-0.017	0.108	0.237
Arunachal Pradesh	0.038	0.0343	-0.0091	0.227
Assam	-0.419	0.034	-0.463	-0.3673
Bihar	1.587**(2)	1.430**(2)	1.539	1.689
Delhi	-0.229	-0.412	-0.675	0.010
Goa	0.105	0.514	-0.130	-0.195
Gujarat	0.114	0.074	0.7438	0.9386
Haryana	-0.007	0.011	0.009	0.1680
Himachal Pradesh	-0.023	-0.089	-0.083	-0.015
Jammu & Kashmir	0.126	-0.140	0.3583	0.1707
Karnataka	-0.030	0.369**(1)	-0.100	-0.063
Kerala	0.0548	0.826	0.1410	-0.060
Madhya Pradesh	0.871**(2)	1.040**(2)	1.3930	1.365**(2)
Maharashtra	0.00059	0.018	-0.010	0.121
Manipur	0.423	0.123	0.5687	0.685
Meghalaya	0.611**(2)	1.430	0.1185	0.220
Mizoram	-0.564	-0.166	-0.095	0.477
Nagaland	-0.379	-0.006	0.1467	0.545
Odisha	1.111**(2)	0.941**(2)	0.4129	0.396
Punjab	0.079	-0.004	-0.021	-0.070
Rajasthan	0.170	0.348	0.6623**(2)	0.6150**(2)
Sikkim	0.086	-0.031	-0.498	-0.371
Tamil Nadu	0.064	0.278	0.1441	0.027
Tripura	0.110	0.132	-0.048	0.181
Uttar Pradesh	0.466	0.411	0.7742	1.172**(2)
West Bengal	0.543**(2)	0.109**(2)	0.3018	0.0823

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level, within parenthesis 1 represents H-H cluster, 2 represents L-L cluster, 3 represents L-H cluster and 4 represents H-L cluster.

In NFHS 1 and 2, about 69% of states have positive relationship with their neighbours. It includes both low-low and high-high relationship. In NFHS 1 out of 26 states 42% states are in Low-Low cluster whereas only 26.9% states are in High-High class. In second time point, 34.6% states are in high-high cluster and the number states in low-low cluster remains same. In NFHS 3 and 4, the percentage of states having positive LMI values are 57.7% and 73.1% respectively. The percentage of states in both High-High and Low-Low cluster has decreased to 19.2% and 38.46% respectively. In terminal time point, again the number of states in high-high and low-low cluster has increased to 26.9% and 46.2% respectively. In each time point, very few states are significantly related with their neighbours. In NFHS 1, only Bihar, Madhya Pradesh, Meghalaya, Orissa and West Bengal are found to have a significant relationship. All these states are belonging to low-low cluster; Karnataka is in low-high cluster. In next time point, Bihar, Karnataka, Madhya Pradesh, Orissa, Gujarat, Tamil Nadu and West Bengal are found to behave the significant relationship. States like Karnataka and Tamil Nadu are in high-high cluster and other states form low-low cluster significantly. But, in NFHS 3, out of 26 states, only five states have the significant relationship; butin the last time point, the number has increased to six. In each time point, most of the states are found to be insignificant, as a result GMI appears to be low significant level. States in both in high-high and low-low clusters are not found to be stable.

Now, I have checked the consistency of the chronic low level health trap obtained from transitional probability matrix and spatial analysis. According to the Transitional Probability Matrix, only Bihar, Uttar Pradesh and Madhya are in extreme low trap. If we consider both extreme low and low class then Assam, Bihar, Orissa, Madhya Pradesh, Uttar Pradesh, Rajasthan and Gujarat are found to be in chronic lower trap whereas spatial analysis defines that Meghalaya, Rajasthan, Bihar, Madhya Pradesh, Gujarat, Orissa, Uttar Pradesh and West Bengal form low-low cluster. The common states are Orissa, Bihar, Madhya Pradesh, Uttar Pradesh, Rajasthan and Gujarat. They are located in the same geographical location. So, they can influence each other. The result of LMI reveals that states under chronic low-level trap have a positive relationship with their neighbours.

Figure-3.7: Venn diagram exploring Chronic low-level trap in respect of HI



Source: Author's estimation

3.5.4.2 Spatial Analysis: Spatial Autoregressive are Error Model (SDAR and SDEM)

The following table shows the complementary result of global and local Moran's index. Spatial Durbin Autoregressive model considers the lagged of dependent variable. Spatial Durbin Error model has focused on lagged residual to examine the presence of spatial dependency across the states. Here, I have run four different models under Spatial Autoregressive model and Spatial Durbin Error model. Under Spatial autoregressive model, all the rho values appear as positive and statically significant. The explanatory variables also have positive and significant impact on health outcome. Only in third model, lagged social infrastructure index has a negative impact on health. If social infrastructure of neighbours increases that will increase the health outcome of this state.

In the following table, ρ represents the impact of lag dependent variable whereas λdefines the impact of lag residual factor on outcome variable. Spatial Durbin Error model shows that all the lagged residual factors have positive significant impact on health outcome. All the explanatory factors also have positive impact whereas all the lagged explanatory have insignificant impact on health index. Here, I have examined both direct and indirect impact of explanatory variables under spatial autoregressive and error model. All the direct impacts are found to have significant whereas under spatial autoregressive model, indirect impact of lagged physical infrastructure index appears significant. This indirect impact can be obtained from coefficient of lagged explanatory variable and from coefficient of dependent variable.

Table-3.16:Result of Spatial Durbin Autoregressive Model and Spatial Durbin Error Model

Explanatory Variables	Spatial Durbin Autoregressive Model				Spatial Durbin Error Model			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Constant	NA	0.409***	-0.203**	NA	NA	0.442***	-0.209	0.268***
W*HI / Rho(ρ)	0.390***	0.0948	0.486***	0.598***				
Lamda(λ)					0.398***	0.389***	0.539***	0.693***
LnPCEE	0.172***				0.173***			
WlnPCEE	-0.036				0.049			
LnPCHE		0.133***				0.130***		
WlnPCHE		0.0278				0.048		
Ln.SII			0.414***				0.413***	
WlnSII			-0.144***				-0.004	
LnPII				0.081***				0.0778***
WlnPII				0.002				-0.009
Log likelihood Ratio	110.64	109.90	102.99	99.08	110.82	112.87	101.60	93.94
Wald Chi-square	198.76***	178.45***	157.78***	137.51***	96.29***	101.96***	35.71***	14.39***
R-Square	0.3929	0.3571	0.1919	0.0047	0.3915	0.4088	0.1645	0.0755
No. of Observation	104	104	104	104	104	104	104	104

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level, WlnPCEE defines weighted lag per capita education expenditure, WlnPCHE is weighted lag per capita health expenditure, WlnSII is weighted lag social infrastructure index, WlnPII defines weighted lag physical infrastructure index.

Table-3.17: Impact of Explanatory Variables under SDAR and SDEM

	Spatial Autoregressive Model				Spatial Error Model			
Impact	PCEE	PCHE	SII	PII	PCEE	PCHE	SII	PII
Direct Impact	0.175***	0.134***	0.421***	0.090***	0.173***	0.130***	0.413***	0.078***
Indirect Impact	0.036	0.034	0.076	0.083**	0.039	0.038	-0.003	-0.008
Total Impact	0.211***	0.168***	0.497***	0.173***	0.212***	0.168***	0.410***	0.070***

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

Spatial analysis clearly supports that there exists a spatial dependency across states in respect of health outcome. Now, I can compare this result with the results obtained from transitional probability matrix. The result of both short run and long run transitional matrix shows that out of 26 Indian states Bihar, Uttar Pradesh and Madhya Pradesh are in extreme low trap whereas Bihar, Uttar Pradesh, Madhya Pradesh, Rajasthan, Orissa, Gujarat and Assam are in extreme low and low-level trap. The Spatial analysis shows that Bihar, Uttar Pradesh, Madhya Pradesh, Rajasthan, Orissa, Gujarat, West Bengal and Meghalaya are found in Low-Low trap. Tamil Nadu and Manipur are the only two states who are stable in the high-high cluster.Both transitional probability matrix and spatial analysis provide us the result of clubs across the states. Out of these states, Orissa, Bihar, Madhya Pradesh, Uttar Pradesh, Rajasthan and Gujarat are found to be common both in chronic low-level trap as well as low-

low cluster. Therefore, here one can expect that space plays an important role behind the chronic low-level trap of health outcomes.

3.6 Major Findings

In this study, I have estimated a health index (HI) comprising three different dimensions of health across 26 states in four time points. The results show that the states are improving in respect of HI; there exist absolute β and conditional convergence in respect of HI. However, we find σ divergent in respect of HI. The result was obtained for education convergence. The inequality-based approach suggests the presence of convergence. The kernel density estimation provides a clear picture about stratification, polarization (bimodal distribution) and uni-modal distributions of states in respect of HI over the period; but in the long run there exist polarisation across states. In NFHS-1, the kernel plot shows the presence of stratification, in NFHS-2, it becomes polarization but in NFHS-3 and 4, the kernel plots become neither polarized nor stratified, rather approaching toward a uni-modal distribution toward mid value of HI. The transitional probability matrix (TPM) shows that in the short run and long run most of the states are found to be stable to their respective class (group). There exists mobility, but upper mobility is higher compared to lower mobility. The major concern arises about the existence of long-run stability of fewer (three out of 26) but bigger in population sizes large states (UP, MP, Bihar) at the lower class (club) of HI.

Appendices

Appendix 3A.1

Table-3A .1: Descriptive statistics of health indicators over time

NFHS 1	Max	Min	Range	Mean	SD	CV
ISR	985.4	887.9	97.5	938.61	24.44	0.026
Well-Nourished	79.61	51.57	28.04	65.38	7.36	0.113
LTFR	0.526	0.207	0.319	0.334	0.076	0.227
NON-ANEMIC	79.11	17.92	61.19	47.99	15.57	0.324
BMI	62.91	55.03	7.89	58.72	2.18	0.037
LE	72.9	54.7	18.2	63.39	4.78	0.075
NFHS 2	Max	Min	Range	Mean	SD	CV
ISR	983.7	911	72.7	942.69	18.80	0.019
Well-Nourished	80.97	56.97	24	69.23	7.62	0.110
LTFR	0.565	0.219	0.346	0.383	0.085	0.223
NON-ANEMIC	77.3	27.48	49.82	49.65	12.54	0.253
BMI	63.03	55.32	7.71	59.17	1.801	0.030
LE	71.7	56.6	15.1	63.65	3.74	0.052

NFHS 3	Max	Min	Range	Mean	SD	CV
ISR	985	927	58	954.02	15.58	0.016
Well-Nourished	78.9	51.67	27.23	68.63	7.58	0.111
LTFR	0.556	0.25	0.306	0.412	0.094	0.229
NON-ANEMIC	67.2	30.7	36.5	49.02	10.56	0.216
BMI	80.05	49.8	30.25	60.20	9.63	0.159
LE	73.9	64.8	10.3	70.06	2.59	0.037
NFHS 4	Max	Min	Range	Mean	SD	CV
ISR	994	949	45	968.38	10.59	0.011
Well-Nourished	84.6	62.33	22.27	74.13	6.67	0.089
LTFR	0.833	0.294	0.539	0.502	0.112	0.224
NON-ANEMIC	75.2	37.3	37.9	52.27	11.25	0.215
BMI	77	50.45	26.55	61.84	6.58	0.106
LE	75.1	64.8	10.3	70.306	2.59	0.037

Source: Author’s Estimation

Appendix 3A.2

Table-3A.2: Rank correlation between LEB and other health indicators, NFHS 1 to 4.

Variables	ISR	LTFR	NS	NW	NUW	NA	BMI
LEB (NFHS1)	0.932***	0.419**	0.677***	0.360	0.744***	0.520***	0.196
LEB (NFHS 2)	0.924***	0.495**	0.715***	0.184	0.611***	0.645***	0.212
LEB (NFHS 3)	0.854***	0.629***	0.721***	0.371	0.680***	0.681***	0.201
LEB (NFHS 4)	0.722***	0.649***	0.738***	0.330	0.571***	0.766***	0.220

Source: Author’s Estimation, LEB implies life expectancy at birth, ISR means Infant Survival Rate, LTFR implies Lower Total Fertility Rate, NS implies Not stunting, NW implies Not Wasted, NUW implies not under-weight, NA implies non-anaemic and BMI implies Body Mass Index. *** implies significance at 1 percent level.** implies significant at 5 percent level

CHAPTER-4

Exploring Long Run Human Capital Trap in India: A Sub-National Analysis

4.1 Introduction

In the growth literature, the main attention has to study income convergence. Both the Neo-classical and Endogenous growth model had focused on convergence in income based on both conditional and unconditional aspects. Neoclassical growth model stated the convergence hypothesis based on diminishing marginal returns to physical capital whereas Endogenous growth model gave more emphasis on human capital (Lucas 1988, Romar 1990). Convergence in human capital is an only path of achieving convergence in income as income or outcome is determined by the human capital (Tamura 1991). Poorer states or countries with lower human capital fail to compete with richer states or countries. Following the properties of human capital, a country with higher human capital always remains far away from poorer country, this may generate two different clubs in the economy. India's economic progress after globalization is spectacular but such economic progress fails to ensure the desirable progress of social sector development. The level of hunger in India is extremely serious; India was ranked 83 out of 113 countries in 2000; but in 2019, the rank has dropped to 102 out of 117 countries (GHI 2019). In addition to this, the decline in the child sex ratio (number of females per thousand male) over the last three decades reinforces the existence of gender discriminatory practices despite improving socioeconomic characteristics. According to World Economic Forum (WEF 2018), in Gender Gap Index India's rank in female literacy rate (FLR) is 113 out of 144 countries, in economic participation its rank is 139 out of 144 and most disappointing result is in women's health and survival, its rank is 142, just ahead of Afghanistan. The regional disparity in India in respect to major social indicators of development has been stark and persistent (Nayyar 2008). A large body of recent literature has shown that the economic reform has indeed accentuated the problem of both inter-state and inter-district disparity, preventing inclusive growth strategy (Kurian 2000; Dholakia 2003; Sen and Himanshu 2004; Raychaudhuri and Haldar 2009; Kundu and Varghese 2010; Roy and Haldar 2010; Singh 2015). Therefore, the issue of development economics in Indian context has opened up critical areas like existence of low level development trap which is caused and governed by self-reinforcing mechanism. Majority of the states after 1991 have experienced economic development but the problems of social sectors pertaining to health, education, and access to other amenities cannot be effectively addressed just by focusing on economic development (Kundu et al 2010). Both health and education are the crucial determinants of human capital. In respect of human capital index India was at 78 out of 122 countries and in 2018, however; in 2020 the rank moved to 116th position out of 157 countries (World Bank). Is India in a stagnant position in terms of human capital? Does it create any trap within the country? In order to answer this, the primary objective is to explore the low level human capital trap that persists over a long period of time across states after structural adjustment programme (SAP) initiated in 1991. The present study does not attempt to compare regional inequality in respect of social and economic variables (like per capita net state domestic product), rather it tries to highlight the existence of low level trap of human capital generated from club convergence approach among the states after SAP (1991).

Majority of the recent studies find absolute β divergent but conditional β convergence in respect of income (Chikte 2011; Cherodian and Thrilwall 2015, Lolayekar et al 2016; Sofi and Durai 2016; Chowdhury 2017; Chakraborty et al 2018; Hembram et al 2019a). A very few studies are available on club convergence based on non-parametric approach.

Studies like Trivedi (2002), Bandopadhyay (2004,2011) Kar et al (2012), Sofi and Durai (2014) have focused on club convergence based on Kernel density estimation whereas Hembram et al (2019a) and Hembram and Haldar (2019b) have used both Kernel density estimation and Transitional Probability Matrix to explore the club convergence in respect of income. Ghosh (2006) used the time series techniques to test the presence of club convergence. Sodsriwiboon and Karla (2010) examine the convergence as well as spill over impact across states using non-stationary panel data techniques. All these study found the result of club convergence across states based on income level.

Using decennial census data (1981-2001), Roy and Bhattacharjee (2009) have found **β** convergence but **σ** divergent of HDI across major Indian states. More or less the same results are found in respect of **β** and **σ** convergence in HDI in India (Ghosh 2006, Mukherjee and Chakraborty 2007, Mukherjee and Chakraborty and Sikdar 2014, Roy 2012). Research shows that the human development index (HDI) across 15 major states does not show the same increase in regional inequality, as in the case of per capita state domestic product (PCNSDP) (Singh et al 2002; Dholakia 2003; Banerjee and Kuri 2015). Haldar, Hembram and Das (2021) have constructed a deprivation index known as Multidimensional Deprivation Index. Based on this index, they have explored the clubs or deprivation trap across Indian states.

4.2 Research Gap and My Contribution

In India no studies are available on human capital convergence. Studies are mostly used the component of human capital as the determinants of economic growth as well as determinants of income convergence. As I have mentioned earlier that human capital is the only path of convergence achievements, since, human capital has the property of increasing returns to scale. Due to this property economy with higher human capital will enjoy higher returns than economies with lower human capital. So, we may have the results of dispersion in terms of outcomes. But, each indicator under human capital is assigned with an upper bound. Each and every economy will try to achieve that upper bound level. So, one can expect convergence outcome in the long run. Keeping in mind the importance of human capital, there is an ample scope to study of convergence of human capital in India. I have already mentioned my contribution to this study in chapter 1. I have formulated following research objectives in this chapter.

4.3 Objectives of the study

Following the research gap, I have five major objectives for convergence analysis of Human Capital. These are:

- Construct the Human capital index for four time points across 26 Indian states.
- Examine the presence of convergence in Human capital index for four time points across 26 Indian states using regression and dispersion-based approaches.
- Examine the regional inequality in terms of human capital index across states using generalized entropy measures of inequality.
- Explore the presence of club convergence or presence of chronic low-level human capital trap across 26 Indian states using distributional dynamics approaches (Kernel density estimation and Markov Process).
- Explore the presence of spatial dependency towards club formation across the states for four time points.

4.4 Data and Methodology

4.4.1 Data

In this chapter, I have constructed the Human Capital index across 26 Indian states for four time points (corresponding to NFHS 1, NFHS 2, NFHS 3 and NFHS 4). To construct the Human Capital Index, in this chapter, I have used education and health index obtained from chapter 2 and 3 respectively. I have already mentioned the data as well as data sources in the respective chapters.

4.4.2 Methodologies

Construction of Human Capital Index

Human capital index is a composite of health and education index and I have already constructed the health index and education index in chapter 2 and 3 respectively. In this section, I am discussing the construction of Human Capital Index. It is simply the geometric mean of health and education index. It can be written as follows;

$$HCI = [HI * EI]^{0.5} \tag{4.1}$$

The **HCI** is best seen as a measure of states's status of human capital; the progress of human capital can easily be measured by observing the difference of HCI over time. Like health and education index, this HCI does satisfy the important properties of an ideal index like transitivity, substitutability, homogeneity, convexity and sub-group decomposability (already mentioned in chapter 1).

4.5 Empirical Findings

Following the methodology of HDI, in this study, I have constructed the human capital index which is the geometric mean of education and health index. Similar to the education and health index, the value of human capital index lies between 0 to 1. Table(4.1) shows the value of the human capital index with their rank across 26 Indian states for four time points.

Table-4.1: Human Capital Index (HCI) across 26 Indian states for four time points (NFHS 1-NFHS 4)

States	HCI_NFHS 1 1992-93	HCI_NFHS 2 1998-99	HCI_NFHS 3 2005-06	HCI_NFHS 4 2015-16
Andhra Pradesh	0.231(16)	0.293(15)	0.390(15)	0.508(20)
Arunachal Pradesh	0.159(19)	0.270(18)	0.333(20)	0.594(13)
Assam	0.146(21)	0.261(19)	0.276(23)	0.478(22)
Bihar	0.043(26)	0.179(26)	0.174(26)	0.386(26)
Delhi	0.477(03)	0.589(03)	0.648(01)	0.705(05)
Goa	0.592(01)	0.608(02)	0.589(04)	0.730(03)
Gujarat	0.322(12)	0.361(12)	0.356(18)	0.508(19)
Haryana	0.325(11)	0.382(11)	0.390(14)	0.583(15)
Himachal Pradesh	0.390(07)	0.494(04)	0.626(03)	0.683(07)
Jammu & Kashmir	0.300(14)	0.291(16)	0.448(11)	0.574(16)
Karnataka	0.303(13)	0.382(10)	0.415(13)	0.590(14)
Kerala	0.577(02)	0.648(01)	0.646(02)	0.807(01)
Madhya Pradesh	0.143(22)	0.210(23)	0.248(25)	0.431(25)
Maharashtra	0.370(09)	0.408(09)	0.485(09)	0.613(10)
Manipur	0.446(05)	0.491(05)	0.541(05)	0.709(04)
Meghalaya	0.191(18)	0.190(25)	0.356(17)	0.543(17)
Mizoram	0.450(04)	0.430(07)	0.538(06)	0.695(06)
Nagaland	0.399(06)	0.333(13)	0.428(12)	0.598(12)
Odisha	0.154(20)	0.235(21)	0.292(21)	0.499(21)
Punjab	0.381(08)	0.438(06)	0.486(08)	0.659(09)
Rajasthan	0.084(25)	0.231(22)	0.284(22)	0.475(23)
Sikkim	0.134(24)	0.307(14)	0.478(10)	0.736(02)
Tamil Nadu	0.353(10)	0.415(08)	0.517(07)	0.668(08)
Tripura	0.230(17)	0.237(20)	0.364(16)	0.606(11)
Uttar Pradesh	0.135(23)	0.208(24)	0.268(24)	0.446(24)
West Bengal	0.278(15)	0.284(17)	0.351(19)	0.530(18)

Sources: Author's estimation, Note: Values in parentheses represent rank

Since it is a development index, higher value means higher level of human capital. The index value lies between 0 and 1. From the table of descriptive statistics, a preliminary idea can be generated about Human Capital Index. It is observed that all the states have been experiencing an upward trend of HCI; the mean HCI is found to be increasing; whereas the dispersion (both range and SD) fluctuates over time. But the coefficient of variations has decreased over time.

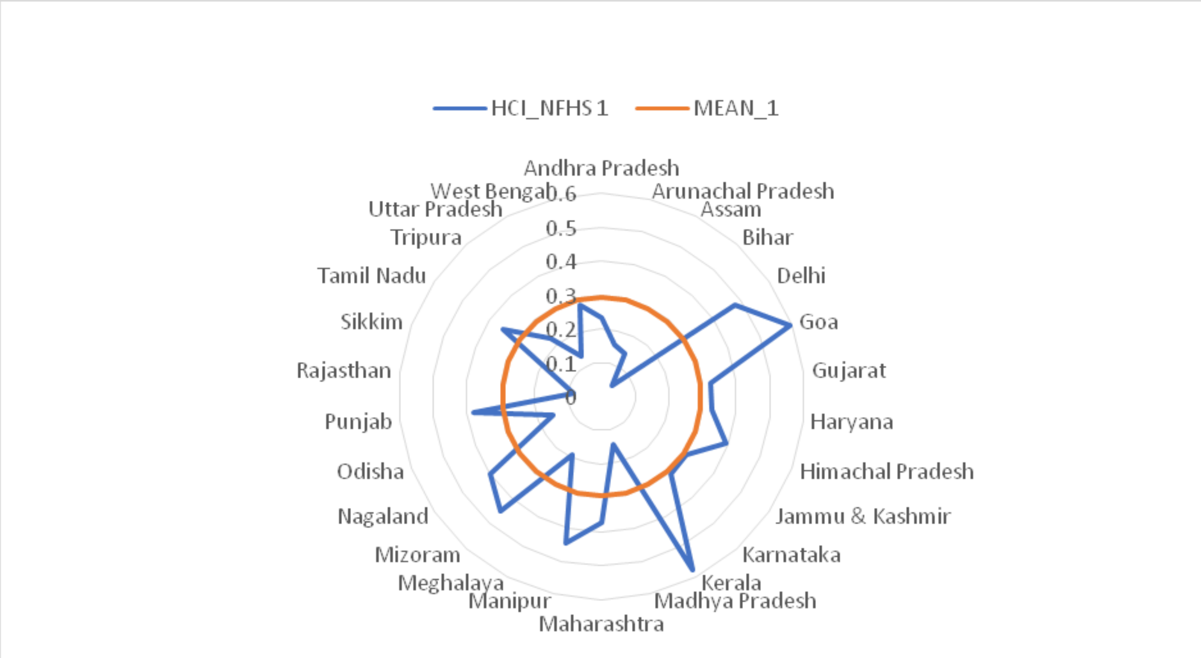
Table-4.2: Descriptive statistics of Human Capital Index over time

Year	MAX	MIN	RANGE	MEAN	SD	CV
NFHS_1	0.592	0.043	0.549	0.293	0.148	0.504
NFHS_2	0.648	0.179	0.469	0.353	0.132	0.375
NFHS_3	0.648	0.174	0.473	0.420	0.129	0.307
NFHS_4	0.807	0.386	0.420	0.591	0.107	0.181

Sources: Author's estimation

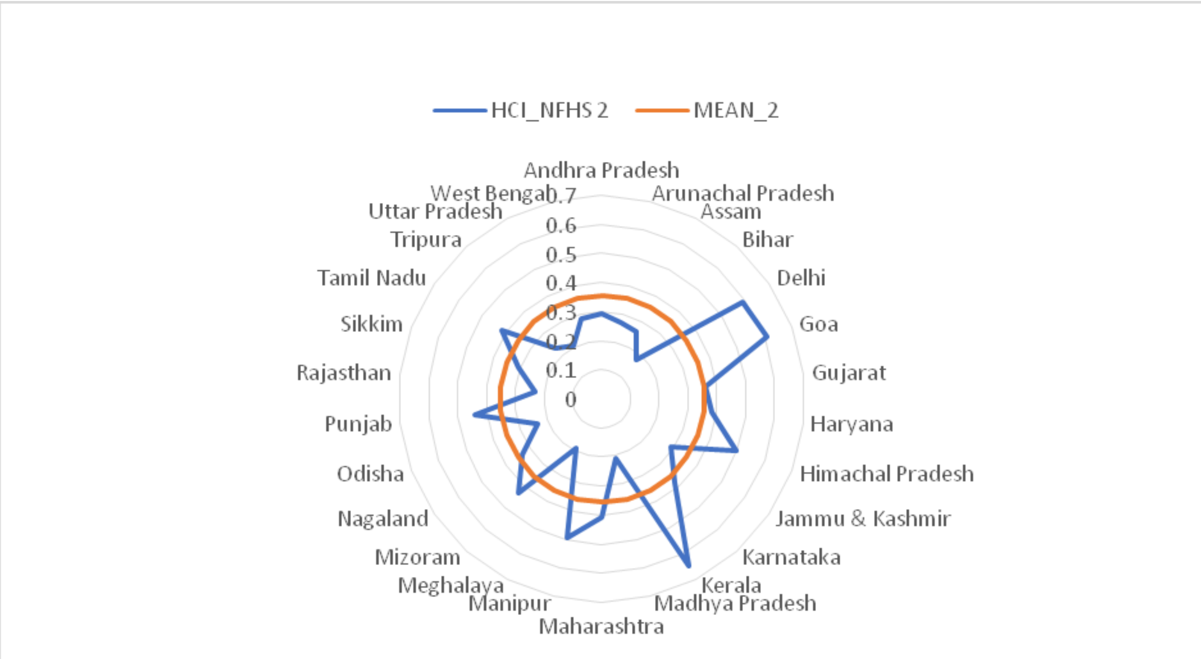
Above table (Table-4.2) describes the summary statistics of human capital index across states. The same can be obtained from graphical representation also. Based on mean values, one can identify the progress or dynamics of the distribution over time.

Figure-4.1(A): Relative position of states in respect of Human Capital Index over mean in NFHS 1



Sources: Author's estimation

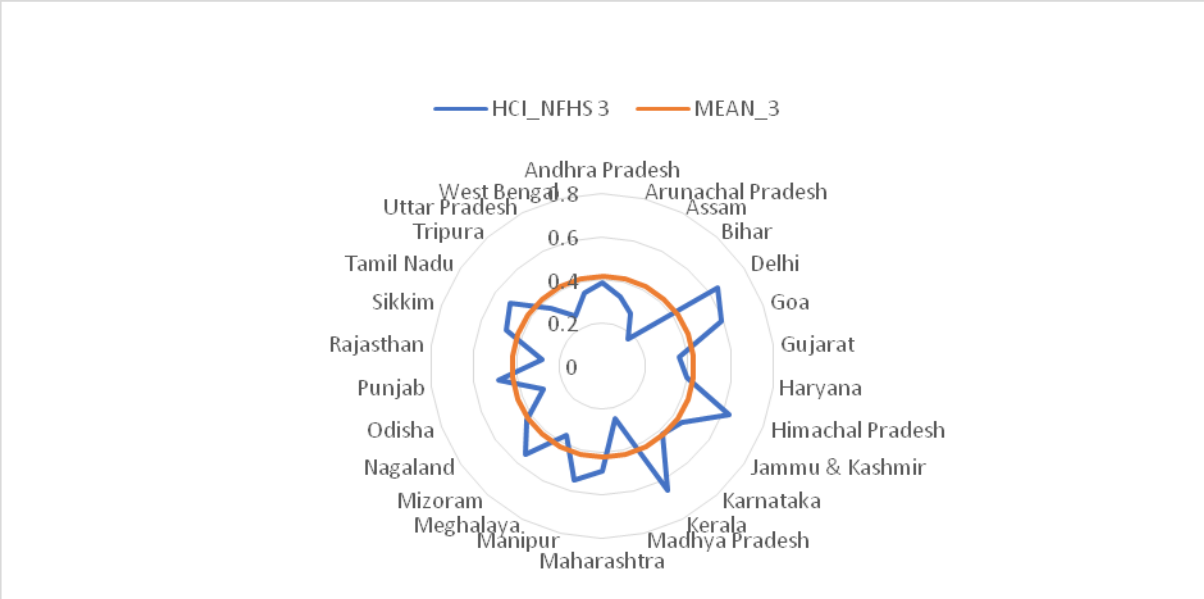
Figure-4.1(B): Relative position of states in respect of Human Capital Index over mean in NFHS 2



Sources: Author's estimation

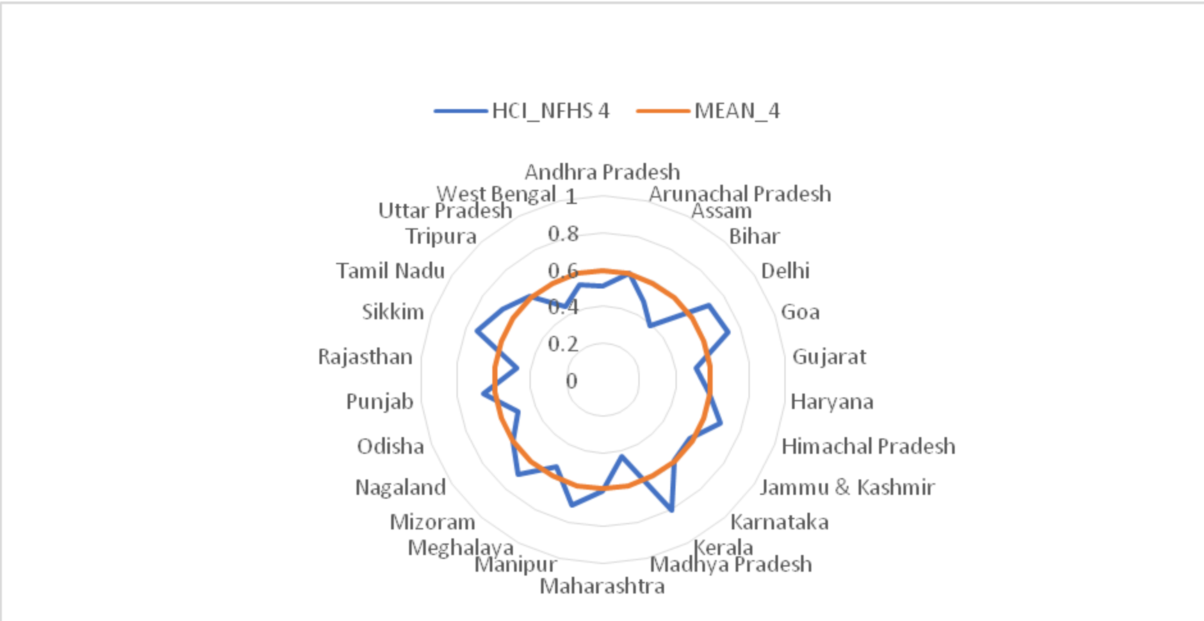
The red circle represents the mean value of HCI for four time points. It can be observed that the mean value has increased over time. In first time point, about 46.15% of states have lower human capital compared to mean value whereas in next two time points, 50% states have lower value. Similarly, in last two time points also same result can be observed. Similar to the education and health index, here, also some states always stay below the mean value (red circle).

Figure-4.1(C):Relative position of states in respect of Human Capital Index over mean in NFHS 3



Sources: Author's estimation

Figure-4.1(D):Relative position of states in respect of Human Capital Index over mean in NFHS 4



Sources: Author's estimation

In order to check the relative progress of states in respect of HCI, I have carried out the rank correlation coefficient of the states over different time points as shown in Table 4.3. The results show that the relative positions of states are found to be more or less remain unaltered over time in respect of HCI.

The rank correlation suggests that the states either belong to the lower class or higher class in HCI; it does not provide us the mobility or transition. This is to be analysed later by using distribution dynamics approach. Univariate descriptive statistics suggests an improvement whereas the bivariate analysis showing a high degree of stability. This creates a contradictory result of convergence of human capital. To answer that I have used both parametric and non-parametric measures of convergence.

Table-4.3: Rank correlation coefficient of Human Capital Index

	HCI_NFHS1	HCI_NFHS2	HCI_NFHS3	HCI_NFHS4
HCI_NFHS1	1.0000			
HCI_NFHS2	0.907***	1.0000		
HCI_NFHS3	0.872***	0.924***	1.0000	
HCI_NFHS4	0.752***	0.842***	0.920***	1.0000

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

Similar to the education and health convergence, in this chapter, I have examined the presence of club convergence using both parametric and non-parametric approach. Under parametric estimation, I have examined the absolute and conditional convergence along with measures of dispersion and inequality of human capital index.

4.5.1 Convergence based on Neoclassical Approach

The result of regression-based approach shows the presence of absolute beta convergence. The Hausman Test result clearly suggests fixed effect model which means state specific characters do matter towards variation of HCI.

Table-4.4 : Result of Absolute Beta (β) Convergence of Human Capital Index

Absolute Beta Convergence of HCI			
Explanatory variables	Coefficients	t	P>|t|
Initial HCI	-0.0789***(0.0117)	-6.72	0.000
Constant	-0.0228***(0.0059)	-3.85	0.000
Within R squared	0.4694		
Between R squared	0.7632		
Overall R squared	0.5535		
F(1,25)	45.11***		
Hausman Test	4.27**		
No. of observations	78		

Source: Authors' estimation. *** implies significance at 1 percent level.** implies significant at 5 percent level

Along with this initial human capital index, I have used four different explanatory variables to examine the presence of conditional beta (β) convergence. In the first model, the conditional variable is per capita education expenditure which has a positive impact on growth of human capital. Similar to the first model, rest of the models, also show the evidence of conditional beta convergence. In each model of conditional beta convergence Hausman statistics suggest that fixed effect is appropriate.

Table-4.5 : Result of Conditional Beta (β)Convergence of Human Capital Index

Explanatory variables	Model 1	Model 2	Model 3	Model 4
Constant	-0.089***(0.0130)	-0.0671***(0.013)	-0.237***(0.020)	-0.260***(0.051)
ln(HCI)_$_{t-j}$	-0.125***(0.017)	-0.133***(0.023)	-0.148***(0.0137)	-0.102***(0.020)
lnPCEE_5	0.039***(0.005)			
lnPCHE_5		0.0283***(0.0049)		
lnSII			0.102***(0.0087)	
lnPII				0.070***(0.014)
R^2 overall	0.3979	0.2817	0.2764	0.0222
R^2 –within	0.5680	0.4329	0.7516	0.3780
R^2-between	0.5386	0.4179	0.3489	0.0008
F(2,50)	32.87***	19.09***	75.65***	15.20***
Huasman Test	24.15***	18.73***	109.44***	26.81***
Number of observations	78	78	78	78

Source: Authors' estimation. *** implies significance at 1 percent level.** implies significant at 5 percent level

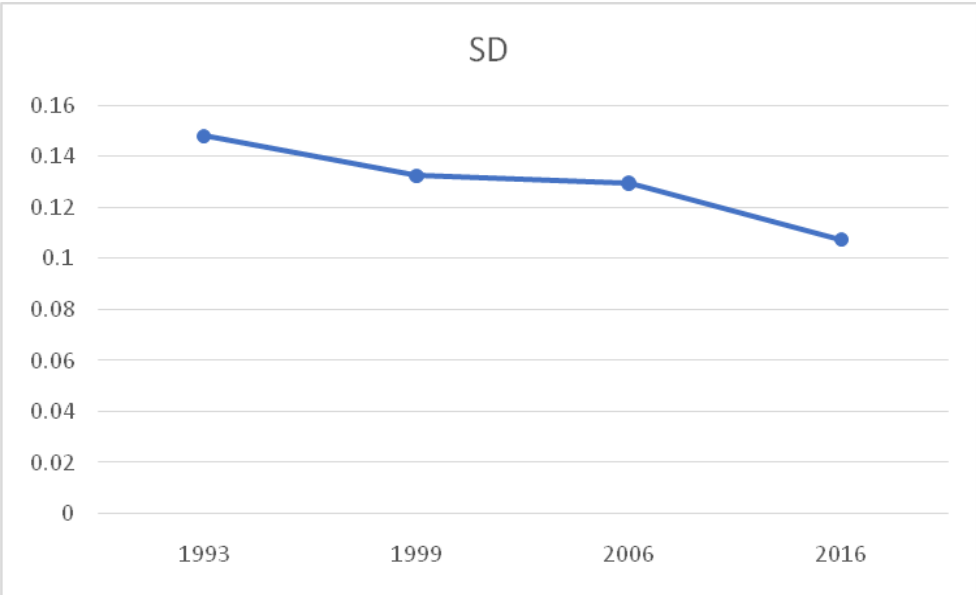
Dispersion based approach also suggests that over time states are converging in terms of human capital index. Over time, the standard deviation has decreased. So, states are experiencing sigma convergence both in the short run as well as long run. This result is found to be different from that education and health index

Table-4.6: Result of Sigma (σ) Convergence/Divergence of HCI

SD	NFHS_1	NFHS_2	NFHS_3	NFHS_4
HCI_SD	0.148	0.132	0.129	0.107

Source: Authors' estimation.

Figure-4.2: Trend of Standard deviation (σ) of HCI over time



Sources: Author's estimation

4.5.2 Convergence based on Inequality Approach

The falling trend of inequality of HCI clearly suggests that the states are converging though inequality is found to be higher among the longer tail of the distribution as shown in Table-4.7.

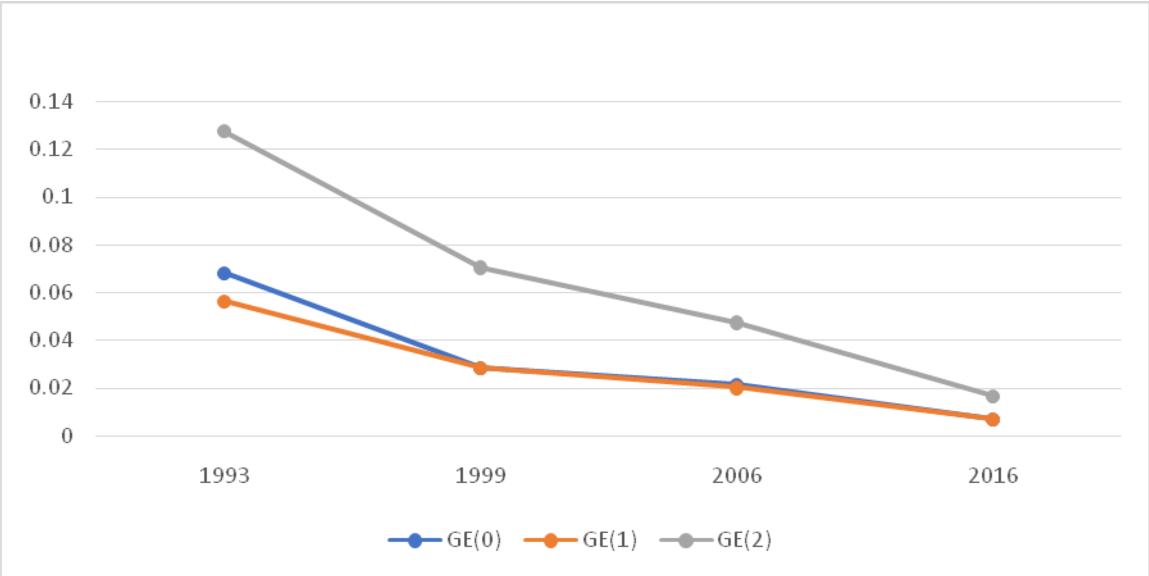
Table-4.7: Result of Generalized Entropy Measures of Inequality of HCI

GE	HCI_NFHS1	HCI_NFHS2	HCI_NFHS3	HCI_NFHS4
GE(0)	0.068	0.028	0.021	0.007
GE(1)	0.056	0.028	0.020	0.006
GE(2)	0.127	0.070	0.047	0.016

Source: Authors' estimation.

Both the tabular as well as graphical representation showthat inequality is found to be sensitive to upper part of the distribution compared to middle and lower. The GE(0) and GE(1) have more or less similar values over time. One important observation is that all the inequalities are found to be decreasing and inequality sensitive to upper part of the distribution converge towards GE(0) and GE(1). This implies states are converging based on inequality-based approach.

Figure-4.3: Trend of Generalized Entropy Measures of Inequality of HCI from NFHS 1 to NFHS 4



Sources: Author's estimation

The graphical representation of entropy measures of inequality shows that all have similar types of trending pattern and GE(0) and GE(1) coincide to each other from NFHS 2 onwards.

4.5.3 Convergence based on Non-Parametric Approach

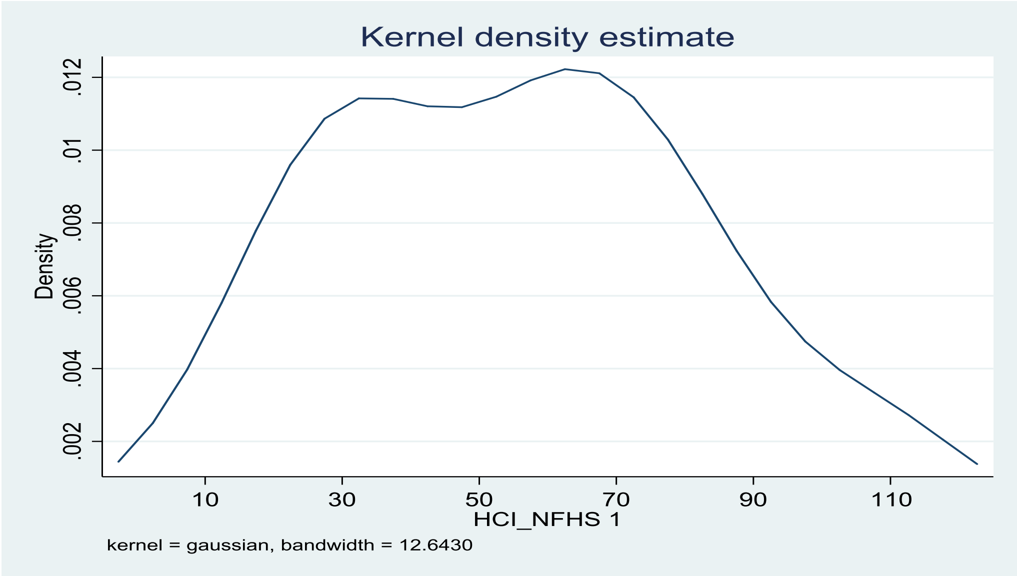
Our empirical findings support the absolute β and σ convergence; this result is not surprising because the indicators of human capital do possess some asymptotic upper value. Now, all these measures of convergence are average in nature. In the result of rank correlation coefficient, we have presence of higher stability which is not captured by absolute beta convergence, sigma convergence and general entropy measures of inequality. Are the states converging at higher level of HCI or at the lower level of HCI? To answer this question, we need the information about dynamics of the distribution as well as intra-distributional variations over time. These are not captured by the regression or dispersion-based approach even the GE measures of inequality fails to analyse this. This is analysed by kernel density which is a visual inspection of the distribution as well as "clubs" whereas the transition probability matrix (TPM) helps us to capture the states's transitional pattern over time.

I have already got some preliminary idea about the dynamics as well as club formation from the radar diagram which is a graphical descriptive statistics of human capital index. From the comparison of four Radar diagrams, it can be observed that some states have consistently lower HCI value for four time points. So, an initial picture of trap can be observed from those four radar diagrams. But again, from the radar diagram it is very difficult to trace within distribution concentration as well as variations. Initially, one can observe the presence of three classes i.e. below mean, nearer the mean and above the mean circle. States are more or less stable to these classes over time. Following this preliminary result of clubs or club convergence, I have analysed the results of non-parametric approach using Kernel density estimation and transitional probability matrix. Instead of three classes, I have constructed five arbitrary class based on relative value of HCI.

4.5.3.1 Non-parametric Approach: Kernel Density Estimation

For different time points, we have different patterns of Kernel density estimation. In NFHS 1, the distribution has two peaks with more density towards upper class. But, the difference between the density of lower class and upper class is not so high. So, initially states are forming two classes. The transition of the distribution can be observed if we compare this density estimation with density estimation for next time point. The distribution of HCI is more or less similar to the education index, since in initial time point, health index has a stratification distribution.

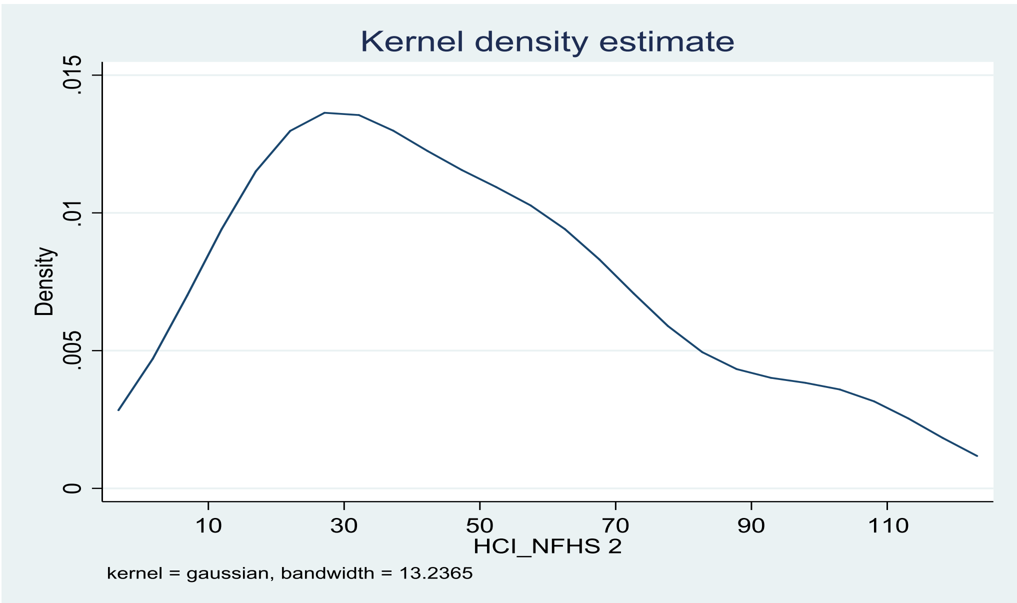
Figure- 4.4(A): Kernel density estimation of Human Capital Index in NFHS 1



Sources: Author's estimation

In the next time point (NFHS 2), the distribution is neither polarised nor stratified. Another important observation is that now states are concentrating towards lower or lower middle class instead of higher class. Radar diagram for second time point also shows that number of states below the mean value has increased from earlier time point and most of the states both in upper and lower side is higher than earlier time point. As a result, we have skewed distribution with more concentration towards extreme low and lower class. This figure is also similar to the Kernel plot of education index of NFHS 2.

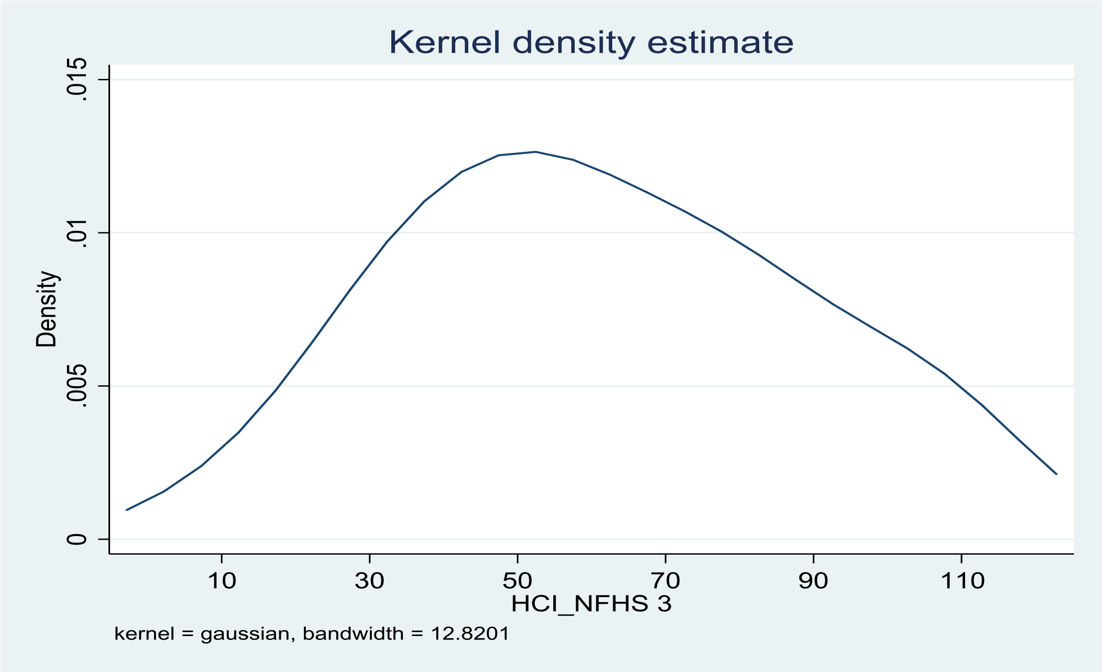
Figure- 4.4(B): Kernel density estimation of Human Capital Index in NFHS 2



Sources: Author's estimation

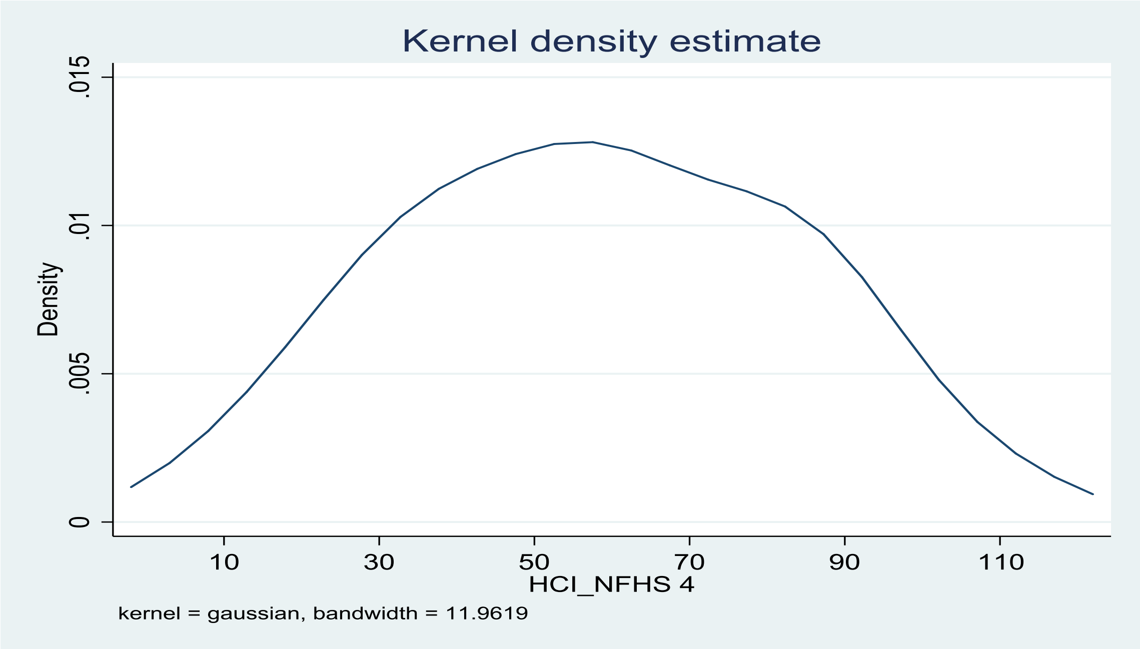
Following the distribution of second time point in NFHS 3, distribution become uni-modal and states are concentrating toward middle class. The distribution is a mixed refection of health and education index.

Figure-4.4(C): Kernel density estimation of Human Capital Index in NFHS 3



Sources: Author's estimation

Figure-4.4(D): Kernel density estimation of Human Capital Index in NFHS 4

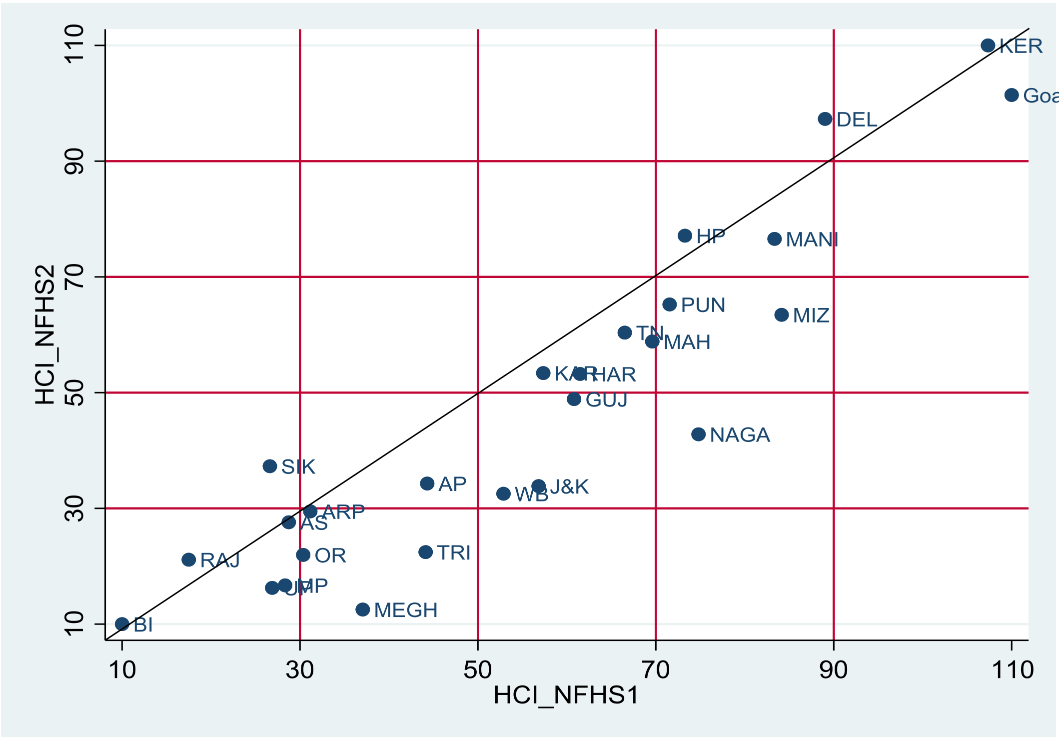


Sources: Author's estimation

Compared to third Kernel density estimation, in NFHS 4 also we have uni-modal distribution. Though health and education index had polarised distribution, the distribution of composite human capital index becomes unimodal. This indicates a clear process of convergence.

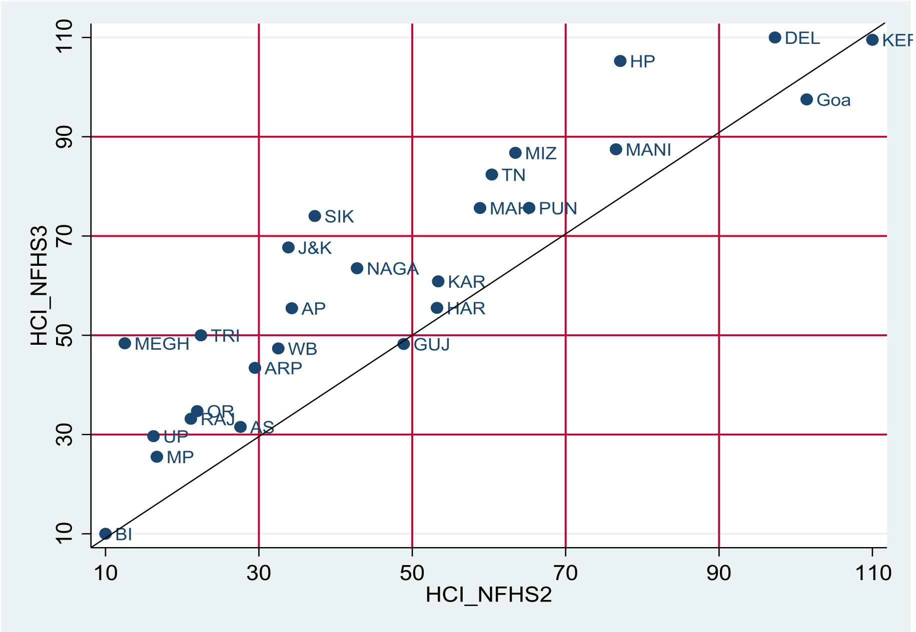
As we know the limitations of Kernel plots, next, I have analysed the results of transitional probability matrix (TPM) which is an empirical reflection of Kernel density estimation. Similar to the earlier chapters, here, also I have used the scatter plot to define short run as well as long run transitional pattern. In first plot, most of the states experienced deterioration in respect to human capital index. This is the reflection of second Kernel plot. At the same time, this scatter plot is consistent with the scatter plot of education index in NFHS 1. Compared to first Kernel plot, states are moving towards lower class in second time point. Second scatter plot captures the transition from NFHS 2 to NFHS 3. Here, most of the states are experiencing improvement in terms of HCI. As a result, in third time point, a unimodal distribution can be observed. In next time point, states are found to be improving but the improvement is very low. This distribution is captured in the last Kernel plot.

Figure- 4.5(A): Scatter Box-Plot of transition of states in respect of HCI from NFHS 1to NFHS 2.



Sources: Author’s estimation

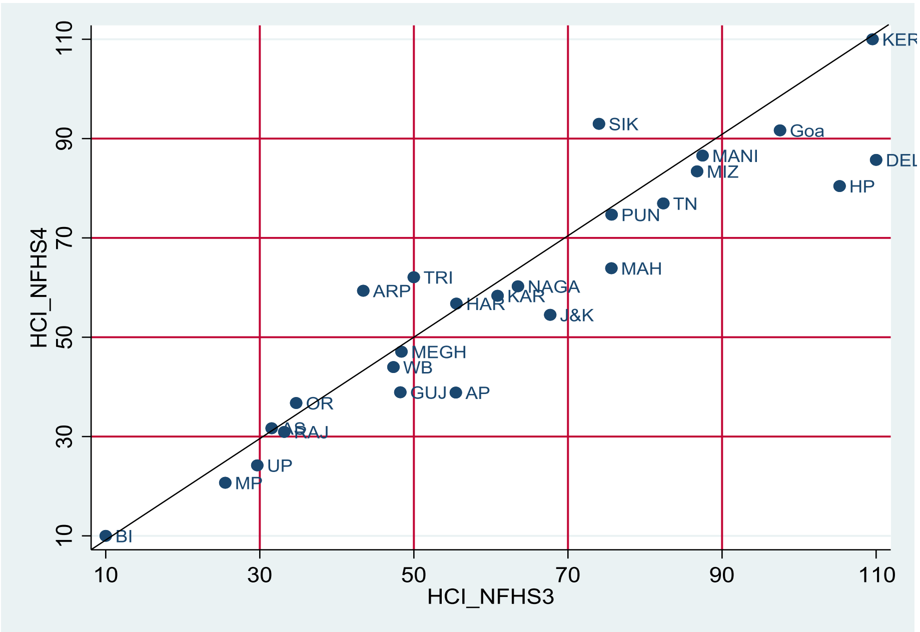
Figure-4.5(B): Scatter Box-Plot of transition of states in respect of HCI from NFHS 2 to NFHS 3.



Sources: Author's estimation

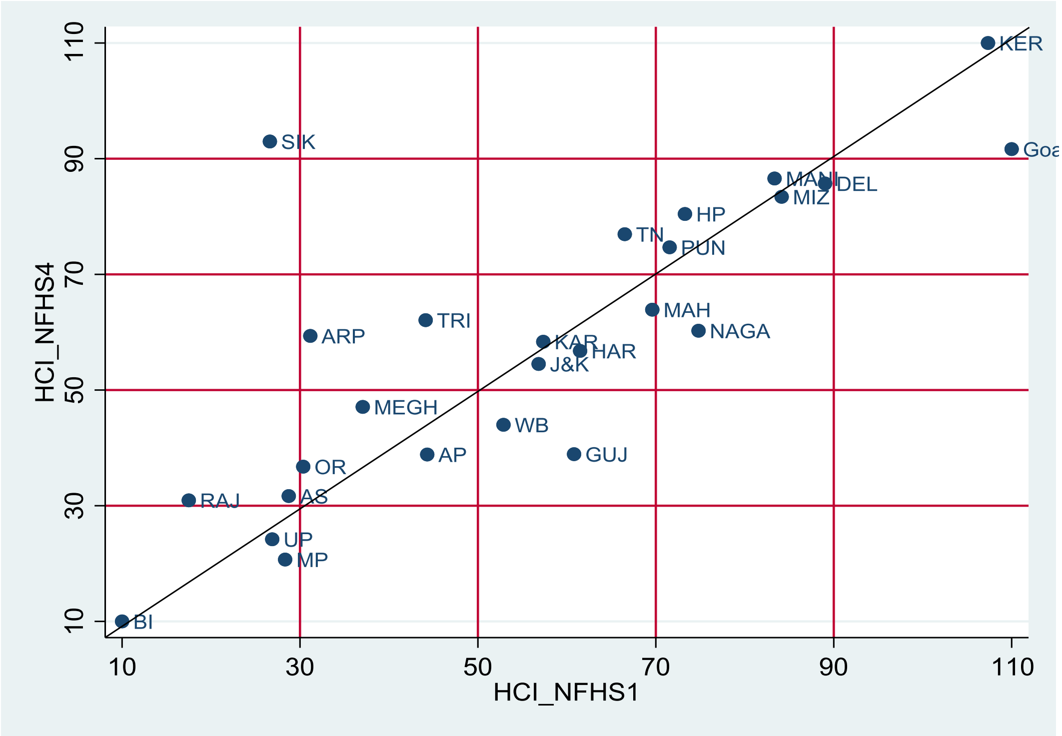
The following figure captures the transition of states from NFHS 2 to NFHS 3. Here, states are improving in terms of human capital level. Both the scatter plots of education index and health index are found to have same transitional pattern. As I have mentioned earlier that Kernel density estimation of human capital index is a mixed outcome of education and health index in NFHS 3. In the last time period, most of the states are staying around the equality line. This scatter plot also a reflection of transition pattern of both education and health index from NFHS 3 to NFHS 4.

Figure-4.5(C): Scatter Box-Plot of transition of states in respect of HCI from NFHS 3 to NFHS 4.



Sources: Author's estimation

Figure-4.5(D): Scatter Box-Plot of transition of states in respect of HCI from NFHS 1 to NFHS 4



Sources: Author’s estimation

4.5.3.2 Non-Parametric Approach: Transitional Probability Matrix

Last scatter plot captures the transition of states from initial time point (NFHS 1, 1992-93) to terminal time point (NFHS 4, 2015-16). The plot reflects the last distribution of Kernel density estimation. Compared to long run transition of education index, health index and human capital index it can be observed that Bihar, Uttar Pradesh and Madhya Pradesh are found to be in a bad position. These scatter plots easily capture the limitation of Kernel plot. Now, following the transition of states from one class to another I have estimated the probability of these transitions over time. Transitional Probability matrix (TPM) is the exact reflection of the above scatter plots. First scatter plot shows that most of the states are falling below the 45^0degree line. In the matrix, diagonal line represents that equality line. First short run matrix shows that lower mobility found to be is higher than upper mobility.

Table-4.8(A): Transitional Probability Matrix (TPM) of states in respect of HCI from NFHS 1 to NFHS 2

		NFHS 2				
		10-30	30-50	50-70	70-90	90-110
NFHS1	**10-30**	0.833	0.1667	0	0	0
	30-50	0.8	0.2	0	0	0
	50-70	0	0.429	0.571	0	0
	70-90	0	0.1667	0.333	0.333	0.1667
	90-110	0	0	0	0	1
	Stability Index(SI)=0.59 Mobility Index(MI)=0.52			Half-Life=1.23		

Source: Author's estimation

The matrix shows that both stability and mobilities are high as a result, the overall stability index and mobility index are more or less same. Since the matrix are not perfectly mobile, I have used the methodology of mobility index developed by Shorrocks (1978). Here, both the indices are more than 50% probability. Following this moderate probability of stability or mobility, the speed of convergence during these 6 years is high with lower value of half-life (1.23). This transitional probability matrix is the combined reflection of first two Kernel plots.

Table-4.8(B): Transitional Probability Matrix (TPM) of states in respect of HCI from NFHS 2 to NFHS 3

		NFHS 3				
		10-30	30-50	50-70	70-90	90-110
NFHS2	**10-30**	0.333	0.667	0	0	0
	30-50	0	0.333	0.5	0.1667	0
	50-70	0	0	0.333	0.667	0
	70-90	0	0	0	0.5	0.5
	90-110	0	0	0	0	1
	Stability Index(SI)=0.5 Mobility Index(MI)=0.625			Half-Life=1		

Source: Author's estimation

The above transitional probability matrix captures the transitional patterns from NFHS 2 to NFHS 3. It is the mathematical representation of second scatter plot. The plot shows that states are improving or they are above the equality line. Here also the matrix captures the same result with probability. Compared to earlier matrix, here upper mobility is higher than lower mobility. The overall mobility index (62.5%) is higher than the stability index (50%). Due to this higher mobility, the speed of convergence is very high. The initial distribution needs only one year to cover the half-distance between current and stationary distribution with a time span of 7 years.

Table-4.8(C): Transitional Probability Matrix (TPM) of states in respect of HCI from NFHS 3 to NFHS 4

		NFHS 4				
		10-30	30-50	50-70	70-90	90-110
NFHS3	**10-30**	1	0	0	0	0
	30-50	0	0.75	0.25	0	0
	50-70	0	0.2	0.8	0	0
	70-90	0	0	0.1667	0.667	0.1667
	90-110	0	0	0	0.5	0.5
	Stability Index(SI)=0.74 Mobility Index(MI)=0.32			Half-Life=5.62		

Source: Author's estimation

In the last short run, transitional matrix concentrates towards central and upper class. The extreme lower class has no mobility. This matrix is the reflection of last two Kernel plots and third scatter plot. Both the plots have more states towards middle and upper class. In the last short run transitional probability matrix, stability index (74%) is higher than the mobility index (32%), because in NFHS 3 and NFHS 4, the distributions are identical (third and fourth Kernel plot). As a result, the matrix shows the presence of higher stability. Due to higher stability, the speed of convergence is very low during this last ten years. The initial distribution needs 5.62 years to cover the half distance towards stationary distribution.

Following the result of short run transitional matrix, I have also constructed the long run transitional matrix. The long run TPM covers the time period from NFHS 1 (1992-93) to NFHS 4 (2015-16). This matrix captures the last long run scatter plot of transition. The plot shows that states are improving or changing their relative position in respect of HCI. But, the change is not so high. As a result, compared to initial position, most of the states are found to be stable to their respective class during this long time period. Few states are moving to the other class. So, the overall stability index is found to be higher than the overall mobility index. Compared to total time period the speed of convergence is very low as the current distribution needs 68.96 years to cover the half distance.

Table-4.8(D): Transitional Probability Matrix (TPM) of states in respect of HCI from NFHS 1 to NFHS 4

		NFHS 4				
		10-30	30-50	50-70	70-90	90-110
NFHS1	10-30	0.5	0.333	0	0	0.1667
	30-50	0	0.6	0.4	0	0
	50-70	0	0.286	0.571	0.143	0
	70-90	0	0	0.1667	0.833	0
	90-110	0	0	0	0	1
	Stability Index(SI)=0.70 Mobility Index(MI)=0.37			Half-Life=68.96		

Source: Author's estimation

All these matrixes failed to provide the stationary distribution since they are non-Ergodic in nature. So, the presence of long run clubs is not clear here. But, I have formed the following table to capture the transition patterns for both short run and long run stability to identify the chronic trap. If we consider only extreme lower class to explore the chronic trap, then we will have a smaller number of states (Bihar, Madhya Pradesh and Uttar Pradesh) with both long run and short run transitional matrix.

Table-4.9: Transition of states in respect of Human Capital Index over time

Clubs	NFHS_1	NFHS_2	NFHS_3	NFHS_4
10-30	BI, RAJ, SIK, UP, MP, AS	BI, MEGH, UP, MP, RAJ, OR, TRI, AS, ARP	BI, MP, UP	BI, MP, UP
30-50	OR, ARP, MEGH, TR, AP	WB, J&K, AP, SIK, NAGA, GUJ	AS, RAJ, OR, ARP, WB, GUJ, MEGH, TR	RAJ, AS, OR, AP, GUJ, WB, MEGH
50-70	WB, J&K, KAR, GUJ, HAR, TN, MAH	HAR, KAR, MAH, TN, MIZ, PUN	AP, HAR, KAR, NAGA, J&K	J&K, HAR, KAR, ARP, NAGA, TRI, MAH
70-90	PUN, HP, NAGA, MANI, MIZ, DEL	MANI, HP	SIK, MAHA, PUN, TN, MIZ, MANI	PUN, TN, HP, MIZ, DEL, MANI
90-110	KE, GOA	DEL, GOA, KE	GOA, HP, KE, DEL	GOA, SIK, KE

Source: Author's estimation

But, if we combine extreme low &low class to explore the chronic trap, then the number of states in the trap may increase. Both extreme low and lower class are below 50% of the relative value of HCI. But, to explore the chronic low-level trap, I have only focused in the extreme lower class only.

4.5.3.2.1 Analysis of variance

As I have considered five arbitrary classes to examine the presence of club convergence, following ANOVA results help me to check the significance mean difference among the groups.

Table-4.10: Mean difference across groups over time

HCI	NFHS_1	NFHS_2	NFHS_3	NFHS_4
Between variation	0.363	0.396	0.396	0.2911
df	4	4	4	4
Within variation	0.021	0.011	0.023	0.012
df	21	21	21	21
MSB	0.090	0.099	0.099	0.072
MSE	0.001	0.0005	0.001	0.0005
F-statistics	90.70***	188.09***	88.99***	123.84***

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

Classes are identical if they possess similar mean. The above table shows the result of analysis of variance on the basis of Fishers' test. In all time points, F statistics are high and statistically significant. Based on between and within variation we can get the result of F statistics. Here, also we can observe the group specific mean difference to observe the actual variation across the groups. In each time, we can observe that groups are significantly differ from other groups; however the NFHS 2 and 3 show a higher between group variations than other two time points whereas within group variations completely follow the opposite trend.

Table-4.11: Group Specific Mean difference across groups over time

NFHS 1	Group 1	Group 2	Group 3	Group 4
Group 2	0.079**			
Group 3	0.207**	0.128**		
Group 4	0.309**	0.230**	0.102**	
Group 5	0.470**	0.391**	0.263**	0.161**
NFHS 2	Group 1	Group 2	Group 3	Group 4
Group 2	0.086**			
Group 3	0.184**	0.097**		
Group 4	0.268**	0.181**	0.083**	
Group 5	0.390**	0.303**	0.205**	0.122**
NFHS 3	Group 1	Group 2	Group 3	Group 4
Group 2	0.096**			
Group 3	0.184**	0.087**		
Group 4	0.277**	0.181**	0.093**	
Group 5	0.397**	0.300**	0.213**	0.119**
NFHS 4	Group 1	Group 2	Group 3	Group 4
Group 2	0.084**			
Group 3	0.172**	0.088**		
Group 4	0.265**	0.180**	0.092**	
Group 5	0.336**	0.252**	0.163**	0.071**

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

In first transitional probability matrix, mobility index is moderate. In next time period, mobility index has increased due to decrease in within group variations. In next time point, both between as well as within variation are higher compared to other time points. As a result, from NFHS 3 to NFHS 4, the stability index is higher than mobility index.

Using the long run and short run TPMs, we can identify that out of 26 states only 7 states are found to be stable in the extremely lower and low level of HCI whereas only three states are found in the extreme lower trap. Surprisingly, all the states belong to the same region. If I consider only extreme lower class then except Assam all the are belonging to same region and they are forming club in terms of HCI. Is it due their geographical location?

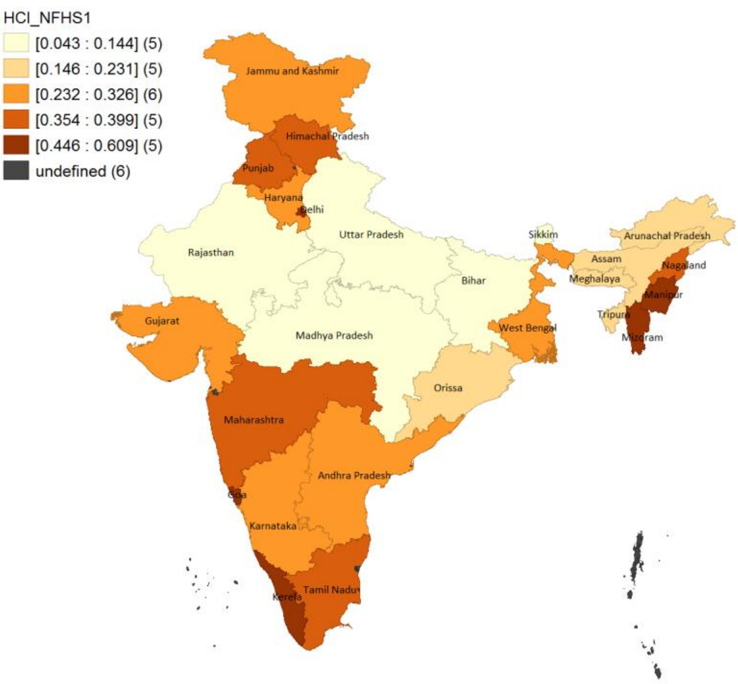
4.5.4 Convergence based on Spatial Analysis

4.5.4.1 Spatial Analysis: Global and Local Moran's Index

I have examined the presence of spatial dependency or autocorrelation across 26 Indian states using Global Moran's Index as reported in Table-4.12. However, I have also analysed the Local Moran's Index to get individual specific spatial dependency. The LMI helps us to identify the clusters as well as outliers within the distribution.

Before going to the empirical analysis of Global and Local Moran's index, first, I have examined the graphical distribution of HCI for four time points. Similar to the geographical distribution of education and health index, states are also forming spatial clusters with neighbouring states in terms of HCI. Northern and Southern states are having higher values of HCI whereas, the states from Central part of India have lower values of HCI. The first map shows the geographical distribution of states in terms of HCI. States from top, middle and bottom part of India are forming different clusters. States from top and bottom part are forming a cluster of higher HCI. Central part shows the concentration of lower HCI. In the next time point, also we have similar type of pattern. At the same time, we can observe the transitions of states due to spatial autocorrelation or due to sharing common border.

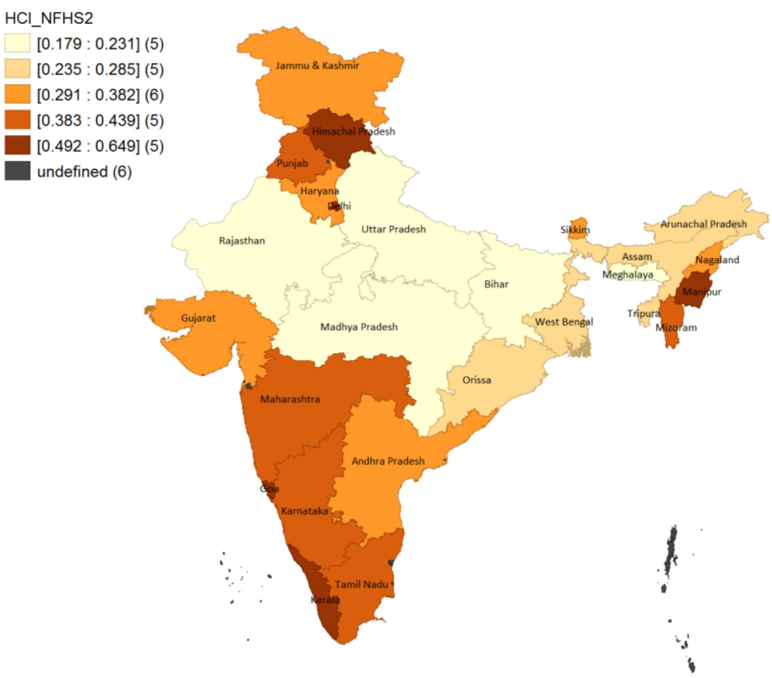
Map-4.1(A): Map Distribution of states in terms of human capital index in NFHS 1



Sources: Author's estimation

From the figures, it can be observed that due to spatial impact, West Bengal has moved from higher class to lower class.

Map- 4.1(B): Map distribution of states in terms of human capital index in NFHS 2



Sources: Author's estimation

States located in similar region are belonging to same class indicates the presences positive spatial autocorrelation across the states. The fitted line also shows the positive relationship between states with their neighbours. Initially (NFHS 1), states like Tamil Nadu, Goa, Haryana, Jammu & Kashmir, Karnataka, Kerala, Maharashtra and Manipur are in the H-H (high-high) cluster. In the next time point out of these 8 states, six states are found to be stable in the H-H cluster. Both, Jammu & Kashmir and Manipur become outlier. Why they have become outlier? To answer this question, we may observe their geographical location. State like Jammu & Kashmir has the lower value but surrounded by higher states on the other side from initial time point. Similarly, Manipur was surrounded by lower states and in the second time point neighbours of Manipur of experience lower human capital status. As a result, Manipur has become an outlier. In NFHS 1, Bihar, Madhya Pradesh, Uttar Pradesh, Andhra Pradesh, Arunachal Pradesh, Rajasthan, Sikkim, West Bengal, Orissa and Meghalaya are found to be in low-low trap, and in the next time point, these states are forming the low-low cluster along with three additional states. These additional states are Assam, Tripura and Nagaland. All these three states are in outlier or dissimilar groups. State like Assam and Tripura are in low-high group. At that region, most of the states are having lower human capital value, at the same time in second period, some of them move to lower class in terms of human capital index. Due to this dominated spatial impact both Assam and Tripura move to low-low cluster. State like Nagaland was in high-low group, but in the Eastern region, influence of lower human capital status is higher than high human capital index. The average neighbourhood value is dominated by lower value. That is why in NFHS 2, Nagaland becomes a member of low-low cluster. About 38.46% and 50% of states are forming L-L cluster in NFHS 1 and 2 respectively and all of them are located in similar region.

Figure-4.6(A): Spatial Autocorrelation of HCI in NFHS 1

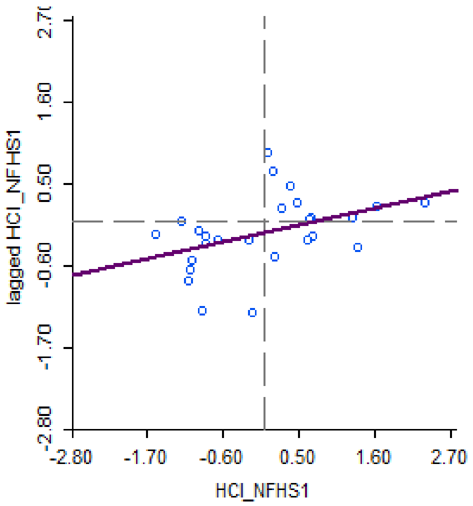
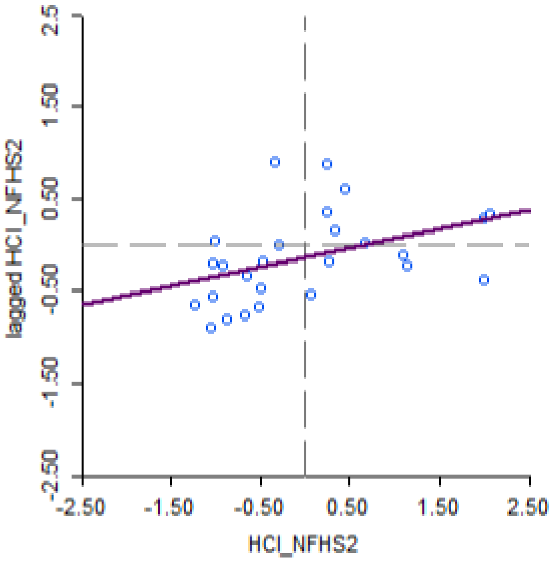


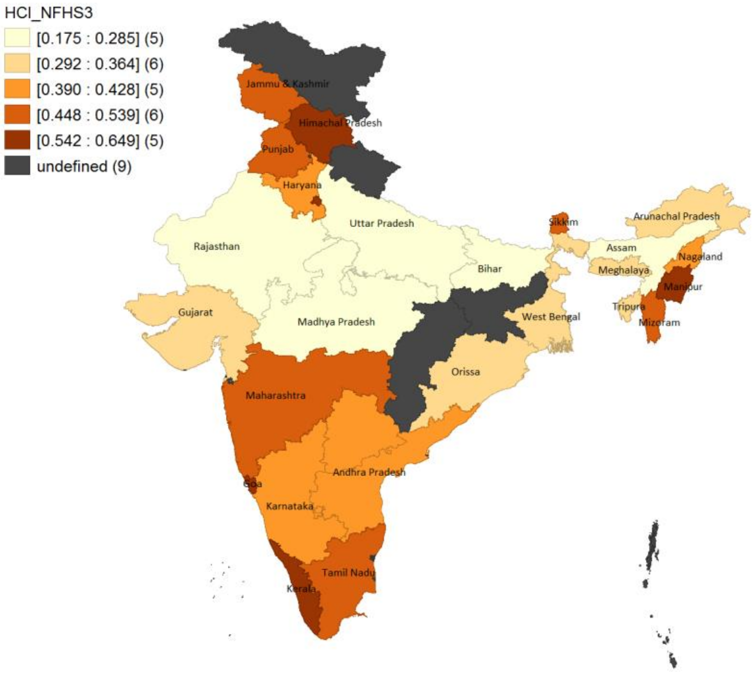
Figure- 4.6(B): Spatial Autocorrelation of HCI in NFHS 2



Sources: Author's estimation

These two figures show the relationship between individual states and their neighbours. In both the figures, a positive slopped fitted line can be observed. The line indicates that there is a positive relationship between individual states and their neighbours. This is an aggregate observation and may not be true for all states because average value may be dominated by extreme values. In similar way, we can compare the transitions as well as formation of clustering for next two time points also. Analysis of next two maps is different than earlier analysis because, here, we have some undefined states and I have not considered them. These undefined states may block the direct impact among the states. In NFHS 3, we can observe that Orissa and West Bengal have different colour than Uttar Pradesh, Madhya Pradesh or Bihar. It is because, now, there is an undefined state among them. But compared to absolute value they are still considered in the lower class. So, here we can see the importance of sharing a common border for spatial impact.

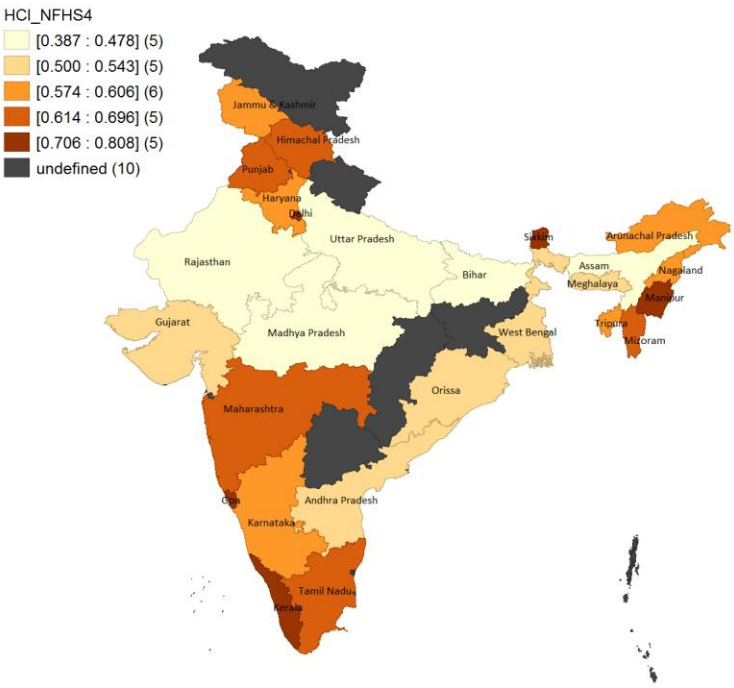
Map-4.1(C): Map distribution of states in terms of human capital index in NFHS 3



Sources: Author's estimation

Similar to NFHS 1 and 2, these two maps show that Northern, Central and Southern states are possessing similar values of human capital index. Only important result is that the importance of sharing common border towards cluster formation.

Map-4.1(D): Map distribution of states in terms of human capital index in NFHS 4



Sources: Author's estimation

In NFHS 3, Punjab, Kerala, Jammu & Kashmir, Goa and Tamil Nadu are in high-high cluster. About 46.2% of states are forming low-low cluster. Out of these states, 10 states are found to be stable compared to earlier time point. State like Andhra Pradesh, Sikkim and Nagaland move to dissimilar clusters. In NFHS 3, compared to its neighbour states like Andhra Pradesh has lower value and the average value is dominated by higher value. As a result, Andhra Pradesh forms a Low-High cluster. But in absolute sense, Andhra Pradesh is a higher state in terms of human capital index. In Eastern region, for the last two time points, the average neighbourhood human capital was dominated by lower value. As a result, here, Tripura and Sikkim are forming high-low cluster.

In NFHS 4, also we have a picture of clustering with the states located in the same region but here, number of states form low-low clustering has decreased. States like Meghalaya, Rajasthan, Bihar, Madhya Pradesh, Gujarat, Orissa, Uttar Pradesh, West Bengal and Andhra Pradesh are in found in low-low cluster. If we look at the stability then, out of 12, only 10 states are found to be stable in low-low cluster. Most of them either belong to Central or Eastern portion of India.

Figure-4.6(C): Spatial Autocorrelation of HCI in NFHS 3

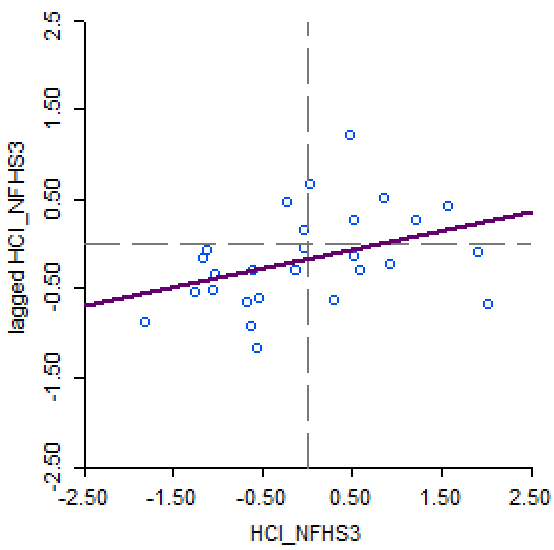
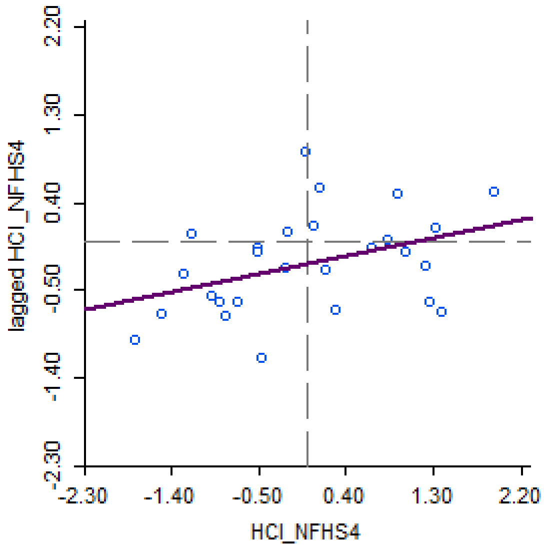


Figure-4.6(D): Spatial Autocorrelation of HCI in NFHS 4



Sources: Author's estimation

Sates like Tamil Nadu, Goa and Kerala are found to be stable in the H-H cluster over four time points whereas according to transitional probability matrix, Goa and Kerala were in higher human capital index. In similar way, one can compare the low-level trap or low-low cluster. States like Bihar, Madhya Pradesh, Uttar Pradesh, Andhra Pradesh, Rajasthan, West Bengal, Orissa and Meghalaya are stable in L-L cluster. Transitional probability matrix shows that in the long run Bihar and Uttar Pradesh are in extreme lower trap. If we extend the range of lower class then, Bihar, Uttar Pradesh, Madhya Pradesh, Rajasthan, Assam and Orissa are in low trap (less than 50% range).

Therefore, the geographical distribution of HCI clearly shows the presence of clustering with neighbouring states. Higher states are forming cluster with higher neighbouring states whereas lower are forming clubs with lower values of HCI states. But, the figures fail to identify the types of dependency. It may be either positive or negative. The result of Global Moran's Index shows the types of dependency across the states in aggregate sense for four time points.

Table-4.12: Result of Global Moran's Index of HCI for four time points

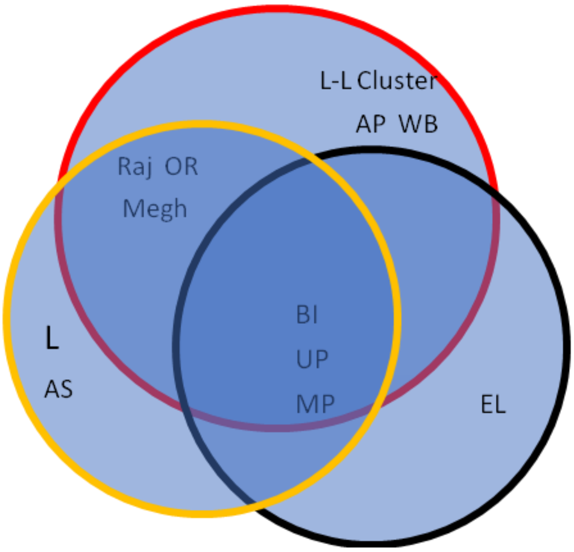
GMI	NFHS_1	NFHS_2	NFHS_3	NFHS_4
HCI	0.200	0.213	0.187	0.209

Source: Author's estimation

The value of Global Moran's Index is positive but insignificant for four time points. Along with the value, the graphical representation of the autocorrelation shows a positive spatial relationship between the value of a particular states with its neighbour. Each quadrant has specific definition and in the following figures, points are located in all these four quadrants. But the result of Global Moran's Index reveals that at individual levels states are randomly distributed. Not all states are affected by their neighbours.

Now, we can compare the chronic trap of low-level human capital with the result obtained from transitional Probability matrix. According to transitional probability matrix, states like Bihar, Uttar Pradesh, Madhya Pradesh, Rajasthan, Assam, Orissa and Meghalaya are in the chronic low-level trap over four time points. Spatial cluster analysis shows that Bihar, Madhya Pradesh, Uttar Pradesh, Andhra Pradesh, Rajasthan, West Bengal, Orissa and Meghalaya are in chronic low-level trap. The common states are Bihar, Orissa, Madhya Pradesh, Meghalaya, Rajasthan and Uttar Pradesh. According to the geographical location, these states are located in the same region;the following Venn diagram clearly shows the comparison between the results obtained from Transitional Probability Matrix and spatial analysis respectively.

Figure-4.7: Venn diagram exploring Chronic low-level trap in respect of HCI



Sources: Author's estimation

Above Venn diagram shows that how space helps to formulate clubs or clusters. All the states from extreme lower trap are belonging to L-L clusters except Assam. Assam plays an outlier.

Now, from the result of LMI, I have examined how these states are spatially influenced by each other. The following table captures the individual spatial autocorrelation across the states for four time points. From these results, we can get the reasons of insignificant Global Moran's Index. Most of the states have insignificant Local Moran's Index value. This implies that status of human capital does not depend on neighbour's status of human capital. As a result, overall Global Moran's index is found to be statistically insignificant.

Table-4.13: Result of Local Moran's Index of HCI across states for four time points

States	NFHS1	NFHS2	NFHS3	NFHS4
Andhra Pradesh	0.080	0.0762	0.028	0.0343
Arunachal Pradesh	0.128	0.2631	0.357	0.0167
Assam	0.093	0.1731	0.028	0.1963
Bihar	1.298**(2)	1.1891**(2)	1.661	1.8188
Delhi	-0.517	-0.788	-1.280	-0.753
Goa	0.6060	0.592	0.3285	0.1343
Gujarat	-0.119	-0.036	0.3146	0.6013
Haryana	0.0004	0.0682	-0.077	-0.001
Himachal Pradesh	-0.034	0.1859	-0.273	-0.200
Jammu & Kashmir	0.0265	-0.407	0.2416	-0.116
Karnataka	0.0561**(1)	0.208**(1)	-0.019	-0.003

States	NFHS1	NFHS2	NFHS3	NFHS4
Kerala	0.4387	0.803	0.6627	0.7256
Madhya Pradesh	0.6866**(2)	0.6502**(2)	0.7518	1.1043
Maharashtra	0.0960	0.0485	-0.080	-0.050
Manipur	0.2586	-0.088	-0.037	-0.001
Meghalaya	0.6766	0.5846	0.5553	0.4702
Mizoram	-0.137	-0.100	-0.185	0.0621
Nagaland	-0.204	0.012	-0.019	0.0019
Odisha	0.7445**(2)	0.755**(2)	0.3840	0.5704
Punjab	-0.072	-0.014	0.0730	-0.070
Rajasthan	0.3012	0.228	0.5830	0.6541
Sikkim	0.1089	0.178	-0.245	-0.768
Tamil Nadu	0.2057	0.326	0.3922	0.3003
Tripura	-0.012	0.044	0.0407	-0.005
Uttar Pradesh	0.3520	0.040	0.2256	0.5834
West Bengal	0.1190**(2)	0.420**(2)	0.4789**(2)	0.3486

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level, within parenthesis 1 represents H-H cluster, 2 represents L-L cluster, 3 represents L-H cluster and 4 represents H-L cluster.

In NFHS 1, out of 26 states 22 states have positive Local Moran's Index whereas in NFHS 2 and NFHS 3, 19 states have positive LMI values. In terminal time point, the number of states having positive LMI has decreased to 14. In the initial time point, out of those 22 states, only 10 are in high-high cluster and 12 states form low-low cluster. In next time point, out of 19 states, 7 states are forming H-H cluster whereas 12 states are in L-L cluster. In NFHS 3, in total we have 19 significant states, out of these states 6 states are found in H-H cluster and 13 states are found in L-L cluster. In terminal time point, out of 14 states, 6 states form H-H cluster and 8 states form L-L cluster.

All the states under the low-low trap, have positive LMI, and some of them are found to be significant. So, we can observe the presence of spatial impact towards club formation. In NFHS 1, Bihar, Madhya Pradesh, Meghalaya, Orissa and West Bengal are forming L-L cluster significantly and Karnataka is in H-H cluster in terms of human capital index. In next time point, out of 12 states only 4 states are in L-L cluster (Bihar, Madhya Pradesh, Orissa and West Bengal) and Karnataka is in H-H cluster. In NFHS 3 and 4, the number of states in L-L cluster has decreased but Karnataka is the only which is fixed at H-H cluster over the time points. None of the states under L-L cluster are found to be stable. They are fluctuating but still they have some spatial dependency.

4.5.4.2 Spatial Analysis: Spatial Autoregressive and Error Model

Similar to the result of Global Moran's Index and Local Moran's Index, regression-based approach also analyses the spatial dependency across states over time. It gives the result of presence of neighbourhood impact across states for four time points. Here, the analysis is based on both dependent and independent variables. This is the advantage of the regression-based analysis of spatial dependency compared to GMI and LMI analysis. The SAR model shows that under each sub model, outcome variable is positively influenced by it's neighbours value.

Table-4.14:Result of Spatial Durbin Autoregressive Model and Spatial Durbin Error Model

Explanatory Variables	Spatial Durbin Autoregressive Model				Spatial Durbin Error Model			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Constant	0.156***	0.336***	NA	0.019	0.195***	0.381***	NA	NA
ρ	0.253***	0.152	0.436***	0.721***				
λ					0.328**	0.323**	0.429***	0.736***
lnPCEE	0.267***				0.261***			
WlnPCEE	-0.052***				0.027			
LnPCHE		0.168***				0.168***		
WlnPCHE		-0.036				0.070**		
Ln.SII			0.663***				0.682***	
WlnSII			-0.191				0.134	
LnPII				0.148***				0.142***
WlnPII				-0.112***				0.066
Log likelihood Ratio	114.80	107.75	110.75	90.79	115.15	109.09	110.57	82.95
Wald Chi-square	379.58***	308.41***	363.76***	216.62***	220.99***	183.15***	168.98***	44.72***
R-Square	0.4539	0.4175	0.0.862	0.1776	0.4801	0.4581	0.0953	0.0669
No. of Observation	104	104	104	104	104	104	104	104

Source: Author's estimation, , *** implies significance at 1 percent level.** implies significant at 5 percent level, WlnPCEE defines weighted lag per capita education expenditure, WlnPCHE is weighted lag per capita health expenditure, WlnSII is weighted lag social infrastructure index, WlnPII defines weighted lag physical infrastructure index.

In the above table ρ represents the impact of lag dependent variable whereas λ defines the impact of lag residual factor on outcome variable. Under SAR model, I have constructed four different model based on different explanatory variables. Out of these four models, first, third and fourth model show that dependent variable of neighbours has a positive and significant impact on the level of human capital. Only in second model the coefficient of lagged dependent variable appears as insignificant. In each model the own explanatory variables have positive and significant impact on human capital whereas for lagged independent variable, I have a mixed result. Lagged per capita education expenditure and lagged physical infrastructure index have negative as well as significant impact on dependent variable.

Similarly, SEM shows that outcome variable is positively related with lagged residuals of neighbours. The impacts are found to be statistically significant. Here, I have four different models. In each model, own dependent variable has positive and significant impact on dependent variable but lagged independent variables do not have any significant input on the outcome variable.

Along with this spill over effect on dependent variable, the following table provides the result of both direct and indirect impact of independent variable. Direct effect of independent variables means, impact of own independent variables of i-th states on dependent variable of the same state. The indirect impact occurs when the coefficient captures the weighted independent variables. At the same time, rho (ρ)consists some indirect impact of independent variables. For different explanatory variables, we have different amount of impact.

Table-4.15: Impact of explanatory variables under SDAR and SDEM

	Spatial Durbin Autoregressive Model				Spatial Durbin Error Model			
Impact	PCEE	PCHE	SII	PII	PCEE	PCHE	SII	PII
Direct Impact	0.268***	0.169***	0.673***	0.146***	0.261***	0.167***	0.682***	0.142***
Indirect Impact	0.015	0.055***	0.121	-0.013	0.022	0.055**	0.106	0.052
Total Impact	0.283***	0.224***	0.794***	0.133***	0.283***	0.222***	0.788***	0.194***

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

Both in SAR and SEM model, all the independent variables have positive and significant impact. The same result was already found in the analysis of conditional beta (β)convergence. Only per capita health expenditure has positive and significant impact on the outcome variable. Initially, all the lagged independent variables had negative impact but due to some hidden indirect impact (included in rho(ρ) and lambda(λ)) the overall indirect impact appears as positive. All these had positive impact on growth. Therefore, spatial dependency based on dependent variable is more prominent than that of index variables.

Now, I can compare the result of clubs or clusters with the result obtained from transitional probability matrix. According to the transitional probability matrix (TPM), states like Assam, Bihar, Orissa, Madhya Pradesh, Uttar Pradesh, Meghalaya and Rajasthan are in extreme lower and low trap over time. Spatial analysis shows that Meghalaya, Rajasthan, Bihar, Madhya Pradesh, Orissa, Uttar Pradesh, Andhra Pradesh and West Bengal are in low-low cluster. By comparing these two clusters obtained from different approaches, it can be observed that Bihar, Orissa, Madhya Pradesh, Meghalaya, Rajasthan and Uttar Pradesh are common in both the two approaches. Therefore, club formation and club convergence is to some extent is influenced by geographical location.

4.6 Major Findings

The present study empirically estimates the convergence of human capital using an index (known as HCI) across 26 Indian states over a period from 1992-93 (NFHS 1) to 2015-16 (NFHS 4). This HCI is more or less identical with the HCI constructed by the World Bank in 2018 in respect of methodology. States are experiencing an upward trend of human capital based on index value; convergence of HCI does hold based on neoclassical growth theory. Keeping in mind the limitations of neoclassical growth theory, I have studied club convergence, regional inequality of HCI and its sources using distribution-based measure of inequality. The results suggest that overall inequality in HCI over time declines and it is more sensitive to the upper tail of the distribution. The results of club convergence based on kernel density and Markov process of probability transition clearly support the existence of polarization of states in respect of HCI and the persistence low level trap of HCI. According to distributional dynamics approach, there are only 8 states are found to be in extreme lower and low-level trap of HCI where extreme lower trap consists only three states (Bihar, Uttar Pradesh and Madhya Pradesh).

Based on the findings of spatial autocorrelation, we can say that human capital is spatially related; high-high and low-low clusters of states in respect of HCI are quite prominent and statistically significant as shown in four-quadrant diagram. Out of those eight states under low-level human capital trap, six states are forming low-low cluster. The geographical distribution shows that they are located in same region and the results of LMI support the positive dependency among those states under chronic trap.

CHAPTER-5

Convergence in Human Capital index: A Sub-State level Analysis

5.1 Introduction

Health and education are the major components of human capital that provide social benefit in an economy. Strengthening such social services is an important contribution to achieve the millennium development goals (MDG). Sustainable development goals (SDG) also focus on these two dimensions along with other socio-economic factors (poverty, environment, inequality, industry-innovation and infrastructure etc.). Most of the development measurement indices are constructed based on these two major components of human capital. Presence of unbalanced regional development across districts is an important problem for policy makers. Since independence most of the policies were related to development of states. In India, states are different in terms of area, population, resources, infrastructures etc. These differences across states generate regional disparity in terms of per capita income. Districts within states serve as an important unit of administration as development policies, programmes and schemes are implemented trough district level administration. Thus, at the beginning of tenth five year plan, policy makers formulated policies to identify the most backward districts across the states. During this planning, the key initiative was Rashtriya Sam Vikash Yojana (RSVY). This scheme had identified 147 most backward districts spread across different states. Another policy known as Backward Regional Grant Fund (BRGF) was used to define the regional inequality across districts during 11th five year plan. This policy had identified around 250 districts are backward in terms of physical and social infrastructure(Programme, Evaluation Organization, Planning Commission, 2014). The chronic incidence of non-monetary aspects of poverty measured by Multidimensional Poverty Index (MPI) creates hindrance to achieve MDG, especially in India. It is estimated that about 1.6 billion people are living in MPI (comprising health, education and standard of living) across the world, and nearly 440 million of them are in eight large Indian states; eight Indian states that have a similar number of poor as in 25 African countries are Bihar, Jharkhand, Madhya Pradesh, Uttar Pradesh, Chhattisgarh, Odisha, Rajasthan and West Bengal; the most impoverished region in South Asia is Bihar (Alkire and Robles 2017). Historically, West Bengal was a rich state, but recent finding of massive concentration of poor people has clearly proved that West Bengal has failed to retain its earlier position whereas the Western and Southern states are performing very well in terms of income as well as in other socioeconomic factors. These eights states captured about 44.23% districts out of 640 districts (according to census 2011). Performance of states depends on the performance of districts. Therefore, it is important to focus on sub state level analysis to reap the benefit from both aggregate and disaggregate level.

Earlier chapters deal with human capital convergence along with its subcomponents at sub national level analysis. Following the same pattern of study in my earlier chapter, in this chapter, I have tried to examine the convergence as well as to explore the chronic extreme low-level trap in terms of education, health and human capital across the districts in India. This is why my study is disaggregated level from the standpoint of geographical as well as administrative units.

Similar to the sub national analysis, most of the study focused on income convergence across districts. Shaban (2006) has examined the presence of convergence in terms of per capita districts domestic products using regression-based as well as dispersion-based approach across 30 districts of Maharashtra during the period 1994-2003. The study found the presence of both beta and sigma convergence across the districts.

Dadibhavi (2019) used districts per capita income to examine the convergence across 27 districts of Karnataka during the period 2000-2013. The study has used both regression and dispersion-based approach to analyse the convergence. In this state, districts are experiencing both absolute beta and sigma divergence.

Singh et al (2014) had used per capita districts domestic product to examine the presence of convergence across districts from nine states in India. The study did not find any evidence of absolute convergence or divergence. However, the study has used several conditioning variables. Finally, the study has found an evidence of conditional beta convergence.

Das et. al. (2015) have focused on maximum number of states as well as districts in their study. They have considered 575 districts from 28 states for the time period 2001-2008. The study has found an evidence of absolute beta convergence for districts within some states (Assam, Chhatisgarh, Kerala, and Rajasthan) whereas for few states the study has found the evidence of absolute beta divergence across districts.

Misra et. al. (2020) have examined the presence of income convergence across 388 districts in 12 states during the period 2001-2011. They have examined the convergence in income both within and between districts across the states. The study has found the evidence of divergence across states as well as districts.

5.2 Research Gap and My Contribution

Earlier literatures have focused on the income convergence only. They did not focus on convergence on human capital or its components (education or health). At the same time none of the study identify the backward districts based on these input factors. Earlier studies have used either regression, dispersion or inequality-based approach, none of study considered non-parametric approach or spatial analysis to explore the club convergence across the districts. Here, I have tried to examine the convergence of HC across districts for better policy prescription. So, similar to the state level analysis, here, also I have an ample scope to explore my research questions. I have already mentioned the contribution of my overall study in chapter 1.

5.3 Objectives of the study

- Construct the Education Index, Health Index and Human Capital Index across 539 districts in India for three time points (NFHS 3 (2005-06), CENSUS 2011 and NFHS 4 (2015-16)).
- Examine the presence of convergence in Education Index, Health Index and Human Capital Index for three time points across 539 districts in India using regression and dispersion-based approaches.
- Examine the trend of inequality in terms of education health and human capital index using generalized entropy measures of inequality.
- Examine the presence of club convergence or presence of chronic low-level trap in terms of Education Index, Health Index and Human Capital Index across 539 districts in India using distributional dynamics approaches.
- Explore the presence of spatial dependency towards club formation across the Indian districts for three time points.

5.4 Data and Methodologies

5.4.1 Data

In this chapter, I have focused on the convergence in human capital index along with its component at sub state level analysis. Similar to the earlier chapters, in this chapter, I have used non parametric analysis to examine the presence of chronic low-level trap. I can compare the result of chronic low-level trap with the result obtained from sub national level analysis. The sub national level analysis started from 1992-93 (NFHS 1) to 2015-16 (NFHS 4). If I consider NFHS 1 for district level analysis then number of districts will be very low. So, in order to cover the maximum number of districts and to keep the analysis consistent with the state level analysis, here, I have started the analysis from 2006 (NFHS 3) to 2016 (NFHS 4). I have split the total time span into two interval, 2006-2011 and 2011-2016.

Due to inadequate data at the district level, I have used only few indicators from each dimension to define human capital. To construct education index, I have considered Gross Enrolment Ratio to primary and upper primary school along with the literacy rate. The data for gross enrolment ratio for primary and upper primary and literacy rate are drawn from DISE, Government of India. Under health dimension, I have considered Infant mortality rate and total fertility rate from child and reproductive health dimensions respectively. These data have been drawn from Census, Government of India. Fourth Round of National Family Household Survey provides us the data on BMI. In NFHS 3 and Census 2011 do not provide the data on BMI. That’s why I have dropped that variable from my analysis.

In order to study the district level variations of education, health and human capital, I have used data from different sources. Some data are interpolated using appropriate methods. Along with these outcome variables, I have used percentage of urban population and some variables from the dimension of social infrastructure. The variables are number of primary schools per 1000 children, upper primary school per 1000 children, Sub centre per 30000 population, Primary health centre per 30000 population and community health centre per 30000 population. These data are drawn from DISE, NITI Aayog GoI and NRHM 2011, 2015-16.I have tried to focus on the maximum number of districts as well as maximum number of indicators from education and health dimensions with a view to cover a comprehensive study of human capital at the district level.

5.4.2 Methodologies

Following the same methodologies of construction of education index, health index and human capital index in earlier chapters, here, I have constructed the education, health and human capital index across 539 districts for three time points [NFHS-3(2005-06), CENSUS 2011 and NFHS-4(2015-16)]. Education index consist gross enrolment ratio to primary and upper primary school and literacy rate. So, under education index, we have two indicators, enrolment and literacy. On the other side, health index considers infant mortality rate and total fertility rate.

Before going to construct the indices, first, I have converted all negative variables into positive term and then normalised those variables in following ways;

$$\frac{\left(X_{rji(t)} - X_{\underset{i,t}{rjMin}}\right)}{R^*_{rj}} \qquad (5.1)$$

where, $\left(X_{\underset{i,t}{rjMax}}\right)$ and $\left(X_{\underset{i,t}{rjMin}}\right)$ are the maximum and minimum values for the j-th indicator in the r-th dimension over time(t=1, 2 and 3) and space(district(i)). Compute, $\left(X_{rji(t)} - X_{\underset{i,t}{rjMin}}\right)$ and divide each value by R^*_{rj}, where, $\left(X_{\underset{i,t}{rjMax}} - X_{\underset{i,t}{rjMin}}\right) = R^*_{rj}$.

Education Index:

Education index is a geometric mean of enrolment ratio (Primary and upper primary) and literacy rate.

$$EI_{it} = (GERI_{it} * LRI_{it})^{0.5} \qquad (5.2)$$

Where, $GERI_{it} = \frac{GER\_P_{it} * w_{11} + GER_{UP\,it} * w_{12}}{w_{11} + w_{12}}$ (5.2.1)

and $LRI_{it} = \frac{Actual\,LR_{it} - \underset{i,t}{Min}\,LR_{it}}{\underset{i,t}{Max}\,LR_{it} - \underset{i,t}{Min}\,LR_{it}}$ (5.2.2)

The weights for these two indicators are assigned from the data set using Principal Component Analysis. Since, enrolment dimension has two indicators, they have equal weights ($w_{11} = w_{12} = 0.836$).

Health Index:

Similar to the education index, I have constructed the health index which is also a geometric mean of infant survival rate and total lower fertility rate.

$$HI_{it} = (ISRI_{it} * LTFR_{it})^{0.5} \qquad (5.3)$$

Where, $ISRI_{it} = \frac{ActualISR_{it} - \underset{i,t}{Min}ISR_{it}}{\underset{i,t}{Max}ISR_{it} - \underset{i,t}{Min}ISR_{it}}$ (5.3.1)

and $LTFRI_{it} = \frac{ActualLTFR_{it} - \underset{i,t}{Min}LTFR_{it}}{\underset{i,t}{Max}LTFR_{it} - \underset{i,t}{Min}LTFR_{it}}$ (5.3.2)

Human Capital Index:

Using the estimated education and health index, I have constructed the human capital index for 539 districts for three time points. The human capital index is the geometric mean of education and health index.

$$HCI_{it} = (EI_{it} * HI_{it})^{0.5} \quad (5.4)$$

The final index (5.4) follows the properties of an ideal index. Now, using HCI, I have tried to explore the presence of convergence as well as club convergence across 539 districts.

The methodologies for convergence analysis are similar with the states level analysis. These methodologies are already discussed in chapter 1 also; therefore, I would like to avoid repetition here.

5.5 Empirical Analysis

In this chapter, I have focused on district level convergence analysis for three time points. The result of human capital index as well as its components are given in Appendix 5A.1. Here, I have used the descriptive statistics for education, health and human capital index to get some preliminary idea about their pattern of the distributions.

Table-5.1: Descriptive statistics of Education, Health and Human Capital Index over time

	Education Index			Health Index			Human Capital Index		
Indicator	EI_1	EI_2	EI_3	HI_1	HI_2	HI_3	HCI_1	HCI_2	HCI_3
Max	0.6239	0.6240	0.9385	0.8185	0.8071	0.8329	0.6068	0.6191	0.7243
Min	0.0046	0.1160	0.2148	0.0030	0.1164	0.0071	0.0239	0.1791	0.0607
Range	0.6193	0.5080	0.7237	0.8155	0.6906	0.8258	0.5828	0.4399	0.6636
Mean	0.3157	0.3988	0.4146	0.3979	0.4260	0.4553	0.3488	0.4066	0.4289
SD	0.0877	0.0685	0.0695	0.1536	0.1473	0.1554	0.1025	0.0900	0.0971
CV	0.2778	0.1717	0.1677	0.3861	0.3457	0.3413	0.2938	0.2215	0.2264

Source: Author's estimation

In each time point both maximum and minimum values for health index are found to be higher than education index. Human capital index is an average of education and health index. Since health status is higher than education index, mean value of health status is also higher than mean value of education. All indices values are found to have a fluctuating trend in standard deviation and range. The coefficient of variance has decreased for education and health index but for human capital index it has a fluctuating trend over time. So, from the table of descriptive statistics it can be observed that districts are improving but the dispersion measures suggest that districts are dispersed in terms of three indices. These results generate a question about the convergence across districts in terms education, health and human capital index.

Table-5.2: Rank correlation coefficient of Education, Health and Human Capital Index

	EI_1	EI_2	EI_3		HI_1	HI_2	HI_3		HCI_1	HCI_2	HCI_3
EI_1	1.00			HI_1	1.00			HCI_1	1.00		
EI_2	0.74***	1.00		HI_2	0.96***	1.00		HCI_2	0.93***	1.00	
EI_3	0.60***	0.71***	1.00	HI_3	0.85***	0.95***	1.00	HCI_3	0.86***	0.94***	1.00

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

The table for rank correlation coefficient exhibits that health index has a higher rank correlation coefficient than education and human capital index. For each index, they are highly correlated with the first lag time point than that for second lag time point. Education index has lower correlation coefficient and the mean value of education index was low compared to health index. From here, we can expect that pattern of achievement of convergence in education as well as health are different. If they have different patterns then how the districts will achieve convergence in terms of human capital index.

5.5.1 Convergence based on Neoclassical Approach

Based on this basic information about education, health and human capital index, in this study, I have explored the presence of convergence using parametric approach. Following table shows the result of absolute beta convergence for education, health and human capital index for 539 districts for 3 time points. Because of unavailability of data, here, I have only examined the absolute beta convergence.

Table-5.3: Result of Absolute Beta (β) Convergence of Education, Health and Human Capital Index

Absolute beta convergence of Education Index				Absolute beta convergence of Health Index			
Explanatory variables	Coefficients	t	P>|t|	Explanatory Variables	Coefficients	t	P>|t|
Initial_EI	-0.188*** (0.0031)	-60.48	0.000	Initial_HI	-0.0987*** (0.0068)	-14.43	0.000
Constant	-0.0738*** (0.00146)	-50.29	0.000	Constant	-0.03471*** (0.0028)	-12.08	0.000
Within R squared	0.8718			Within R squared	0.2791		
Between R squared	0.6279			Between R squared	0.1135		
Overall R squared	0.7033			Overall R squared	0.1217		
F(1,538)	3658.16***			F(1,538)	208.26***		
Hausman Test	639.21***			Hausman Test	88.86***		
No. of observations	1078			No. of observations	1078		

Absolute beta convergence of Human Capital Index			
Explanatory variables	Coefficients	T	P>|t|
Initial_HCI	-0.1632***(0.003)	-41.78	0.000
Constant	-0.0620***(0.0017)	-35.71	0.000
Within R squared	0.7644		
Between R squared	0.3584		
Overall R squared	0.4025		
F(1,538)	1745.81***		
Hausman Test	813.25***		
No. of observations	1078		

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

Above table exhibits that there exist absolute beta convergence in terms of education, health and human capital index. The panel model suggest that fixed effect model is appropriate than random effect. This clearly indicates that districts level characteristics do matter towards variation of EI, HI and HCI. Due to inadequate data of infrastructure as well as expenditure on social, health or education, I have only used data on social infrastructure as conditional variable. Here, an uneven distribution of data exists; schools or hospitals are not available for some districts. Because of this reason, I fail to construct social infrastructure index across districts and I have constructed different models. Following table shows the result of conditional beta convergence and here the conditional variables are number primary and upper primary school of 525 districts.

Table-5.4(A): Result of Conditional Beta (β) Convergence of Education, Health and Human Capital Index

Explanatory variable	Education Index	Health Index	Human Capital Index
Constant	-0.080***	-0.041***	-0.072***
Initial Index	-0.197***	-0.112***	-0.181***
No. of Primary School	0.008***	0.0078***	0.010***
No. of Upper Primary School	-0.006***	-0.005***	-0.007***
Within R Squared	0.8746	0.3103	0.7827
Between R Squared	0.6580	0.1200	0.3802
Overall R Squared	0.7079	0.1270	0.3974
F(3,522)	1213.21***	78.29***	626.68***
Huasman Test	413.57***	103.31***	610.31***
No. of Observation	1050	1050	1050

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

There exists conditional beta convergence across districts as the coefficient of each initial value is negative and statistically significant. For each index, no. of primary school has significant positive impact whereas no. of upper primary school has inverse impact with growth of each index. In similar way, I have constructed three different model with three different explanatory or conditioning variables (Sub Centre, Primary Health Centre and Community Health Centre). Surprisingly in each table, it can be observed that due to considering sub centre, primary health centre and community health centre as conditioning variable there exist conditional beta divergence. Presence of these infrastructure causes the dispersion across districts in terms of health index.

Table-5.4(B): Result of Conditional Beta(β) Convergence of Education, Health and Human Capital Index

Explanatory variable	Education Index	Health Index	Human Capital Index
Constant	-0.081***	0.016***	-0.064***
Initial Index	-0.185***	0.035***	-0.157***
No. of Sub Centre	0.0132***	0.006***	0.0070***
Within R Squared	0.8930	0.0316	0.7350
Between R Squared	0.6191	0.0358	0.3333
Overall R Squared	0.7125	0.0242	0.3670
F(2,500)	2087.08***	8.15***	693.43***
Huasman Test	868.85***	27.05***	719.96***
No. of Observation	1004	1004	1004

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

Table-5.4(C): Result of Conditional Beta(β) Convergence of Education, Health and Human Capital Index

Explanatory variable	Education Index	Health Index	Human Capital Index
Constant	-0.072***	0.021***	-0.059***
Initial Index	-0.186***	0.034***	-0.158***
No. of Primary Health Centre	0.0085***	0.006***	0.0059***
Within R Squared	0.8914	0.0320	0.7348
Between R Squared	0.6526	0.0488	0.3349
Overall R Squared	0.7303	0.0334	0.3678
F(2,498)	2043.06***	8.24***	689.83***
Huasman Test	749.12***	31.42***	732.20***
No. of Observation	1000	1000	1000

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

On the other hand, districts are experiencing conditional beta convergence in terms of education and human capital index in presence of sub centre and community health centre.

Table-5.4(D): Result of Conditional Beta(β) Convergence of Education, Health and Human Capital Index

Explanatory variable	Education Index	Health Index	Human Capital Index
Constant	-0.061***	0.019***	-0.054***
Initial Index	-0.190***	0.031***	-0.161***
No. of Community Health Centre	0.0162***	0.000***	0.0088***
Within R Squared	0.8938	0.0237	0.7316
Between R Squared	0.6134	0.0449	0.3277
Overall R Squared	0.7182	0.0312	0.3634
F(2,485)	2041.81***	5.90***	661.02***
Huasman Test	879.40***	23.87***	691.24***
No. of Observation	974	974	974

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

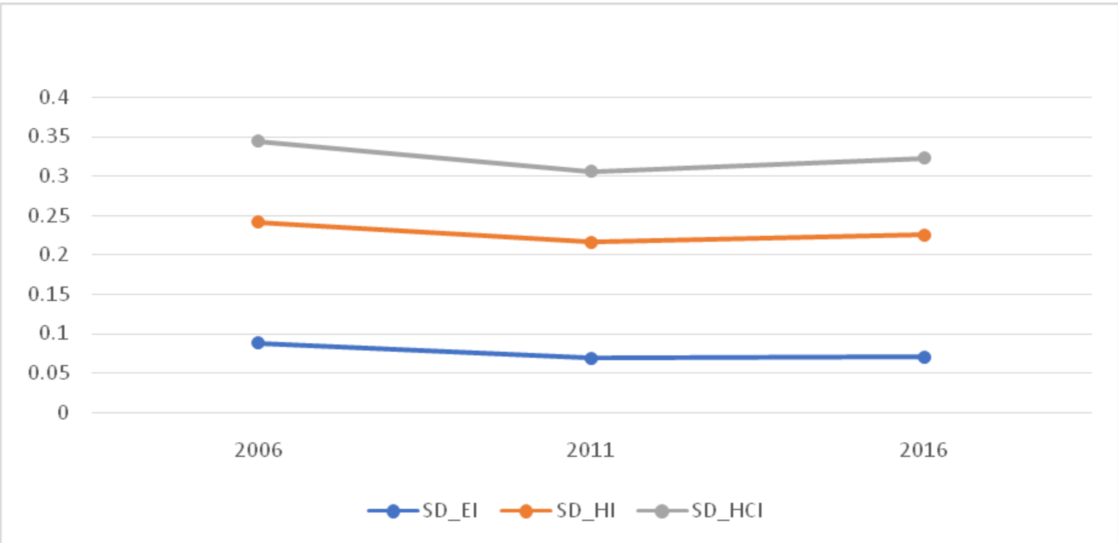
As I have mentioned earlier that standard deviation has a fluctuating trend for each index. So, it is very difficult to conclude about presence of sigma convergence rather there exist sigma divergence. But if we compare the value of standard deviation of initial value and terminal value then there exist sigma convergence in terms of education index as well as human capital index. It is not for Health index because, for health index, standard deviation at terminal time point is higher than that of initial time point.

Table-5.5: Result of Sigma (σ) Convergence/Divergence of EI, HI and HCI

SD	2006	2011	2016
EI_SD	0.087	0.068	0.069
HI_SD	0.153	0.147	0.155
HCI_SD	0.102	0.090	0.097

Source: Author's estimation

Figure-5.1: Trend of Standard deviation (σ) over time of EI, HI and HCI



Graphical representation of standard deviation also shows that none of them has a decreasing trend over time. The value of standard deviation for health index is high for all time points compare to education and human capital index. The result of dispersion-based approach suggests an opposite result of absolute beta convergence. **These results prove the statements that beta convergence is necessary but not sufficient for sigma convergence.**

5.5.2 Convergence based on Inequality Approach

As we know that decreasing trend in inequality indicates the presence of convergence across economies. Here, the result of general entropy measures of inequality suggests the presence of convergence across districts in terms of education, health and human capital index. As we know that the generalized entropy measures of inequality is distribution sensitive and it captures the inequality of observed variable based on the sensitivity within the distribution.

Table-5.6: Result of Generalized Entropy Measures of Inequality of EI, HI and HCI

Education Index			Health Index			Human Capital Index		
GE(0)	GE(1)	GE(2)	GE(0)	GE(1)	GE(2)	GE(0)	GE(1)	GE(2)
0.022477	0.018	0.038	0.036	0.032	0.074	0.022	0.019	0.043
0.006854	0.006	0.014	0.027	0.026	0.059	0.011	0.010	0.024
0.006044	0.005	0.014	0.029	0.026	0.058	0.012	0.011	0.025

Source: Author's estimation

Dispersion does not mean the reduction in inequality. The above table as well as the following graphs reveals that compared to initial time point the inequality has decreased at the terminal time point. For human capital index, the inequality is sensitive to all parts of the distribution has increased from second time point to third time point. Education index has decreasing trend in each inequality measurement whereas for health index, only inequality is sensitive to middle and upper part of the distribution. Inequality sensitive to the lower part has a fluctuating trend. For each index, inequality is sensitive to upper part of the distribution and it is higher than lower and middle part of the distribution.

Figure-5.2(A):Trend of Generalized Entropy Measures of Inequality of EI

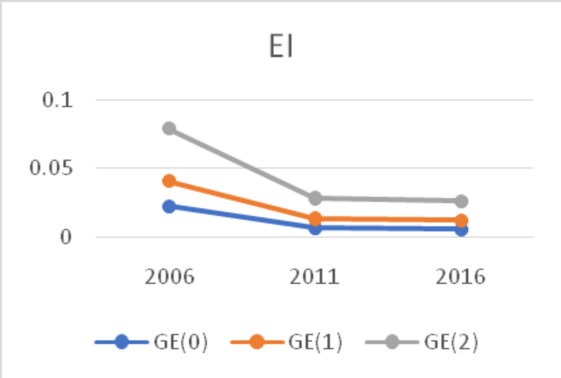


Figure-5.2(B): Trend of Generalize Entropy Measures of Inequality of HI

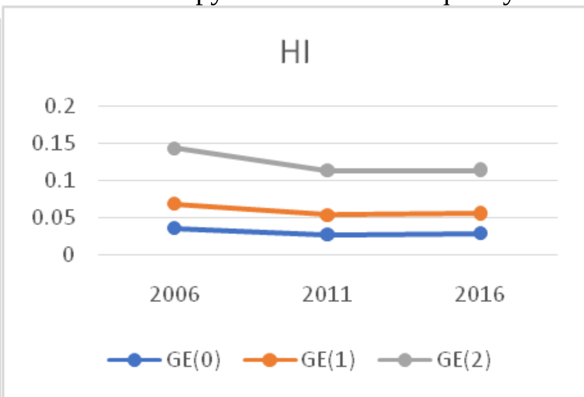
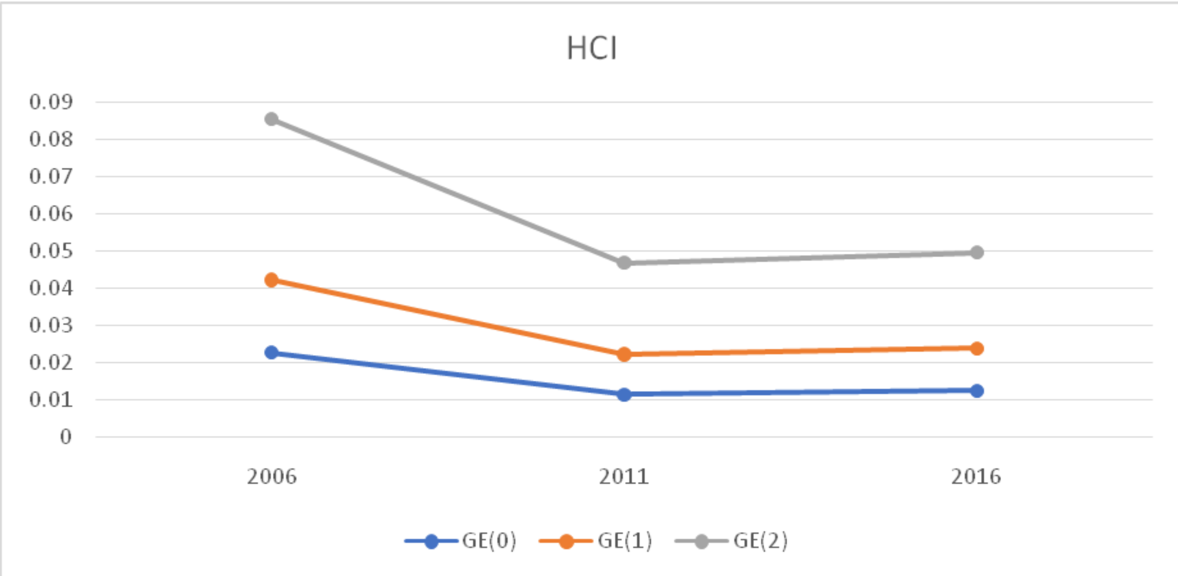


Figure-5.2(C): Trend of Generalized Entropy Measures of Inequality of HCI



So, on the basis of inequality-based approachwe have the result of convergence in education and health index but not in human capital index. All these above methodologies provide the information about convergence on based on average measurement. All above approaches fail to capture the transition as well as dynamic of the distribution over time. That is why here I have used the non-parametric approach to capture dynamics and the within distribution variation over time. In this approach first I have examined the dynamics of the distribution using Kernel density estimation and then following the limitation of Kernel density estimation I have used Transitional Probability Matrix to identify the transition over time.

5.5.3 Convergence based on Non-Parametric Approach

5.5.3.1 Non-Parametric Approach: Kernel Density Estimation

Following figure shows the Kernel density estimation of education index across 539 districts for three time points (NFHS 3, CENSUS 2011 and NFHS 4). At initial time point, the distribution is stratified in nature. There exist three peaks in this distribution. A very few districts are in extreme lower class whereas last two peaks occur around lower middle and upper middle classes. So, it can be assumed that districts are forming three classes or clubs.

Figure-5.3(A): Kernel density estimation of Education Index in 2006

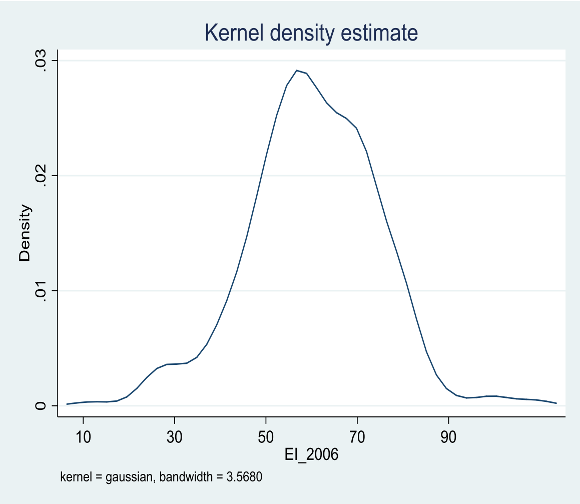


Figure-5.3(B): Kernel density estimation of Education Index in 2011

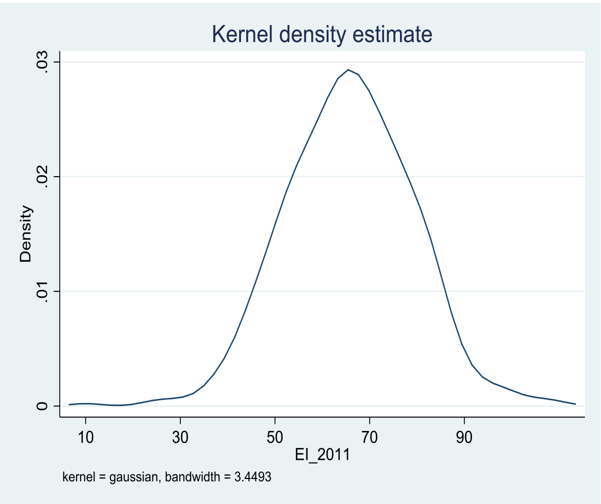
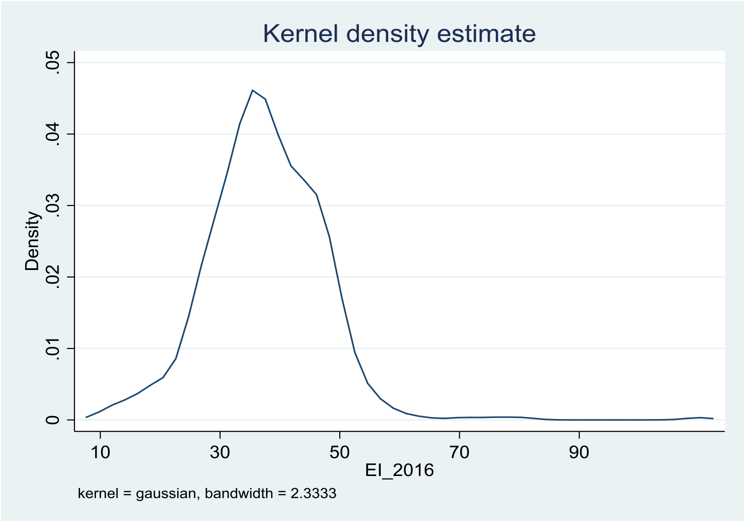


Figure-5.3(C): Kernel density estimation of Education Index in 2016



In the next time point (2011), the distribution has changed from stratification to unimodal distribution. Most of the districts have concentrated towards lower and upper middle classes.

No clubs are there. This distribution suggests the result of convergence. The kernel density estimation for last time point shows that the distribution again changed to stratification. But, here, the districts are concentrating towards lower and lower middle class.

Here also most of the districts are falling in extreme lower or low class. Now, we can compare the dynamics of the distribution of education index with the dynamics of the distribution of health index across the districts. For that purpose, I have constructed the Kernel density estimation for health index over time.

Following three figures are the Kernel density estimation of health index for three time points (2006, 2013 and 2016). First figure shows that there exist more than three peaks. First peak covers extreme lower and low class whereas second peak consist lower middle class. Last two peaks are consisting upper middle and higher class.

Figure-5.4(A): Kernel density estimation of Health Index in 2006

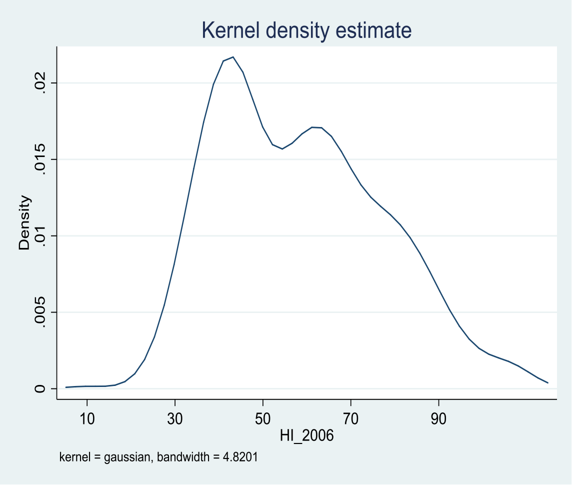


Figure-5.4(B): Kernel density estimation of Health Index in 2011

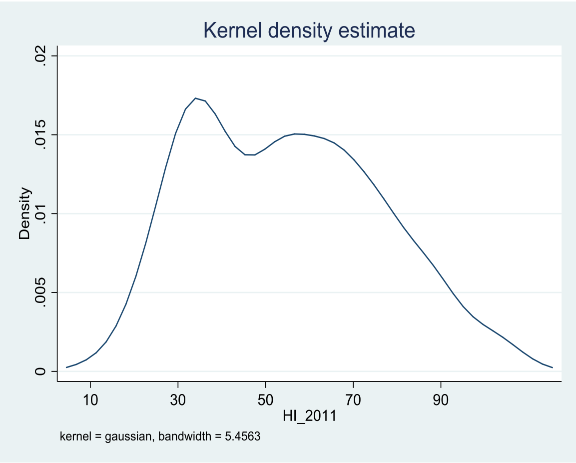
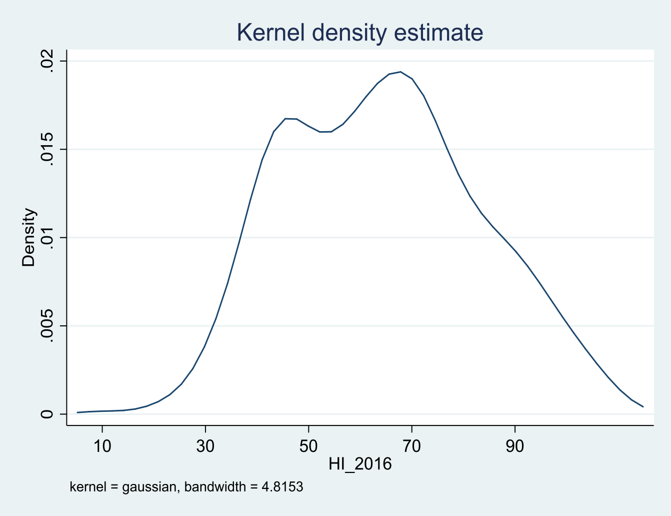


Figure-5.4(C): Kernel density estimation of Health Index in 2016



In next time point, the distribution has changed to polarization. First peak covers extreme lower and low class and second peaks covers lower middle, upper middle and higher classes. In the terminal time also, we have same polarized distribution but here the second peak has higher density than earlier time point. So, compared to education, in the long run, both have presence of club convergence, but graphically it can be observed that in terms of health index districts are in a better position compared to education index.

Since human capital index is a composite of health and education index, so, we can expect a mixed reflection of these two indices. Here, also we have the Kernel density estimation for three time points (2006, 2011 and 2016) for 539 districts.

Figure-5.5(A): Kernel density estimation of Human Capital Index in 2006

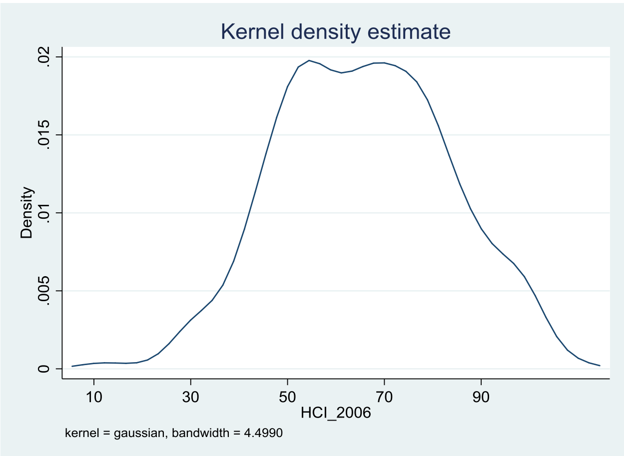


Figure-5.5(B): Kernel density estimation of Human Capital Index in 2011

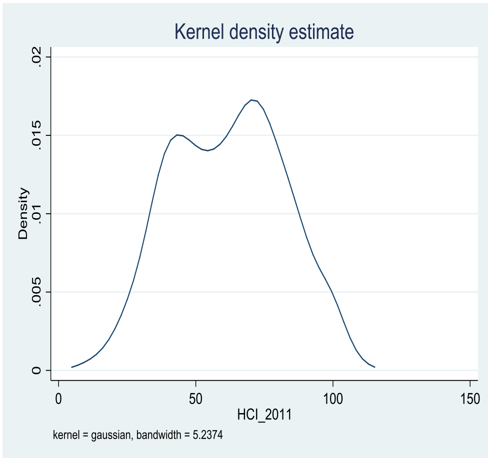
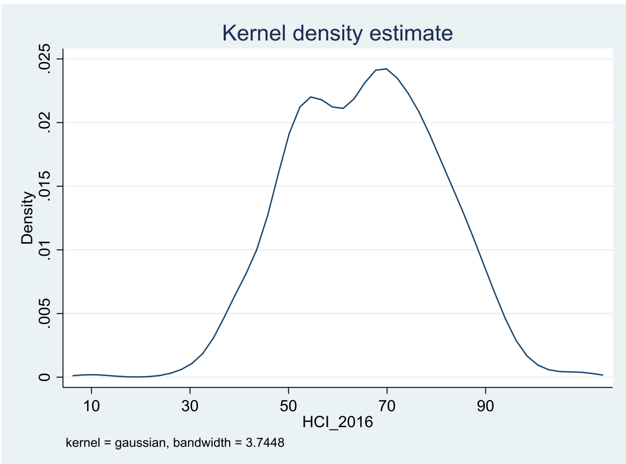


Figure-5.5(C): Kernel density estimation of Human Capital Index in 2016



In first time point, districts are forming three different classes. First peak covers two arbitrary classes (Extreme lower and low class) whereas second peak has the range from 50-70 to 70-90 and last peak has the range of 90-110. The next kernel plot shows that districts are forming two distinct classes. The second peak has larger density than the first one. The last Kernel density estimation shows a similar result of first kernel. In this figure,first peak covers the range from 10 to 70 rest of the portion is covered by the right tail. In the terminal time point, districts are forming two different classes. In respect of human capital index (HCI) districts are found to be more concentrated in the middle portion of the distribution. Presence of extreme lower-level chronic trap is not clear from the earlier analysis as the Kernel density estimation is a visual inspection of club convergence. It fails to identify the districts falling in the extreme lower trap as pointed out earlier.

5.5.3.2 Non-Parametric Approach: Transitional Probability Matrix

To identify the districts falling in the extreme low-level trap of HCI, I have examined the transition pattern of the districts in terms of education index, health index and human capital index over the time points. For each index, I have constructed two short run transitional probability matrix and one long run transitional probability matrix. Due to large number of observations, I could not use the scatter plot to define the transition of districts over time.

Following table shows the transition pattern of districts from 2006 to 2011 in terms of education index. As I have mentioned earlier that I have constructed five arbitrary classes (extreme low, low, lower middle, upper middle and higher class). Therefore, the matrix shows the movement of districts along these five classes. All the diagonal elements are representing individual stability within the respective classes; off diagonal elements are used to define either upper or lower mobility of districts over the time point. Elements bellow the diagonal value are representing lower mobility whereas the elements above the diagonal values are used to define upper mobility. From this first short run transitional matrix, it can be observed that overall mobility index is lower than stability index. The matrix also shows that districts are found to be more concentrated towards middle part of the distribution. This transition was captured by second Kernel plot of education index. Districts are found to be stable in such a way that the speed of convergence is very low compared to total time span.

Table-5.7(A): Transitional Probability Matrix (TPM) of districts in respect of EI from 2006-2011

		2011				
		10-30	30-50	50-70	70-90	90-110
2006	10-30	0.111	0.667	0.222	0	0
	30-50	0.02083	0.35417	0.5625	0.0625	0
	50-70	0	0.04225	0.6831	0.26761	0.00704
	70-90	0	0.01504	0.17293	0.76692	0.04511
	90-110	0	0	0	0	1
	Stability Index(SI)=0.58306 Mobility Index(MI)=0.52118			Half-Life=22.75		

Source: Author’s estimation

Second transition matrix captures the transition from 2011 to 2016. During this time period most of the districts have experienced downward mobility. Due to this higher mobility the overall mobility index is higher compared to stability index. As a result, during this time period, the speed of convergence is very high.

Table-5.7(B): Transitional Probability Matrix (TPM) of districts in respect of EI from 2011-2016

		2016				
		10-30	30-50	50-70	70-90	90-110
2011	10-30	0.75	0.25	0	0	0
	30-50	0.75	0.25	0	0	0
	50-70	0.17091	0.82182	0.00727	0	0
	70-90	0.02717	0.85326	0.1087	0.01087	0
	90-110	0	0.375	0.5	0.0625	0.0625
	Stability Index(SI)=0.21613 Mobility Index(MI)=0.97984			Half-Life=0.25		

Source: Author's estimation

The second transitional matrix capture the transition of districts from 2011 to 2016. Here, lower mobility is higher than upper mobility at the same time,the overall mobility index is higher than stability index. We find that Concentration towards lower portion is also clear here.

Table-5.7(C): Transitional Probability Matrix (TPM) of districts in respect of EI from 2006-2016

		2016				
		10-30	30-50	50-70	70-90	90-110
2006	10-30	0.7778	0.2222	0	0	0
	30-50	0.4375	0.54167	0.02083	0	0
	50-70	0.14085	0.82746	0.02817	0.00352	0
	70-90	0.03008	0.84962	0.11278	0.00752	0
	90-110	0	0.125	0.625	0.125	0.125
	Stability Index(SI)=0.29603 Mobility Index(MI)=0.87997			Half-Life=0.675		

Source: Author's estimation

The above table captures the long run transition of districts from one class to another class. The long run transitional probability matrix is the total reflection of the two short run matrices. Here also lower mobility is very high compared to upper mobility and the overall mobility is found to be higher than stability index. This indicates high speed of convergence.

From the transitional probability matrix (both short run and long run),I can easily identify the transition of all districts as well as the districts who are stucking in extreme low-level trap in terms of education index. Out of 539 districts only 2 districts are there in extreme lower trap.

If, I extend the range of lower class then out of 539 districts, 51 districts are found to be in extreme low- and low-level class. They are in the trap both in the short run and long run time periods. Since, the long run transitional probability matrix is ergodic in nature. So, from here we will get stationary distribution for the current distribution. About 65% districts are in extreme low-level class, 33% are in lower class and very few districts are there in lower middle, upper middle and higher class.

Table-5.8: Long run Stationary Distribution of EI

EL (10-30)	L (30-50)	LM (50-70)	UM (70-90)	H (90-110)
0.65	0.33	0.007	0.003	0.00

Source: Author's estimation

Similarly, we can check both short run and long run transitional pattern for health index also. First short run transitional matrix (2006-2011) shows that overall stability index is higher than mobility. Due to higher value of individual stability index, the overall stability index is higher than mobility index. As a result, speed of convergence is very low.

Table-5.9(A): Transitional Probability Matrix (TPM) of districts in respect of HI from 2006-2011

		2011				
		10-30	30-50	50-70	70-90	90-110
2006	10-30	1	0	0	0	0
	30-50	0.24878	0.726829	0.028249	0	0
	50-70	0	0.124294	0.813559	0.062147	0
	70-90	0	0	0.181034	0.758621	0.060345
	90-110	0	0	0	0.206897	0.793103
	Stability Index(SI)=0.818423 Mobility Index(MI)=0.226972			Half-Life=11.20		

Source: Author's estimation

Similarly, the transition of districts for next time period (2011-2016) is captured by the following transition matrix. Here the upper mobility is high compared to lower and individual stabilities arefound to be high. Districts from upper class are more stable whereas in extreme low and low-level are found to be less stable to their respective classes. As a result, the overall stability is slightly higher than mobility index. During this time period, the speed of convergence is very high.

Table-5.9(B): Transitional Probability Matrix (TPM) of districts in respect of HI from 2011-2016

		2016				
		10-30	30-50	50-70	70-90	90-110
2011	10-30	0.079365	0.920635	0	0	0
	30-50	0.011696	0.473648	0.473648	0.035088	0
	50-70	0	0.011765	0.594118	0.382353	0.011765
	70-90	0	0	0.047619	0.72381	0.228571
	90-110	0	0	0.0667	0	0.9333
	Stability Index(SI)=0.562032 Mobility Index(MI)=0.547461			Half-Life=1.59		

Source: Author's estimation

The long run transitional matrix is the mixed result of first two short run probability matrices. Here both way transition can be observed. As a result, the gap between overall mobility and stability index has decreased and surprisingly overall mobility index and stability index are found to be more or less same. Since the districts are improving in terms of health index, the speed of convergence is very high.

Table-5.9(C): Transitional Probability Matrix (TPM) of districts in respect of HI from 2006-2016

		2016				
		10-30	30-50	50-70	70-90	90-110
2006	10-30	0.25	0.75	0	0	0
	30-50	0.009756	0.619512	0.35122	0.019512	0
	50-70	0.011299	0.033898	0.564972	0.350282	0.039548
	70-90	0	0	0.146552	0.62931	0.224138
	90-110	0	0	0	0.275862	0.724138
	Stability Index(SI)=0.557586 Mobility Index(MI)=0.553017			Half-Life=2.19		

Source: Author's estimation

All matrices are ergodic in nature, but here I have focused on long run stationary distribution. The long run matrix shows that most of the districts are converging towards upper class (upper class and higher class).

Table-5.10: Long run Stationary Distribution of HI

EL (10-30)	L (30-50)	LM (50-70)	UM (70-90)	H (90-110)
0.00	0.00	0.2	0.4	0.4

Source: Author's estimation

Similar to the education index, here, we can identify the chronic trap of districts in terms of health index. Here, I have considered only extreme low-level class to identify the presence of trap. So, in terms of health index, out of 539 districts only three districts are found in chronic low-level trap in terms of health index. The three districts are Jaintia Hills (Meghalaya), Kishanganj (Bihar), West Khasi Hills (Meghalaya). Here, also if we extend the range for chronic low-level trap then the number of districts in the chronic trap has increased from 3 to 141. Now, we can examine the presence of chronic trap in terms of human capital index.

First short run transitional matrix shows that districts are experiencing both upper as well as lower mobility over this short time period. Individual stability indices are higher than mobility index. Due to this higher individual stability, during this short time period, overall stability index is higher than mobility index. Ultimately the speed of convergence is very low across the clubs.

Table-5.11(A): Transitional Probability Matrix (TPM) of districts in respect of HCI from 2006-2011

				2011		
		10-30	30-50	50-70	70-90	90-110
2006	10-30	1	0	0	0	0
	30-50	0.2088	0.7582	0.033	0	0
	50-70	0	0.3607	0.5479	0.0913	0
	70-90	0	0.0059	0.2118	0.7294	0.0529
	90-110	0	0	0	0.2245	0.7755
	Stability Index(SI)=0.7622 Mobility Index(MI)=0.2972			Half-Life=6.44		

Source: Author's estimation

The second short run transitional probability matrix has the opposite result. Here the overall mobility index is higher than stability index. Except the extreme low and low-level class, all classes have experienced a higher individual stability index. But these two low-level individual stabilities have reduced the overall stability or enhance the overall mobility index. As a result, the speed of convergence during this time period is found to be high.

Table-5.11(B): Transitional Probability Matrix (TPM) of districts in respect of HCI from 2011-2016

				2016		
		10-30	30-50	50-70	70-90	90-110
2011	10-30	0.03418	0.93103	0.03448	0	0
	30-50	0.00671	0.32886	0.65101	0.01342	0
	50-70	0	0.01887	0.8239	0.15723	0
	70-90	0	0	0.11613	0.86452	0.01935
	90-110	0	0	0	0.57477	0.42553
	Stability Index(SI)=0.49546 Mobility Index(MI)=0.63068			Half-Life=2.29		

Source: Author's estimation

The Long run transitional probability matrix captures the transitional pattern from 2006 to 2016. During this long run time period the overall mobility index is found to be very high compared to stability index. Therefore, from these transitional probability matrices we can identify the contribution of each index to human capital index.

Table-5.11(C):Transitional Probability Matrix (TPM) of districts in respect of HCI from 2006-2016

		2016				
		10-30	30-50	50-70	70-90	90-110
2006	10-30	0	1	0	0	0
	30-50	0.01099	0.56044	0.41758	0.01099	0
	50-70	0.00457	0.07763	0.76712	0.14612	0.00457
	70-90	0	0.00588	0.23529	0.71765	0.04118
	90-110	0	0	0.02041	0.67347	0.30612
	Stability Index(SI)=0.47027 Mobility Index(MI)=0.66217			Half-Life=1.839		

Source: Author's estimation

The pattern of the long run transitional probability matrix in respect of human capital index is similar to the long run transitional probability matrix of health index. Both health and human capital indices did experience upper mobility than education index. In terms of human capital index out of 539 districts, no districts are there in extreme low-level trap. However, if we increase the range of low-level (containing 10-50) trap, then out of 539 districts, 62 districts are found to be in chronic low-level trap. As we can see that the long run transitional probability matrix is ergodic in nature, so, this matrix provides the long run stationary distribution in which the current distribution will converge. The long run stationary distribution shows that most of the districts are converging towards middle classes (lower middle and upper middle).

Table-5.12: Long run Stationary Distribution of HCI

EL (10-30)	L (30-50)	LM (50-70)	UM (70-90)	H (90-110)
0.003	0.1	0.54	0.34	0.024

Source: Author's estimation

If we compare all these traps in respect of education index, health index and human capital index, it can be observed that out of 539 districts only 28 districts are in trap in all the indices (Appendix 5.A.2). The districts falling in chronic low level trap (range between 10-50) including both extreme low and low-level class are Aligarh, Araria, Bahraich, Balarampur, Banswara, Bara Banki, Bareilly, Barwani, Budaun, Bulandshahr, Darbhanga, Dibang Valley, Gajapati, Jhabua, Katihar, Kaushambi, Koraput, Madhepura, Malkangiri, Mon, Muzaffarnagar, Nabarangapur, Paschim Champaran, Purnia, Rampur, Rayagada, Saharsa, Shahjahanpur. But for extreme low class (10-30), I could not find any overlapping district.

5.5.3.2.1 Analysis of Variance

To examine the presence of club convergence and chronic low-level trap, I have constructed five arbitrary classes, extreme low, low, lower middle, upper middle and high. They are all non-overlapping classes. Here, I have used the analysis of variance to check the significance mean difference among these arbitrary classes. The analysis of variance also provides the information on stability and mobility of districts over time. Following table shows that there exists significance mean difference across different groups. Over time, the between variance has decreased whereas within variation is found to have a fluctuating trend. This implies that districts are converging. As a result, mobility index is found to be higher than the stability index.

Table-5.13: Mean difference across groups over time in respect of Education Index

EI	2006	2011	2016
Between variation	3.581	2.134	1.834
Df	4	4	4
Within variation	0.557	0.390	0.769
Df	534	534	534
MSB	0.895	0.533	0.458
MSE	0.001	0.0007	0.001
F-statistics	857.52***	730.56***	318.39***

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

Along with the aggregate result of mean difference, the following table support the result of significance mean difference across class. From 2006 to 2016, the distance between each group has decreased. But in next time between group variation has increased but within variation has increased.

Table-5.14: Group specific mean difference over time in respect of Education index

2006	Group 1	Group 2	Group 3	Group 4
Group 2	0.116**			
Group 3	0.214**	0.098**		
Group 4	0.313**	0.197**	0.099**	
Group 5	0.470**	0.354**	0.256**	0.157**
2011	Group 1	Group 2	Group 3	Group 4
Group 2	0.113**			
Group 3	0.195**	0.082**		
Group 4	0.280*	0.167**	0.084**	
Group 5	0.381**	0.268**	0.185**	0.100**
2016	Group 1	Group 2	Group 3	Group 4
Group 2	0.105**			
Group 3	0.208**	0.102**		
Group 4	0.368**	0.262**	0.159**	
Group 5	0.618**	0.512**	0.409**	0.249**

Source: Author's estimation, *** implies significance at 1 percent level.** implies significant at 5 percent level

Due to high level of between and within variations districts are found to be more mobile over time and they are converging in the long run stationary distribution. From the analysis of variance, one can identify the nature of transition over time based on within and between variations. In similar way, I have examined the mean difference across groups based on health index also.

Table-5.15: Mean difference across groups over time in respect of Health index

HI	2006	2014	2016
Between variation	11.66	10.85	11.86
Df	4	4	4
Within variation	1.038	0.821	1.136
Df	534	534	534
MSB	2.916	2.713	2.966
MSE	0.001	0.001	0.002
F-statistics	1500.23***	1762.82***	1393.69***

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

The above table shows that there exists significant mean difference among the classes at the same time, both within and between variations are found to have fluctuating trend over time. In 2011, both within and between variations are found to be higher than those at the initial level. Due to that reason, first TPM shows that stability index is higher than mobility index. As mobility index has increased from 2011 to 2016, the variations across groups have reduced. From the following table, the group specific mean difference can be observed over time.

Table-5.16: Group specific mean difference over time in respect of health index

2006	Group 1	Group 2	Group 3	Group 4
Group 2	0.118**			
Group 3	0.279**	0.160**		
Group 4	0.434**	0.315**	0.154**	
Group 5	0.591**	0.472**	0.312**	0.157**
2011	Group 1	Group 2	Group 3	Group 4
Group 2	0.096**			
Group 3	0.244**	0.148**		
Group 4	0.378**	0.282**	0.134**	
Group 5	0.508**	0.412**	0.264**	0.129**
2016	Group 1	Group 2	Group 3	Group 4
Group 2	0.156**			
Group 3	0.310**	0.154**		
Group 4	0.458**	0.301**	0.147**	
Group 5	0.613**	0.457**	0.303**	0.155**

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

The composite index of health and education also follows the significant mean difference among groups as F-statistics suggest to accept alternative hypothesis. Here, also the trend of between and within group variations are found to have fluctuating trend. Similar to health index, here, in 2011, both between and within group variations are lower than those in 2006 and 2016. The mobility index was higher in 2011-2016 than that of 2006-2011.

Table-5.17: Mean difference across groups over time in respect of Human Capital Index

HCI	2006	2011	2016
Between variation	5.078	4.051	4.324
Df	4	4	4
Within variation	0.574	0.313	0.753
Df	534	534	534
MSB	1.269	1.012	1.081
MSE	0.001	0.0005	0.001
F-statistics	1179.96***	1725.96***	766.58***

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

Group specific mean difference also reflects the fluctuating trend of between group over time. in 2006, the variation are found to be low compared to initial and terminal time point.

Table-5.18: Group specific mean difference over time in respect of Human Capital Index

2006	Group 1	Group 2	Group 3	Group 4
Group 2	0.111**			
Group 3	0.209**	0.097**		
Group 4	0.320**	0.208**	0.111**	
Group 5	0.426**	0.315**	0.217**	0.106**
2011	Group 1	Group 2	Group 3	Group 4
Group 2	0.076**			
Group 3	0.163**	0.086**		
Group 4	0.242**	0.165**	0.079**	
Group 5	0.323**	0.246**	0.160**	0.080**
2016	Group 1	Group 2	Group 3	Group 4
Group 2	0.164**			
Group 3	0.271**	0.107**		
Group 4	0.392**	0.227**	0.120**	
Group 5	0.499**	0.334**	0.227**	0.107**

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

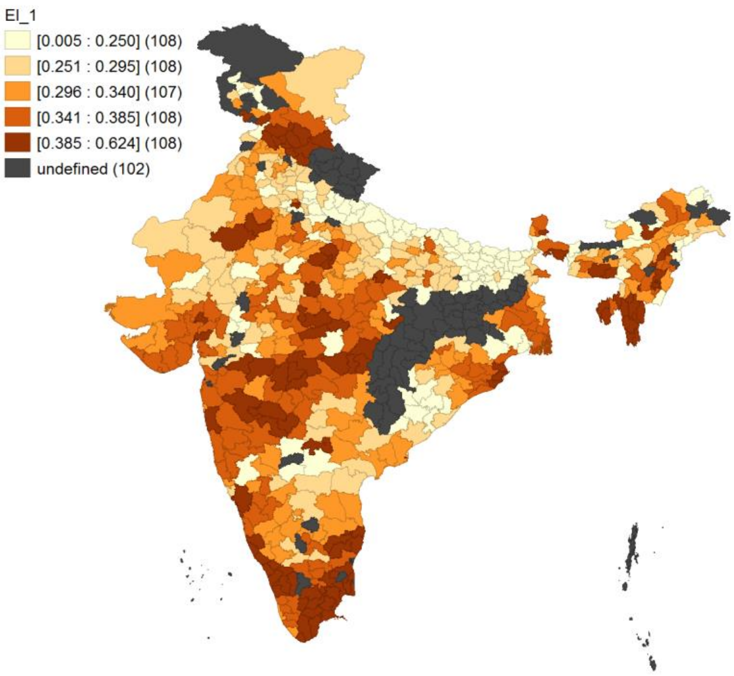
5.5.4 Convergence based on Spatial Analysis

5.5.4.1 Spatial Analysis: Global and Local Moran's Index

The result of spatial analysis also suggests that how districts are forming cluster based geographical location. The result of GMI shows the presence of aggregate spatial dependency across districts in terms of education, health and human capital index.

Districts nearer to each other may have same features as well as structures. As a result, they may experience similar educational status or health status or human capital status. So, these similar districts may form similar cluster among themselves. Before going to the analysis of spatialdependency, first using the graphical representation, we can preview the distribution of education index, health index and human capital index for the respective time points. First three maps show the distribution of education index across 539 districts for three time points. Out of 539 districts some of the districts are forming homogeneous cluster with similar districts. The clusters are formed in terms of lower value or in higher value.

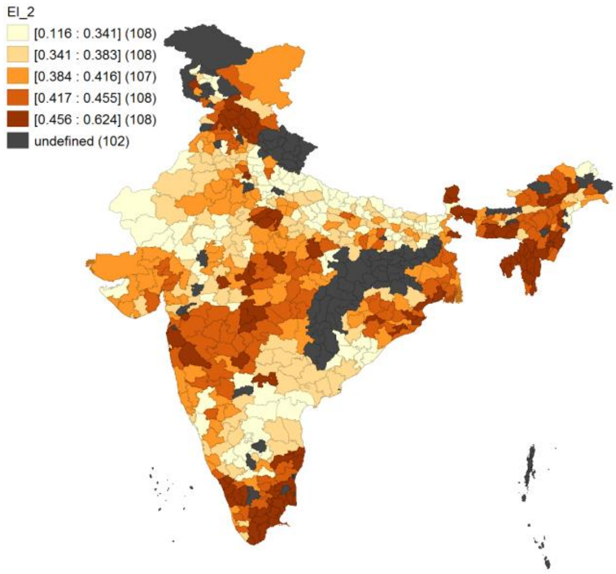
Map-5.1(A): Map Distribution of districts in respect of Education Index in 2006



Source: Author's estimation

Darker colour represents the higher education index value whereas the light shaded area shows the districts with lower value. Black regions are the undefined region not included in the analysis. Comparing all these three maps it can be observed that the colour of map has changed from darker to lighter. It means the districts are moving from higher education status to lower. This transition was already captured in non-parametric approach (Kernel density estimation and Transitional Probability Matrix).

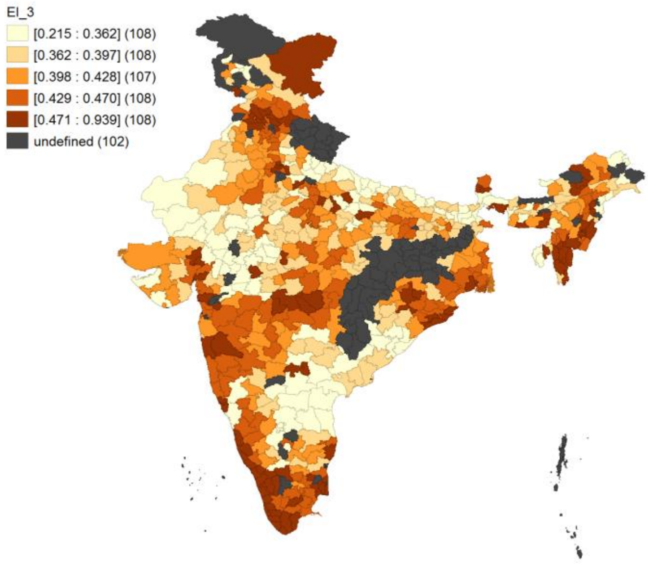
Map-5.1(B): Map Distribution of districts in respect of Education Index in 2011



Source: Author's estimation

In 2006, districts from Northern, Middle, Southern and Eastern part of India have higher education index, but in 2011, some of the districts from these regions have moved to lower index value. In 2016, the transformation of colour is clear. Preliminary we can argue that due to negative impact from poorer districts, the neighbouring districts are positively influenced over time.

Map-5.1(C): Map Distribution of districts in respect of Education Index in 2016



Source: Author's estimation

But, in all time points a clear clustering of both lower classes and upper classes can be observed. From the mapping of the distribution, the nature of spatial autocorrelation is not clear across the districts. Following table shows as well as support the presence of clustering among low-low as well as high-high districts. Since the value of GMIs are positive and statistically significant over time. this result implies that there exists positive spatial autocorrelation. Districts with lower educational index are forming cluster with districts with lower value. In similar way, districts with higher educational status are forming clusters among themselves. Over time, the value of the Global Moran's Index has decreased. Initially, the value of GMI is 0.590 whereas in next two time points, the value of GMIs stand at 0.526 and 0.411 respectively. This implies that over time the spatial dependency across the districts has decreased in respect of educational status.

Table-5.19: Result of Global Moran's Index of Education Index over time

GMI	2006	2011	2016
GMI_EI	0.590***	0.526***	0.411**

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

Graphically we can observe a positively slopped fitted line across the districts since, the values of GMIs are positive and statistically significant. These figures show the pattern of clustering of homogeneous districts along with outlier. Here, also over time the fitted line shifts from steeper to flatter due to decreasing trend in GMI.

Figure-5.6(A): Spatial Autocorrelation of EI in 2006

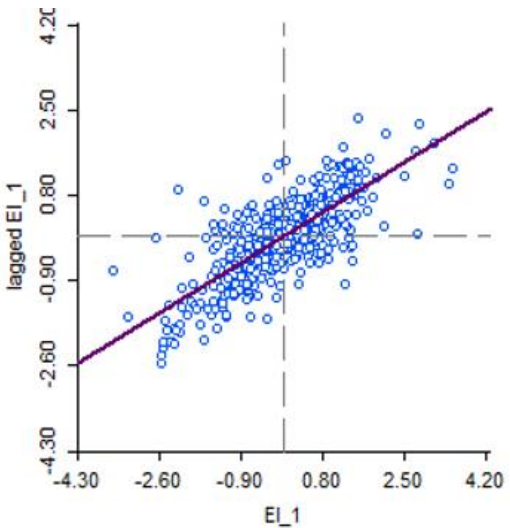


Figure-5.6(B): Spatial Autocorrelation of EI in 2011

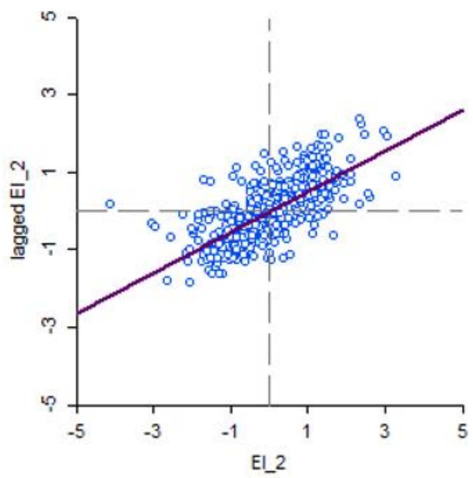
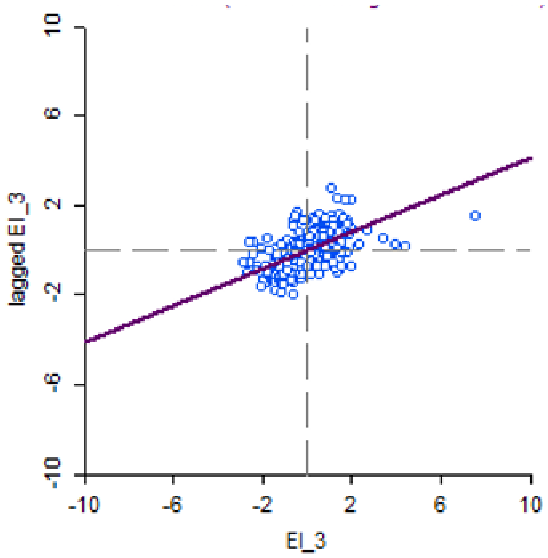


Figure-5.6(C): Spatial Autocorrelation of EI in 2016



Source: Author's estimation

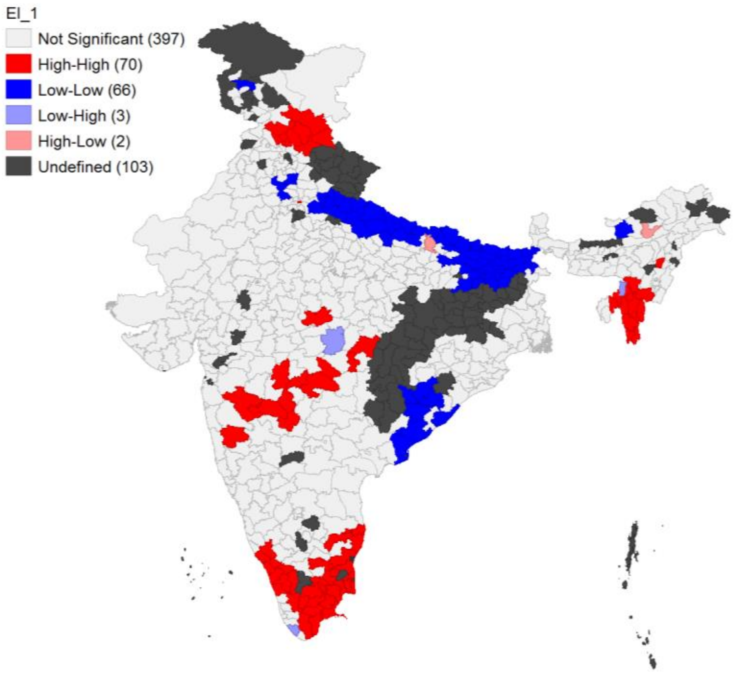
Each quadrant has distinct significance. Top right quadrant shows the high-high clustering, bottom left quadrant is capturing low-low clustering, whereas rest of the quadrants are capturing districts with opposite value.

In 2006, districts were more scattered. As time goes up the districts are found to be more concentrating towards origin. In initial time point, out of 539 districts, 214 and 212 districts are in high-high and low-low quadrant respectively. Some districts are found in high-low and low-high quadrant (60 and 67 respectively). But, they are not statistically significant. Based on the significance level the number of districts in each clustering has decreased. Out of 539 districts, only 70 districts (12.9%) are forming high-high clustering whereas 66 districts (12.2%) are in low-low clustering. Only 3 and 2 districts are in low-high and high-low clustering (outlier classes). These results of significance dependency of districts are obtained from Local Moran's Index. In next time point (2011), again, we have large number of districts in high-high and low-low clustering (216 in high-high clustering and 231 in low-low clustering) whereas based on significance level only 56 districts are in high-high clustering and 71 districts are low-low clustering. Surprisingly, the number of outlier districts has increased compared to earlier time point. In 2016, the number of districts forming significant clustering has decreased to 51 and 64 for high-high and low-low clustering respectively. Over time, the number of insignificant districts have increased. From these high-high and low-low clustering, I have identified the stable districts to examine the persistence of spatial dependency. That's mean districts are having independent behaviour. Since, the result of

GMI is aggregate in nature. it fails to identify the individual dependency of districts over time whereas Local Moran's Index provides the individual dependency.

Similar to the earlier chapters, in this chapter, I have explored the chronic low-level trap based spatial dependency along with the non-parametric approach. Overall, the GMI shows that how districts are dependent to each other at the aggregate and disaggregate level.

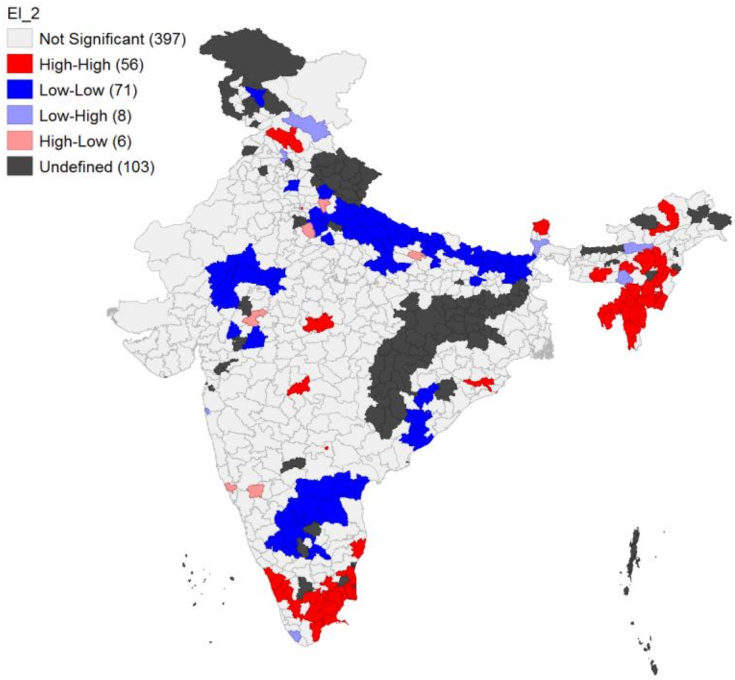
Map-5.2(A): Cluster of districts in respect of Education Index in 2006



Source: Author's estimation

The result of Local Moran's Index shows that in 2006, 66 districts (about 12.24% of districts) are forming low-low trap and out of which,21 districts are belonging from Uttar Pradesh and 30 districts are belonging from Bihar. Rest of the districts are belonging from Andhra Pradesh, Arunachal Pradesh, Haryana, Jammu & Kashmir, Odisha and West Bengal. From the earlier chapters, it is already found that all these states are belonging to either extreme lower or low classes (Extreme low and low-level in respect of education index at state level analysis, Chapter 2). But over time the number of districts in low-low cluster has decreased.

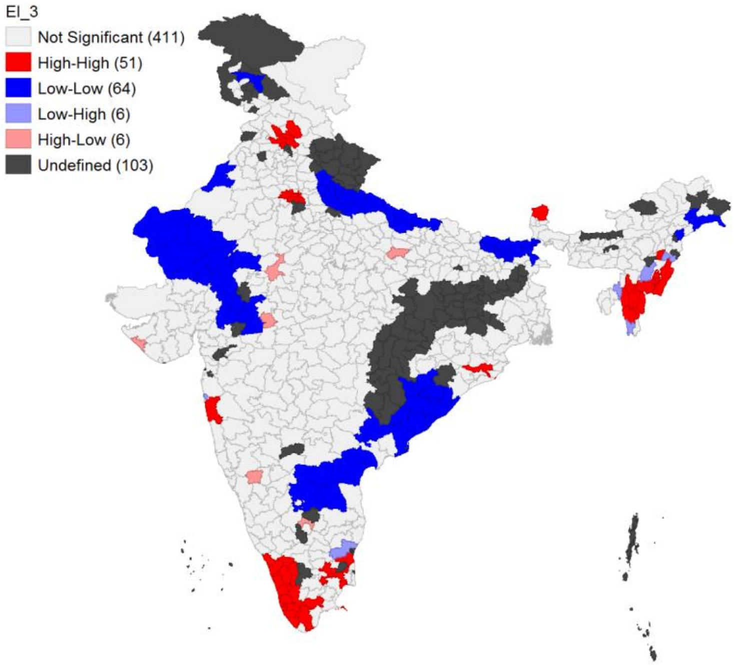
Map-5.2(B): Cluster of districts in respect of Education Index in 2011



Source: Author's estimation

In 2011, only 13.17% districts are in low-low trap, number districts from Uttar Pradesh have increased (29 districts) but the number has decreased from Bihar (16 districts only). Surprisingly in 2011, the number of districts falling in the low-low trap has increased. At the same time the number of districts also has increased. In 2006, districts are belonging to eight states whereas in 2011 it has increased to 11 states. In terminal time (2016) point, the number of districts falling in the low-low cluster has decreased (11.87% only). Districts are belonging to 12 different states. In this time point, surprisingly the number of districts from Uttar Pradesh and Bihar has decreased to 15 and 8 respectively. Now if we compare the low-low clusters for these three time points, then only 24 districts are found to be stable in this low-low cluster. These 24 districts have lower educational index and their neighbour's average education status is also low.

Map-5.2(C): Cluster of districts in respect of Education Index in 2016

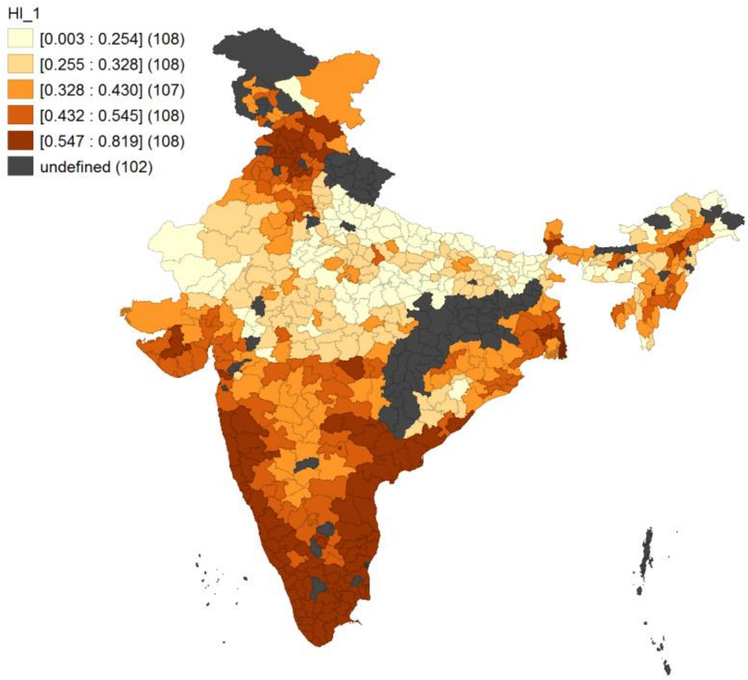


Source: Author's estimation

The above three maps show the number of districts forming low-low and high-high cluster over time. The blue colour defines the low-low cluster and red colour represents the high-high cluster. The number of districts in low-low cluster is found to be fluctuating over time, the important observation is that the districts are located in similar region; they are belonging to the states which are already poor in terms of education level.

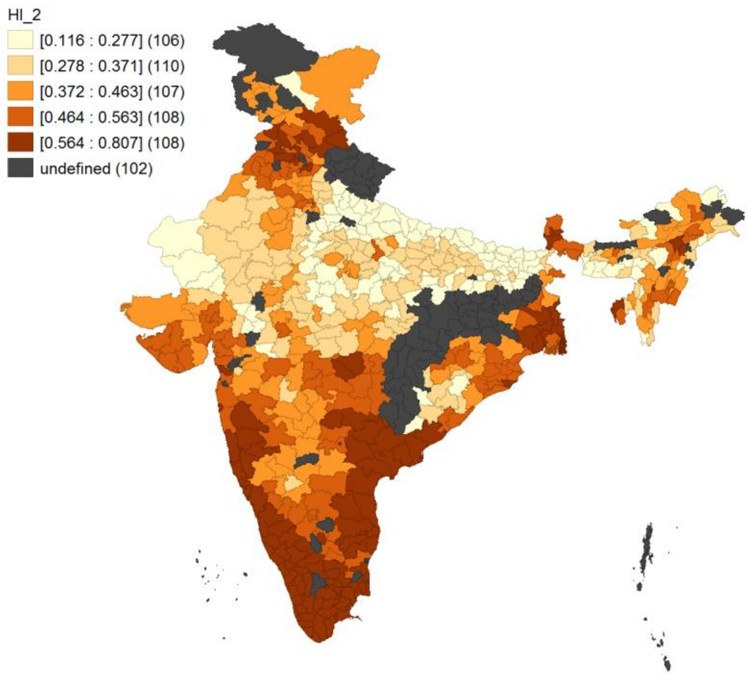
In similar way, I have examined the spatial dependency in terms of health index across 539 districts over three time points. Here, also initially I have used the map to define the distribution of districts in terms of health index over time. Comparing these maps, it can be observed that districts are improving over time because the colour has changed from lighter to darker. Just the opposite result of education index. We can preliminarily argue that districts are getting positive impact from their neighbours. In 2006, the map shows that northern and southern districts have higher health index compare to central and eastern districts.

Map-5.3(A): Map Distribution of districts in respect of Health Index in 2006



Source: Author's estimation

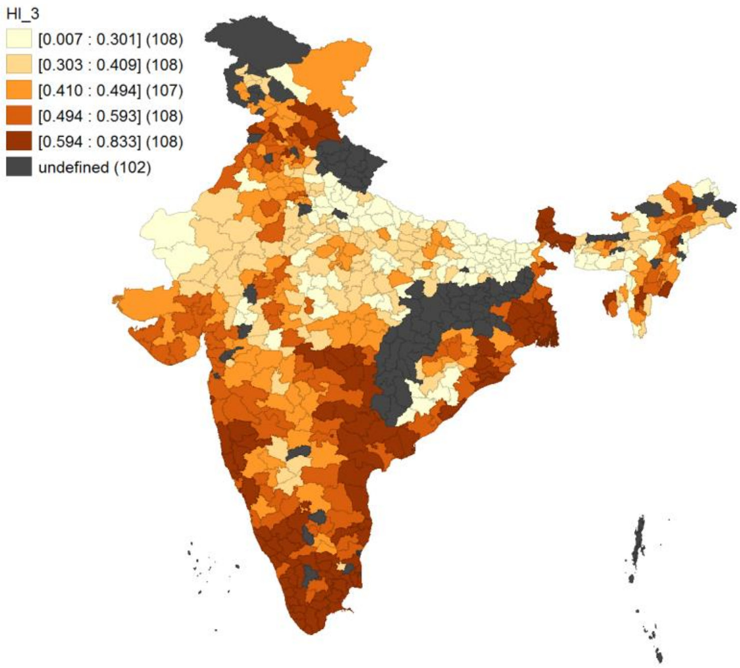
Map-5.3(B): Map Distribution of districts in respect of Health Index in 2011



Source: Author's estimation

In 2011 also we have same type of distribution of health index across the districts.

Map-5.3(C): Map Distribution of districts in respect of Health Index in 2016



Source: Author's estimation

Districts from Southern and South-East part of India have higher value of health index and districts from Middle and Northern zone have lower health status. These three maps also suggest that clustering among high-high districts is more than clustering among low-low districts. From the table for Global Moran's Index for health index a higher spatial dependency can be observed. So, in aggregate, there exists higher significant spatial impact across districts.

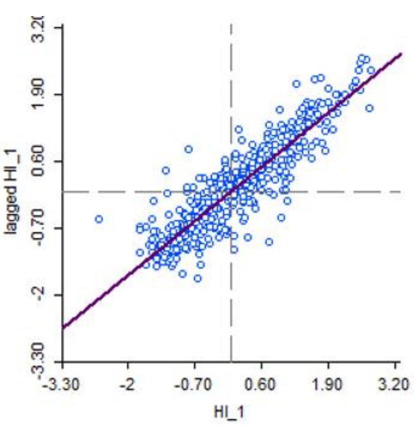
Table-5.20: Result of Global Moran's Index of Health Index over time

GMI	2006	2013	2016
HI	0.812***	0.797***	0.703***

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

Compared to the scatter plot of education index, here, a dispersed scatter can be observed. In each diagram, a positive fitted line shows that districts are having positive neighbourhood impact over time. A large number of districts are found both in high-high and low-low cluster, but we will focus only on those districts which are forming clusters significantly.

Figure-5.7(A): Spatial Autocorrelation of HI in 2006 Figure-5.7(B): Spatial Autocorrelation of HI in 2011



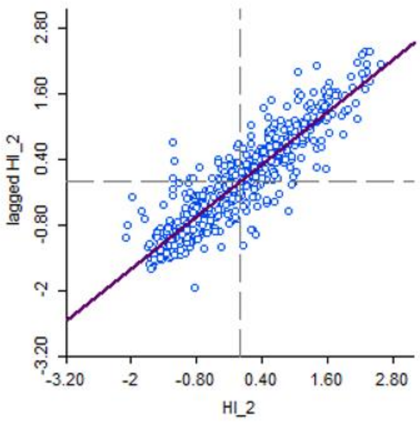
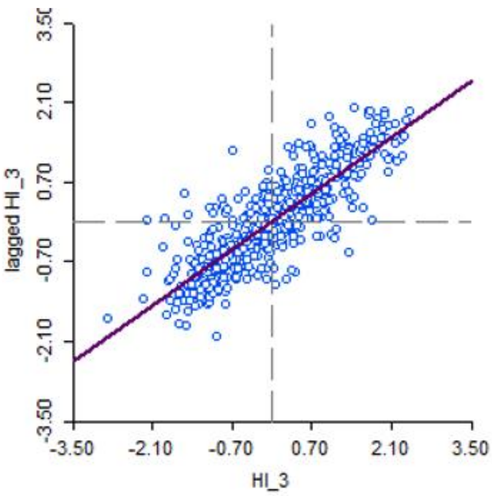


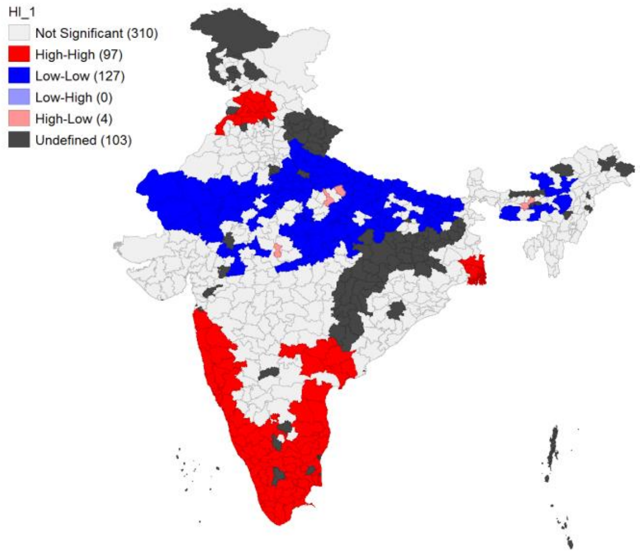
Figure-5.7(C): Spatial Autocorrelation of HI in 2016



Source: Author's estimation

In initial time point, out of 539 districts, 250 districts are forming low-low clustering as they are in the third quadrant. The number has decreased in next two time points (248 in 2011 and 232 in 2016). From the result of Local Moran's Index, we have comparatively lower number of districts in low-low cluster. In 2006, 23.56% districts (127 districts out of 539 districts) are significantly forming low-low cluster. This number is higher than that of education index. In 2006, the number of districts has decreased to 120 and in terminal time point it has decreased to 103. Based the result of Local Moran's Index, in 2006, out of 250 districts only 127 districts are forming significant low-low cluster. These 127 districts belong to Arunachal Pradesh, Assam, Bihar, Meghalaya, Madhya Pradesh, Rajasthan and Uttar Pradesh. From chapter 3 I have already found that these states were in the low-low cluster in terms of health index.

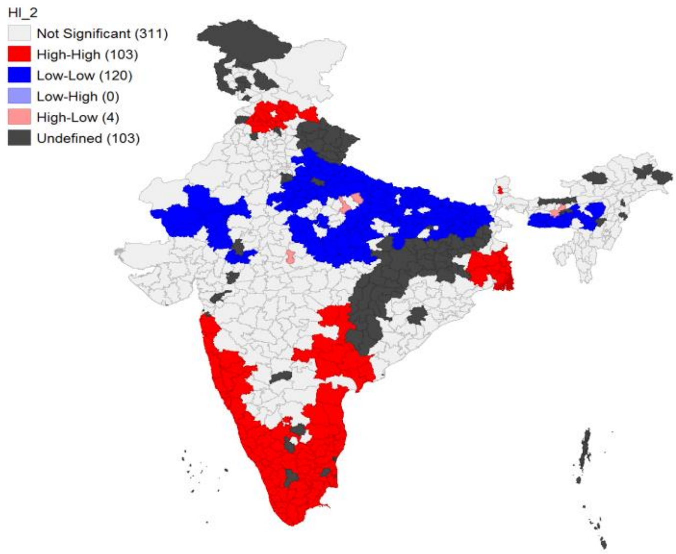
Map-5.4(A): Cluster of districts in terms of health index in 2006



Source: Author's estimation

It can be observed that in initial time point, most of the districts in low-low clustering are belonging from Bihar (26 district), Madhya Pradesh (20 districts), Rajasthan (19 districts) and Uttar Pradesh (52 districts). In chapter 3, both the non-parametric analysis and spatial analysis show that Bihar, Madhya Pradesh and Uttar Pradesh are in extreme lower trap. Rajasthan was also in a bad position. So, in initial time point, we have a consistent result of state level and district level analysis of convergence as well as club convergence in terms of health index.

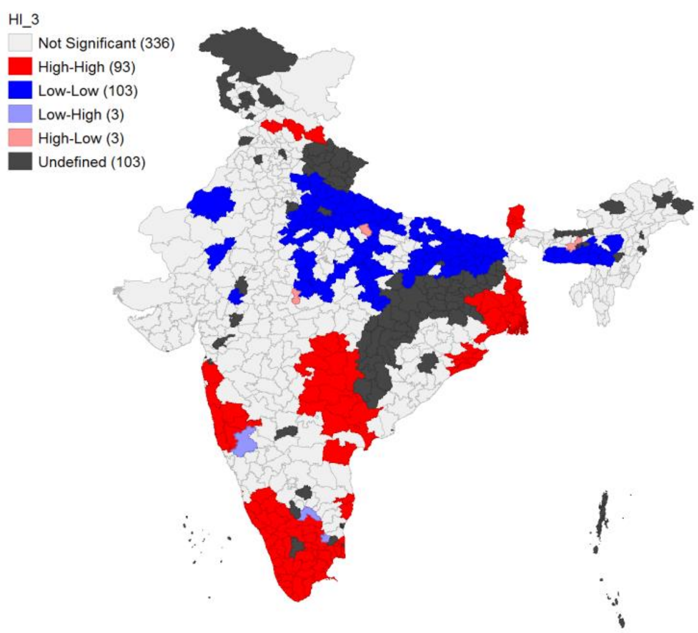
Map-5.4(B): Cluster of districts in terms of health index in 2011



Source: Author's estimation

In 2011, total number of districts forming significant low-low cluster was 120 which is lower than in 2006. In this time point, districts are belonging to those seven states and out of these seven states Uttar Pradesh and Bihar consist higher number of district (52 from Uttar Pradesh and 33 from Bihar). In terminal time, the number of districts forming significant clustering has decreased to 103. Again, all these districts are belonging from those seven states. Similar to the earlier time points, Bihar and Uttar Pradesh consist of maximum number districts (44 districts from Uttar Pradesh and 33 districts from Bihar). Similar to the non-parametric approach, here, also I have identified the districts which are stable in this significant low-low clustering over three time points. The result shows that over three time points, 82 districts (15.21%) are stable in low-low cluster in terms of health index in India.

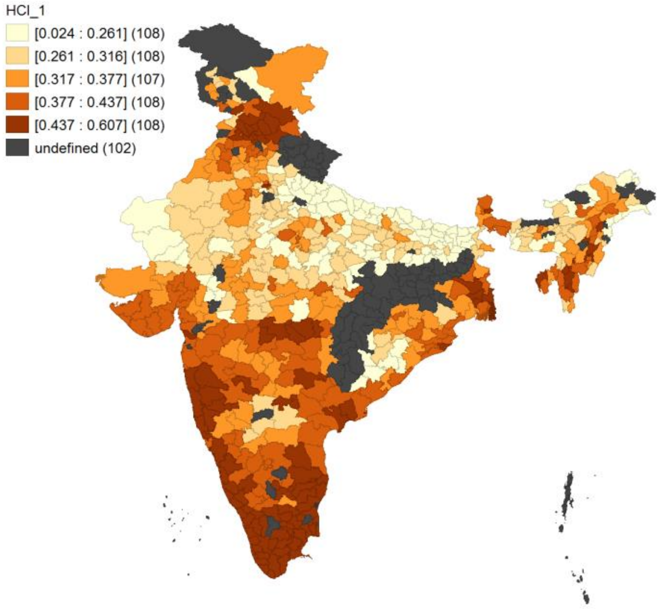
Map-5.4(C): Cluster of districts in terms of health index in 2016



Source: Author’s estimation

Human Capital index is comprised of education and health index. Thus, we can observe a mixed result across the districts for three time points. All three maps show that districts from Southern, Northern and Eastern part of India have higher value of human capital index. Districts from Central part of India have comparatively lower value of human capital index. Not only in terms of human capital index, these districts have lower education as well as health index compared to other districts. But over time, districts are moving from higher status to lower status, as the map shifted from darker colour to lighter colour.

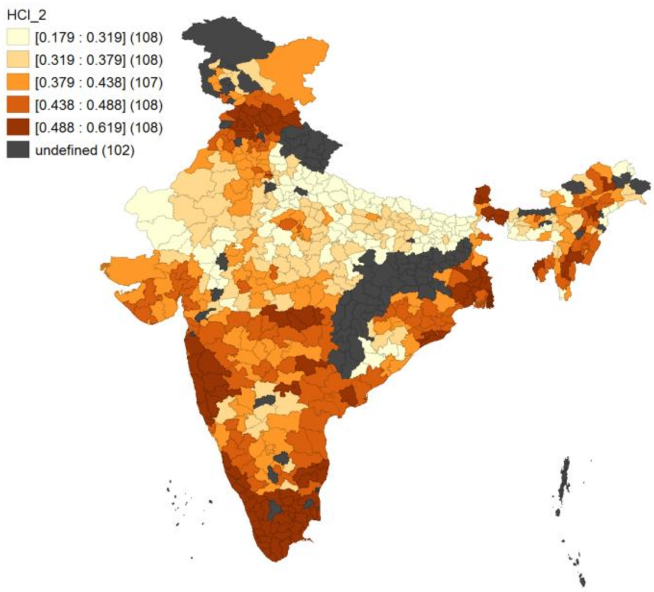
Map-5.5(A): Map Distribution of districts in respect of Health Index in 2006



Source: Author's estimation

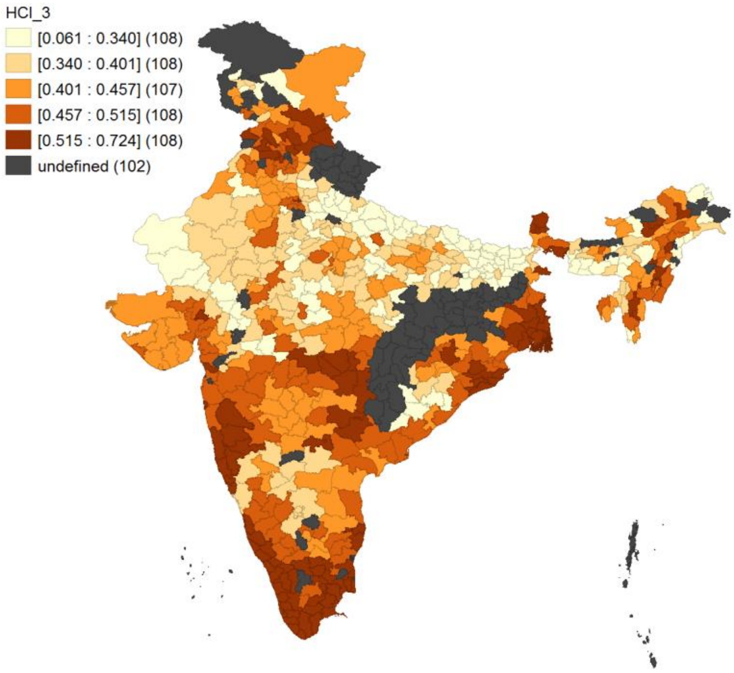
Similar to education and health index, here the clustering among homogenous districts can be observed. Districts with lower value are located in the same region. This is true for higher value also. As the distribution changed from dark colour to light colour then we can preliminarily guess about the neighboring influence of districts. So, the question may arise that, are the richer districts influenced by poorer district? Why do we have transition from upper value to lower value? The transition of districts are already captured in transitional probability matrix. The matrix reveals the presence of lower transition.

Map-5.5(B): Map Distribution of districts in respect of Human Capital Index in 2011



Source: Author's estimation

Map-5.5(C): Map Distribution of districts in respect of Human Capital Index in 2016



Source: Author's estimation

Based on the distribution of districts in terms of human capital index, I have estimated the Global Moran's Index for three time points. The following table shows the result of Global Moran's Index across 539 districts for three time points. The index values are statistically significant. This implies districts are forming clustering with homogeneous districts, i.e. high-high and low-low clustering.

Table-5.21: Result of Global Moran's Index of Human Capital Index over time

GMI	GMI_2006	GMI_2013	GMI_2016
HCI_GMI	0.749***	0.752***	0.668**

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

Both education and health index have the positive spatial autocorrelation across the districts. As a result, Human Capital Index also has the positive neighbourhood impact across the districts. The following figures capture that relationship with an upward slopping fitted line.

Figure-5.8(A): Spatial Autocorrelation of HCI in 2006

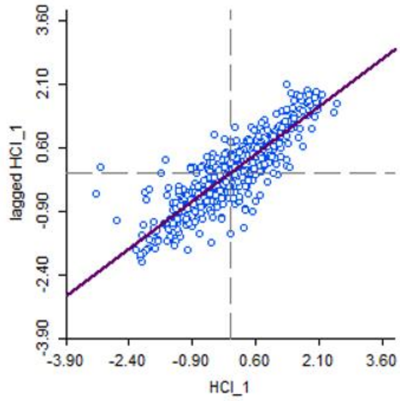


Figure-5.8(B): Spatial Autocorrelation of HCI in 2011

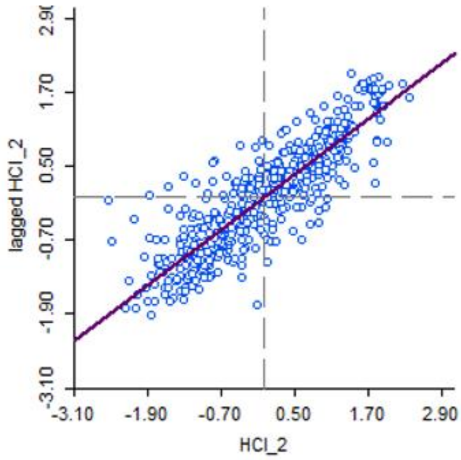
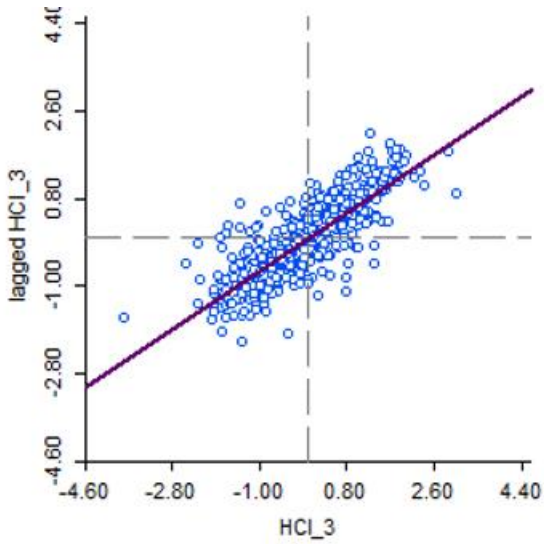


Figure-5.8(C): Spatial Autocorrelation of HCI in 2016

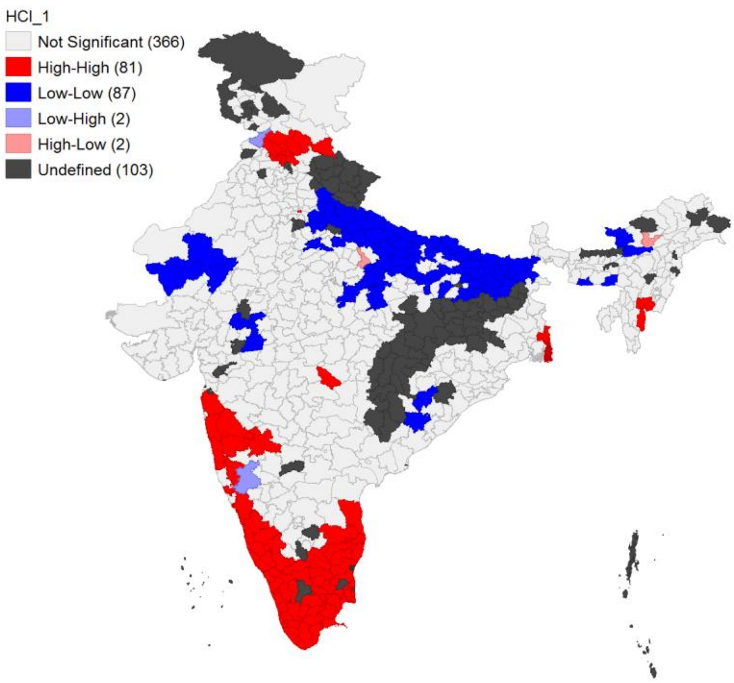


Source: Author's estimation

Scatter plots of education index are more clustered towards origin of the four quadrants whereas the opposite distribution was found for health index. The mixed result is occurred for Human capital index.

Now, here, also we can identify the number of districts which are falling in similar quadrant along dissimilar clusters. In 2006, out of 539 districts, 237 districts are in low-low trap out of which 87 districts are statistically significant. The result of significant clustering is obtained from the analysis of Local Moran's Index.

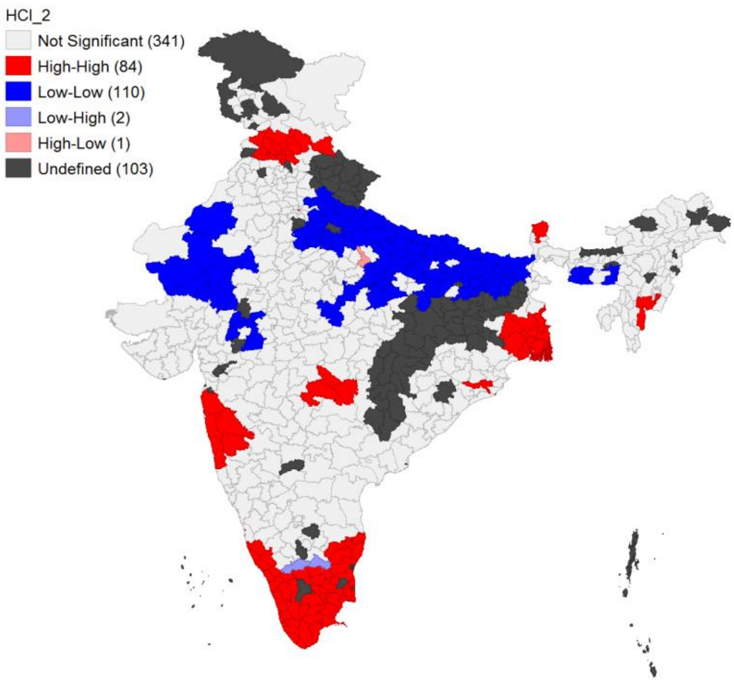
Map-5.6(A): Cluster of districts in respect of Human Capital Index in 2006



Source: Author's estimation

In next time point (2011), 232 districts are in low-low clustering and out of 232 districts 110 districts are in significantly forming the low-low clustering.

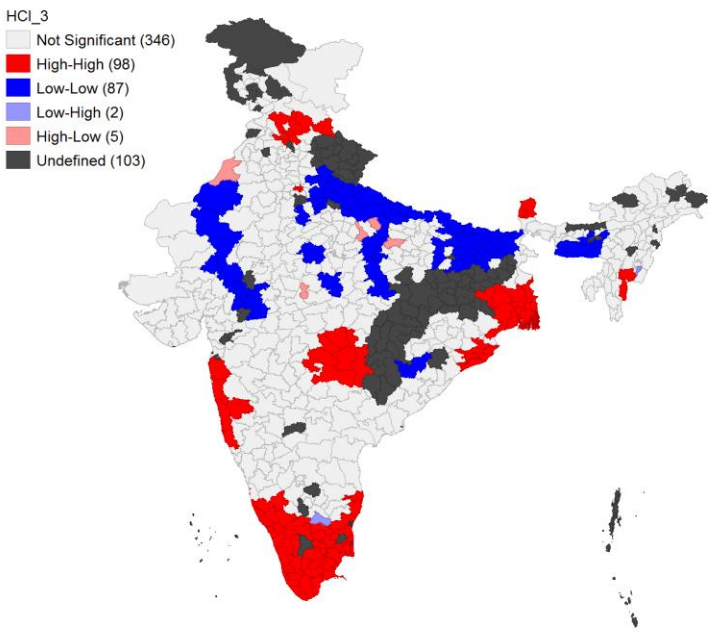
Map-5.6(B): Cluster of districts in respect of Human Capital Index in 2011



Source: Author's estimation

In 2016, the number of districts forming general clustering has increased to 234 whereas number of districts forming significant clustering has decreased to 87. The result of high-high clustering is also found to be very prominent compared to the result of low-low clustering. Rest of the districts are insignificant. They are not dependent to their neighbours.

Map-5.6(C): Cluster of districts in respect of Human Capital Index in 2016



Source: Author's estimation

Similar to the education and health index, here, I have identified the district which are stable in low-low cluster for three time points. Out of 539 districts 64 districts are in low-low cluster in terms of human capital index. Most of the districts are belonging to Bihar and Uttar Pradesh. From chapter 4, I have already found that these two states are in lower trap as well as lower cluster in respect to non-parametric analysis and spatial analysis.

5.5.4.2 Spatial Analysis: Spatial Analysis: Spatial Autoregressive are Error Model

If we compare all these clusters in terms of education, health and human capital index, it can be observed that only 4.45% districts are stable in terms of education index, 15.21% districts are stable in respect to health index whereas in terms of human capital index only 11.87 districts are stable. Outcomes of these districts are found to be dependent on the outcomes of their neighbours. Presence of spatial dependency across these districts is shown in the figures manifesting clustering. Among these traps, I have also identified the districts which are in trap in respect to all the indices. Out of total districts only 18 districts are common in all low-low clusters. All these 18 districts have lower value of education, health and human capital index and they are surrounded by districts with lower value in all the indices also. Thus, based on spatial analysis, we have found the presence of low-level trap across the districts. Now using regression-based approach under spatial analysis, one can identify spatial spillover effect of dependent and independent variables along with residual factor. Since due to inadequate data of health infrastructure across districts, I have run panel regression only with school infrastructure under the regression approach.

Table-5.22: Result of Spatial Durbin Autoregressive Model

Spatial Durbin Autoregressive Model			
Coefficient	Education Index	Health Index	Human Capital Index
Lag_dependent	0.864***	0.8179***	0.884
No. of Primary School	-0.01.6*	-0.018*	-0.019**
Lag_no. of primary school	0.020.	0.0098	0.0169
No. of Upper Primary School	0.040***	0.0138*	0.0288***
Lag_ No. of Upper Primary School	-0.0240**	-0.009	-0.019*
Wald Chi2(5)	2025.33**	971.79***	2194.22***
Pseudo R2	0.0198	0.0174	0.0010
Number of Observation	1512	1512	1512

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

Above table shows the result of spatial dependency across the districts based on regression approach. Here, I have used Spatial Durbin Autoregressive model and Spatial Durbin Error model to captures the dependency with respect to dependent variable and residual term. In the above table, I have inserted only the result of SDAR model for education index, health index and human capital index. For all indices, there exist a positive spatial dependency across districts. The outcomes (indices) are positively influenced by outcome of neighbour's districts. surprisingly number of primary schools has negative impact on education, health and human capital index and number of primary school of neighbours has insignificant impact on these indices. Upper primary school has a mixed impact. It has positive impact on education, health and human capital index but lagged upper primary school has inverse impact on these three respective impacts, out of which the impact is insignificant for health index. Here we have both direct and indirect effect of explanatory variables on outcome. Direct impact captured by the coefficient of number of primary school (PS) and upper primary school (UPS); indirect impact captured by the coefficient of lag number of PS and lag number of UPS. But some of the indirect impacts of explanatory variables are also captured by the coefficient of lag dependent variables (ρ). All these direct and indirect impact of explanatory variables are given in the following table.

Table-5.23: Impact of explanatory variables under SDAR

Spatial Durbin Autoregressive Model						
	Education Index		Health Index		Human Capital Index	
Impact	No. of PS	No. of UPS	No. of PS	No. of UPS	No. of PS	No. of UPS
Direct Impact	-0.018	0.043***	-0.019*	0.0143**	-0.020**	0.0304***
Indirect Impact	0.0131	0.043*	-0.015	0.0067	-0.003	0.0262
Total Impact	-0.005	0.086***	-0.034	0.0211	-0.023	0.0566***

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

It can be observed that there exists a mixed result of neighboring impact. All the direct effects of number of primary schools are negative whereas most of the indirect impact have positive impact on education, health and human capital index. All the direct and indirect impact of upper primary school are positive but the indirect impacts are insignificant. As a result, based on the power of impact on outcome, the total impact of number of primary schools is insignificant whereas total impact of upper primary school is significant for education and human capital index only. No significant impact of primary and upper primary school on health index is found.

Following two tables (5.24 and 5.25) represent the result of spatial error model considering the spatial impact of residual factor. The outcome levels are influenced by the residual of neighbours. The impacts are positive as well as significant also. Following result also shows that education health and human capital index are positively influenced by upper primary school, whereas primary school has inverse impact on these indices. Lag of primary school has mixed result but the result is insignificant. Similar to the upper primary school, lag upper primary school generates positive impact on outcome, the impact is significant only for education index.

Table-5.24: Result of Spatial Durbin Error Model

Spatial Durbin Error Model			
Coefficient	Education Index	Health Index	Human Capital Index
Lag_Error	0.866***	0.818***	0.885***
No. of Primary School	-0.019*	-0.017*	-0.020**
Lag_no. of primary school	-0.027	0.001	-0.012
No. of Upper Primary School	0.0422***	0.0144**	0.0298***
Lag_ No. of Upper Primary School	0.0410**	0.0017	0.0193
Wald Chi2(4)	63.76***	5.05	42.69***
Pseudo R2	0.0603	0.0028	0.0152
Number of Observation	1512	1512	1512

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

Again, I have checked the decomposition of impact of explanatory variables on dependent variables. Similar to the earlier result, here, primary school has inverse impact on education, health and human capital index but the impacts are significant. Upper primary school has positive and significant on these three indices. Most of the indirect impacts are insignificant, only indirect impact of upper primary school on education index is significant. In aggregate, only impact of upper primary school has positive and significant impact on education and human capital index, no significant impact is found on health index.

Table-5.25: Impact of explanatory variables under SDEM

Spatial Durbin Autoregressive Model						
	Education Index		Health Index		Human Capital Index	
Impact	No. of PS	No. of UPS	No. of PS	No. of UPS	No. of PS	No. of UPS
Direct Impact	-0.019*	0.042***	-0.0179*	0.014**	-0.020**	0.029***
Indirect Impact	-0.022	0.032**	0.0009	0.001	-0.009	0.015
Total Impact	-0.041	0.075***	-0.017	0.015	-0.030	0.045***

Source: Author's estimation,*** implies significance at 1 percent level.** implies significant at 5 percent level

Now the result can be compared with chronic low and low-level trap obtained from non-parametric analysis. This comparison will help us to define the role of space towards club formation. In terms of education index, out of 539 districts, only 51 districts are there in extreme low and low-level trap for three time points and in low-low cluster, there exist only 24 districts. Now, comparing these two traps and clusters, it can be observed that 16 districts are common in two analyses. These districts are Araria, Bahraich, Balrampur, Bareilly, Buduan, Darbhanga, Gonda, Koraput, Madhepura, Pulwama, Purnia, Rampur, Saharsa, Shahajahanpur, Shrawasti and Siddhartnagar. Most of the districts are belonging to Uttar Pradesh and Bihar.

Similarly, I have found the presence of spatial dependency towards club formation across the districts for three time points. From the non-parametric analysis, I have found that out of 539 districts, 141 districts are in extreme low and low-level trap over time. Spatial analysis shows that only 82 districts are forming low-low clustering. Comparing these two results, it can be found that 69 districts are common in these two analyses. They are in extreme low and low-level trap and they are space dependent.

Similar to education and health index, I have examined the overlapping situation for human capital index also. There are 62 districts in extreme low and low-level trap obtained from non-parametric analysis whereas spatial analysis shows that only 64 districts are forming significant low-low clustering over the time points. The comparison shows that only 35 districts are common. The clubs with these 35 districts are dependent on space. In the state level analysis, the result of Global and Local Moran's index were insignificant whereas from the district-level analysis it can be observed that districts are significantly forming clusters based on the specific variables. Now, the question may arise about the location of districts in each state of low-level trap. Since, all the districts under low-low cluster are belonging to those states which are already in chronic extreme lower-level trap. The States are not forming significant spatial cluster but the districts of these states are forming clusters. This is because districts are smaller administrative units compared to state.

5.6 Major Findings

In this chapter, I have constructed the education index, health index and human capital index based on some selective indicators from both education and health dimensions across 539 districts for three time points. I have found the presence of absolute beta convergence in terms of education, health and human capital index. Dispersion based approach shows that Education index, health index and human capital index are found to have a fluctuating trend over time. Similar to the dispersion-based approach, the inequality-based approach reveals that (except education index) both health and human capital index have experienced fluctuating trend over time. Non parametric approach provides more clear result than regression or dispersion-based approaches. In terms of education index, Kernel density estimation shows the presence of polarisation across 539 districts for three time points. Presence of polarisation means districts are forming two different classes. The concentration of districts is more prominent towards low and lower middle class. Health index also shows the presence of two classes. But health index is found to be polarized and the second peak has the higher density compared to first peak. The result is different from the education index. In education index, the concentration was found in low or lower class but in health index, the Kernel plot shows that districts are concentrating towards upper part of the distribution. The result of visual inspection also suggests the presence of polarization. The nature of the distribution of human capital index is, somehow reflects the dynamics of the distribution over time. Initially, human capital index shows polarized distribution. It can be observed that human capital is highly influenced by health dimension. As a complementary estimation of Kernel density estimation under this non-parametric analysis, I have constructed five respective classes to obtain transitional probability matrix. Both short run and long run transitional matrix for education index show that districts are more mobile towards lower classes. Both health and human capital index have an even distributional pattern over time. Transitional Probability Matrix also shows that in the long run, districts are converging towards lower classes whereas in terms of health index, districts are converging at the higher level of health status. Since, human capital index is a composite of education and health index. The long run stationary distribution of reveals that districts are converging towards middle class or middle values. Analysis of variance also support the classification of these arbitrary classes as well as provides an indication about mobility or stability over time. Non-parametric analysis reveals that out of 539 districts, only few districts are in chronic low-level trap based on education, health and human capital index. Only two districts are there in chronic extreme trap in terms of education index whereas out of 539 districts only three districts are in chronic extreme trap in terms of health index. Surprisingly, none is falling in the chronic trap in terms of human capital index. The number of districts in low level trap has increased if we extend the range for trap. Both the kernel plots and transitional probability matrix show that districts are concentrating towards low, lower middle and upper middle. I have few districts under extreme low-level class. After extending the range from 10-30 to 10-50, the number of districts in chronic low-level trap in terms of education index has increased to 51, in terms of health index and human capital index the number of districts under chronic trap have increased to 141 and 62 respectively. Comparing all these traps, out of 539 districts only 28 districts are found to be common in all the traps (education, health and human capital index).All these districts are belonging to those states which are also poor in terms of education health and human capital index obtained from state level analysis. Spatial analysis also reveals similar type of result. Out of 539 districts, 24 districts, 82 districts and 64 districts are forming significant low-low cluster in terms of education, health and human capital index respectively.

Appendix 5A.1: EI, HI and HCI across 539 districts for three time points (2006, 2011 and 2016)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Adilabad	0.2944(326)	0.3476(416)	0.3599(437)	0.4894(150)	0.5270(139)	0.5712(129)	0.3796(210)	0.4280(239)	0.4534(228)
Agra	0.2502(432)	0.2834(519)	0.3528(452)	0.3079(341)	0.3082(389)	0.3071(424)	0.2776(390)	0.2955(477)	0.3291(452)
Ahmadabad	0.3406(215)	0.3937(286)	0.4689(114)	0.5307(116)	0.5463(126)	0.5630(135)	0.4251(128)	0.4638(156)	0.5138(110)
Ahmednagar	0.3863(105)	0.4278(178)	0.4463(170)	0.4766(164)	0.5121(161)	0.5516(143)	0.4291(121)	0.4681((147)	0.4961(142)
Aizawl	0.5887(003)	0.6020(003)	0.5376(014)	0.4645(171)	0.5335(133)	0.6172(091)	0.5229(031)	0.5667(025)	0.5760(033)
Ajmer	0.3131(271)	0.3632(379)	0.3916(345)	0.3045(345)	0.3181(375)	0.3317(396)	0.3088(336)	0.3399(394)	0.3604(391)
Akola	0.4141(066)	0.4658(090)	0.4748(093)	0.4767(163)	0.4975(181)	0.5198(181)	0.4443(099)	0.4814(123)	0.4968(140)
Aligarh	0.2485(439)	0.2914(512)	0.3575(442)	0.2248(472)	0.2547(476)	0.2873(453)	0.2364(469)	0.2725(505)	0.3205(468)
Allahabad	0.2878(345)	0.3462(418)	0.4175(250)	0.2157(489)	0.2799(430)	0.3522(381)	0.2491(451)	0.3113(444)	0.3834(351)
Aloppuzha	0.3048(296)	0.4007(261)	0.4900(060)	0.8023(003)	0.7631(008)	0.7173(032)	0.4945(048)	0.5530(030)	0.5928(021)
Alwar	0.3236(252)	0.4049(252)	0.4025(307)	0.2566(429)	0.3132(380)	0.3786(356)	0.2882(372)	0.3561(360)	0.3904(337)
Ambala	0.2513(430)	0.4009(260)	0.4609(134)	0.5690(084)	0.5649(108)	0.5553(140)	0.3781(213)	0.4759(128)	0.5059(125)
Ambedkar Nagar	0.3391(218)	0.4283(177)	0.4475(166)	0.2826(384)	0.3356(354)	0.3998(332)	0.3096(334)	0.3791(323)	0.4230(289)
Amravati	0.4116(069)	0.4572(106)	0.4792(085)	0.4684(167)	0.5619(111)	0.6681(054)	0.4391(105)	0.5069(078)	0.5658(042)
Amreli	0.3440(208)	0.3750(341)	0.4058(291)	0.5151(124)	0.5065(169)	0.4937(215)	0.4210(139)	0.4358(218)	0.4476(239)
Amritsar	0.2592(414)	0.3495(412)	0.4582(141)	0.5084(136)	0.5482(123)	0.5952(107)	0.3630(243)	0.4377(216)	0.5222(097)
Anand	0.3884(102)	0.4321(167)	0.4816(079)	0.4423(205)	0.4696(210)	0.4983(208)	0.4145(147)	0.4504(190)	0.4899(156)
Anantang	0.2143(479)	0.2900(514)	0.2756(525)	0.4338(214)	0.3935(305)	0.3652(365)	0.3049(343)	0.3378(398)	0.3172(474)
Anantapur	0.2848(356)	0.3325(450)	0.3443(468)	0.5131(127)	0.4816(198)	0.4253(305)	0.3823(205)	0.4002(288)	0.3827(352)
Anugul	0.3474(196)	0.4423(146)	0.4466(168)	0.4167(236)	0.4500(232)	0.4890(223)	0.3805(209)	0.4461(197)	0.4673(192)
Anuppur	0.4370(036)	0.3873(310)	0.3652(424)	0.3822(276)	0.3200(372)	0.1725(532)	0.4087(159)	0.3520(368)	0.2510(526)
Araria	0.0925(536)	0.3069(494)	0.3355(486)	0.1967(506)	0.1832(532)	0.1686(533)	0.1349(532)	0.2371(530)	0.2378(534)
Ashoknagar	0.4347(039)	0.3900(300)	0.3696(411)	0.2983(354)	0.2667(453)	0.1780(531)	0.3601(248)	0.3225(423)	0.2565(523)
Auraiya	0.3664(159)	0.4151(220)	0.4838(076)	0.2742(399)	0.3060(395)	0.3410(388)	0.3170(323)	0.3564(359)	0.4062(316)
Aurangabad	0.2538(423)	0.4165(216)	0.4495(161)	0.2674(411)	0.2713(445)	0.2743(470)	0.2605(432)	0.3361(401)	0.3512(412)
Aurangabad	0.3349(226)	0.4458(136)	0.4704(108)	0.3982(256)	0.4244(262)	0.4524(267)	0.3652(236)	0.4350(220)	0.4613(206)
Azamgarh	0.2929(332)	0.3849(318)	0.4141(262)	0.2434(448)	0.3329(356)	0.4400(289)	0.2670(419)	0.3579(356)	0.4269(280)
Badgam	0.1851(505)	0.3192(475)	0.2563(531)	0.4446(203)	0.4264(258)	0.4093(324)	0.2869(375)	0.3690(343)	0.3239(462)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Bagalkot	0.3129(273)	0.3856(313)	0.4010(310)	0.3839(273)	0.3991(296)	0.4150(313)	0.3466(274)	0.3923(302)	0.4079(315)
Baghpat	0.2702(389)	0.3345(445)	0.4068(288)	0.3044(346)	0.3146(378)	0.3245(409)	0.2868(377)	0.3244(419)	0.3633(385)
Bahraich	0.1053(530)	0.2551(532)	0.2743(526)	0.1686(525)	0.1902(527)	0.2126(519)	0.1332(533)	0.2203(533)	0.2415(531)
Balaghat	0.4154(064)	0.4370(157)	0.4415(179)	0.3363(317)	0.4014(292)	0.4758(244)	0.3738(219)	0.4188(257)	0.4583(214)
Balangir	0.2772(373)	0.3936(288)	0.3908(349)	0.3431(313)	0.3796(316)	0.4148(314)	0.3084(338)	0.3865(311)	0.4026(319)
Balarampur	0.1031(531)	0.2579(530)	0.2872(521)	0.1427(535)	0.1867(530)	0.2267(512)	0.1213(536)	0.2194(534)	0.2551(524)
Baleshwar	0.3599(172)	0.4651(091)	0.4648(128)	0.4343(212)	0.4751(203)	0.5229(178)	0.3953(183)	0.4701(141)	0.4930(149)
Ballia	0.2795(369)	0.3461(419)	0.4078(283)	0.3628(293)	0.3576(337)	0.3395(390)	0.3184(320)	0.3518(369)	0.3721(373)
Banaskantha	0.2877(346)	0.3999(266)	0.3900(353)	0.3124(336)	0.3539(340)	0.4000(331)	0.2998(353)	0.3762(329)	0.3950(330)
Banda	0.2785(371)	0.3736(350)	0.3935(341)	0.2262(469)	0.2488(484)	0.2726(474)	0.2510(447)	0.3049(461)	0.3275(455)
Bangalore	0.3538(177)	0.3425(428)	0.3357(485)	0.6515(031)	0.5936(079)	0.5165(184)	0.4801(062)	0.4509(187)	0.4164(298)
Bangalore Rural	0.3018(308)	0.3295(457)	0.4455(172)	0.5555(098)	0.5499(121)	0.5406(155)	0.4095(158)	0.4257(241)	0.4907(154)
Banka	0.1473(517)	0.3293(458)	0.3641(426)	0.2390(455)	0.2610(465)	0.2834(459)	0.1876(514)	0.2932(481)	0.3212(465)
Bankura	0.3469(198)	0.4131(224)	0.4073(287)	0.4908(148)	0.5598(114)	0.6396(076)	0.4127(152)	0.4809(124)	0.5104(116)
Banswara	0.2309(459)	0.3191(476)	0.3303(492)	0.1994(504)	0.1975(524)	0.1884(528)	0.2145(494)	0.2510(522)	0.2495(527)
Bara Banki	0.2302(461)	0.3044(496)	0.3343(487)	0.2180(483)	0.2362(498)	0.2522(496)	0.2240(484)	0.2682(507)	0.2903(501)
Baramula	0.2023(493)	0.3477(415)	0.3979(323)	0.4135(238)	0.4184(272)	0.4033(329)	0.2892(370)	0.3814(318)	0.4006(325)
Baran	0.3282(242)	0.3708(357)	0.3851(372)	0.2737(400)	0.3182(373)	0.3686(361)	0.2997(355)	0.3435(383)	0.3767(363)
Bardwan	0.3552(175)	0.4115(229)	0.4266(222)	0.5427(111)	0.6050(069)	0.6798(048)	0.4390(106)	0.4989(089)	0.5385(076)
Bareilly	0.2053(488)	0.2922(510)	0.3295(494)	0.2184(481)	0.2577(472)	0.3011(432)	0.2117(498)	0.2744(504)	0.3150(478)
Bargarh	0.3058(291)	0.3941(284)	0.4283(217)	0.4457(198)	0.5150(152)	0.5911(114)	0.3692(228)	0.4505(189)	0.5031(130)
Barmer	0.3236(253)	0.3368(440)	0.2990(515)	0.1529(533)	0.2008(522)	0.2530(494)	0.2224(486)	0.2601(517)	0.2750(210)
Barpeta	0.2858(353)	0.3917(296)	0.3491(458)	0.3212(328)	0.4118(281)	0.4931(219)	0.3030(348)	0.4016(283)	0.4149(302)
Barwani	0.1913(500)	0.2942(507)	0.2358(535)	0.1675(526)	0.2426(493)	0.3208(415)	0.1790(515)	0.2672(510)	0.2750(509)
Basti	0.2574(419)	0.3273(460)	0.4078(284)	0.2370(458)	0.2926(415)	0.3583(377)	0.2470(452)	0.3095(446)	0.3823(353)
Bathinda	0.3187(260)	0.3941(285)	0.4115(269)	0.5004(142)	0.5273(137)	0.5567(138)	0.3993(178)	0.4559(173)	0.4786(177)
Baudh	0.3110(278)	0.5069(023)	0.4756(092)	0.3155(332)	0.3509(343)	0.3894(344)	0.3133(329)	0.4217(249)	0.4303(271)
Begusarai	0.2050(490)	0.3934(290)	0.3984(320)	0.2380(456)	0.2525(479)	0.2664(478)	0.2209(488)	0.3152(436)	0.3258(461)
Belgaum	0.2409(449)	0.2463(534)	0.2701(530)	0.4611(180)	0.4539(228)	0.4433(284)	0.3333(295)	0.3344(404)	0.3460(419)
Bellary	0.3255(246)	0.3739(349)	0.3906(350)	0.3663(291)	0.3767(319)	0.3870(347)	0.3453(278)	0.3753(331)	0.3888(338)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Betul	0.3778(135)	0.3935(289)	0.3893(357)	0.2818(385)	0.3346(355)	0.3993(333)	0.3263(310)	0.3628(350)	0.3943(331)
Bhadrak	0.3925(094)	0.4358(160)	0.4038(299)	0.4087(244)	0.4722(205)	0.5466(151)	0.4006(173)	0.4536(178)	0.4698(184)
Bhagalpur	0.1941(495)	0.3445(426)	0.3768(394)	0.2424(451)	0.2619(463)	0.2818(462)	0.2169(491)	0.3004(468)	0.3258(460)
Bhandara	0.3945(091)	0.4285(176)	0.4650(126)	0.4921(147)	0.5566(118)	0.6329(078)	0.4406(103)	0.4884(108)	0.5425(074)
Bharatpur	0.3469(200)	0.3884(306)	0.3805(381)	0.2230(475)	0.2628(460)	0.3066(426)	0.2781(389)	0.3194(431)	0.3415(426)
Bharuch	0.3469(199)	0.4152(219)	0.4645(129)	0.4782(160)	0.5055(172)	0.5361(159)	0.4073(161)	0.4582(168)	0.4990(136)
Bhavnagar	0.35084(186)	0.4170(213)	0.3899(354)	0.4317(217)	0.4545(227)	0.4791(241)	0.3891(195)	0.4353(219)	0.4322(267)
Bhilwara	0.2418(446)	0.3195(473)	0.3575(441)	0.2590(427)	0.2937(412)	0.3327(395)	0.2503(448)	0.3063(456)	0.3449(422)
Bhind	0.3900(098)	0.4681(085)	0.4377(185)	0.2806(387)	0.3431(348)	0.4133(318)	0.3308(299)	0.4008(285)	0.4253(284)
Bhiwani	0.2622(403)	0.4065(244)	0.4188(245)	0.4284(221)	0.4586(222)	0.4913(221)	0.3351(293)	0.4318(228)	0.4536(226)
Bhojpur	0.2645(401)	0.4271(182)	0.4303(212)	0.2837(381)	0.2927(414)	0.3009(433)	0.2739(400)	0.3535(364)	0.3598(392)
Bhopal	0.4377(032)	0.4640(093)	0.4901(059)	0.4071(248)	0.4597(221)	0.5212(180)	0.4221(136)	0.4618(160)	0.5054(127)
Bid	0.3884(103)	0.4376(155)	0.4252(225)	0.3999(255)	0.4124(280)	0.4254(304)	0.3941(187)	0.4248(243)	0.4253(285)
Bidar	0.3437(209)	0.4424(145)	0.4187(246)	0.4023(252)	0.4379(247)	0.4782(242)	0.3718(222)	0.4402(208)	0.4475(240)
Bijapur	0.3378(221)	0.4202(204)	0.3927(344)	0.3939(259)	0.3853(313)	0.3766(357)	0.3648(237)	0.4024(281)	0.3846(347)
Bijnor	0.2909(337)	0.3963(280)	0.4004(316)	0.2512(437)	0.2727(443)	0.2910(450)	0.2703(412)	0.3287(411)	0.3413(428)
Bikaner	0.2938(327)	0.3740(346)	0.3549(449)	0.2803(389)	0.3231(367)	0.3711(360)	0.2870(374)	0.3476(374)	0.3629(387)
Bilaspur	0.4324(042)	0.4620(097)	0.4732(099)	0.5744(082)	0.5431(127)	0.4936(216)	0.4984(044)	0.5009(084)	0.4833(166)
Birbhum	0.3428(210)	0.4297(173)	0.4063(289)	0.4258(225)	0.4925(185)	0.5733(127)	0.3820(207)	0.4600(162)	0.4827(168)
Bishnupur	0.3736(148)	0.4684(084)	0.4659(125)	0.4769(162)	0.5007(176)	0.5247(177)	0.4221(137)	0.4843(117)	0.4944(146)
Bongaigaon	0.2932(331)	0.4230(198)	0.4076(285)	0.3049(344)	0.3387(352)	0.3685(362)	0.2990(357)	0.3785(326)	0.3876(343)
Budaun	0.1483(516)	0.2499(533)	0.2560(532)	0.1259(536)	0.1750(534)	0.2284(510)	0.1367(531)	0.2091(536)	0.2418(530)
Bulandshahr	0.2373(453)	0.3086(492)	0.3701(409)	0.2506(439)	0.2628(458)	0.2735(471)	0.2439(458)	0.2848(495)	0.3181(472)
Buldhana	0.4060(074)	0.4612(100)	0.4549(144)	0.4176(233)	0.4416(244)	0.4678(251)	0.4117(155)	0.4513(186)	0.4613(207)
Bundi	0.2961(320)	0.3329(449)	0.3483(459)	0.2856(374)	0.3528(341)	0.4326(301)	0.2908(368)	0.3427(385)	0.3882(342)
Burhanpur	0.3446(205)	0.3369(439)	0.3330(488)	0.4557(189)	0.3949(302)	0.3229(410)	0.3963(181)	0.3647(349)	0.3279(454)
Buxer	0.2666(395)	0.4156(217)	0.4297(213)	0.2624(420)	0.2640(457)	0.2631(481)	0.2645(425)	0.3313(408)	0.3362(438)
Cachar	0.3246(249)	0.4616(098)	0.4391(184)	0.3524(299)	0.3901(309)	0.4232(308)	0.3382(289)	0.4243(244)	0.4311(269)
Central	0.3983(085)	0.3894(303)	0.4906(058)	0.5983(065)	0.6324(057)	0.6691(053)	0.4882(052)	0.4962(097)	0.5730(039)
Chamarajanagar	0.2886(343)	0.2726(525)	0.3441(470)	0.5517(103)	0.6027(070)	0.6630(063)	0.3991(180)	0.4054(279)	0.4776(178)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Chamba	0.3839(112)	0.4632(094)	0.4197(244)	0.4660(170)	0.4545(226)	0.4383(291)	0.4230(134)	0.4588(166)	0.4289(275)
Champhai	0.5007(008)	0.5608(007)	0.5131(026)	0.3511(301)	0.3672(327)	0.3834(352)	0.4193(143)	0.4538(177)	0.4435(249)
Chanalang	0.2600(412)	0.3980(274)	0.3710(407)	0.2503(440)	0.3132(381)	0.3674(364)	0.2551(440)	0.3531(367)	0.3692(375)
Chandauli	0.3795(127)	0.3982(273)	0.4030(304)	0.2431(450)	0.3132(379)	0.3938(339)	0.3037(346)	0.3532(366)	0.3984(328)
Chandel	0.2078(486)	0.4273(180)	0.4320(208)	0.4494(194)	0.5212(144)	0.6100(097)	0.3056(341)	0.4719(134)	0.5134(112)
Chandrapur	0.3694(156)	0.4089(238)	0.4553(143)	0.4875(155)	0.5675(102)	0.6663(058)	0.4244(129)	0.4817(122)	0.5508(061)
Chennai	0.4392(030)	0.5025(029)	0.4890(061)	0.7185(014)	0.7408(013)	0.7603(016)	0.5617(004)	0.6101(002)	0.6098(011)
Chhatarpur	0.2961(321)	0.4079(242)	0.4009(311)	0.1927(509)	0.2543(477)	0.3279(402)	0.2389(466)	0.3220(425)	0.3625(388)
chhindwara	0.1238(524)	0.4028(255)	0.4680(117)	0.2980(355)	0.3651(331)	0.4422(286)	0.1921(513)	0.3835(315)	0.4549(222)
Chikmagalur	0.3001(312)	0.3451(423)	0.4311(210)	0.6284(047)	0.6087(068)	0.5672(131)	0.4343(110)	0.4583(167)	0.4945(145)
Chitradurga	0.3304(235)	0.3496(409)	0.4084(280)	0.4846(158)	0.5070(167)	0.5315(167)	0.4001(175)	0.4210(252)	0.4659(196)
Chitrakoot	0.4400(029)	0.3986(271)	0.3304(491)	0.1763(520)	0.2165(510)	0.2608(484)	0.2785(388)	0.2937(480)	0.2935(496)
Chittaurgarh	0.2585(418)	0.2631(527)	0.3454(466)	0.2920(363)	0.3595(334)	0.4435(281)	0.2747(398)	0.3075(453)	0.3914(336)
Chittoor	0.3321(231)	0.3682(364)	0.3769(393)	0.5806(077)	0.5639(109)	0.5361160)	0.4391(104)	0.4557(174)	0.4495(234)
Churachandpur	0.3344(227)	0.5009(032)	0.5107(027)	0.4559(187)	0.4770(202)	0.4972(209)	0.3905(193)	0.4888(107)	0.5039(128)
Churu	0.3377(222)	0.3587(391)	0.3658(422)	0.2961(356)	0.3496(344)	0.4122(321)	0.3162(324)	0.3541(363)	0.3883(341)
Coddalore	0.4259(052)	0.4624(095)	0.4526(152)	0.6082(058)	0.6459(046)	0.6898(045)	0.5090(039)	0.5465(034)	0.5588(053)
Coimbatore	0.4280(049)	0.4673(087)	0.6016(005)	0.6667(027)	0.7446(011)	0.8329(001)	0.5342(025)	0.5899(003)	0.7078(002)
Cuttack	0.3449(203)	0.4021(256)	0.4515(154)	0.4629(175)	0.5532(119)	0.6636(062)	0.3995(177)	0.4716(135)	0.5474(067)
Dakshin Dinajpur	0.3622(167)	0.4586(104)	0.4336(206)	0.3708(286)	0.5181(148)	0.7267(025)	0.3665(234)	0.4874(112)	0.5613(049)
Dakshin Kannada	0.4005(083)	0.4110(230)	0.4865(069)	0.7160(015)	0.6794(025)	0.6318(080)	0.5355(023)	0.5285(051)	0.5544(059)
Damoh	0.3508(184)	0.4233(197)	0.4037(300)	0.2182(482)	0.3062(393)	0.3988(334)	0.2767(392)	0.3600(353)	0.4013(323)
Darbhanga	0.1637(513)	0.3134(484)	0.3424(473)	0.2456(446)	0.2475(486)	0.2482(499)	0.2005(506)	0.2785(502)	0.2915(500)
Darjiling	0.2490(437)	0.2809(521)	0.2482(533)	0.5644(088)	0.6585(037)	0.7725(012)	0.3749(218)	0.4301(233)	0.4379(256)
Darrang	0.2496(435)	0.3727(353)	0.3402(476)	0.2849(377)	0.3041(400)	0.3221(413)	0.2667(421)	0.3366(400)	0.3310(447)
Datia	0.3963(088)	0.4524(117)	0.4006(314)	0.2565(430)	0.3227(371)	0.4011(330)	0.3188(318)	0.3821(317)	0.4008(324)
Dausa	0.3519(180)	0.4104(233)	0.3956(331)	0.2432(449)	0.2817(427)	0.3247(408)	0.2926(365)	0.3400(393)	0.3584(396)
Davangere	0.3518(181)	0.3828(326)	0.4308(211)	0.4982(143)	0.5328(135)	0.5734(126)	0.4186(145)	0.4516(185)	0.4970(139)
Debagarh	0.3073(287)	0.4415(148)	0.4103(275)	0.3519(300)	0.4014(291)	0.4587(263)	0.3289(305)	0.4210(253)	0.4338(264)
Deoria	0.2615(404)	0.3309(453)	0.4043(298)	0.2670(412)	0.3453(347)	0.4406(288)	0.2642(426)	0.3380(397)	0.4220(292)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Dewas	0.3226(255)	0.4000(264)	0.3952(334)	0.3076(342)	0.3783(318)	0.4606(260)	0.3150(326)	0.3890(307)	0.4267(281)
Dhalai	0.3478(195)	0.5417(012)	0.5177(022)	0.3679(288)	0.3651(330)	0.3623(369)	0.3577(255)	0.4447(200)	0.4331(265)
Dhar	0.2611(409)	0.3833(324)	0.3236(502)	0.2831(383)	0.3290(360)	0.3798(355)	0.2718(407)	0.3552(361)	0.3506(414)
Dharmapuri	0.2513(431)	0.2728(524)	0.3686(416)	0.5106(132)	0.5042(174)	0.4798(238)	0.3582(252)	0.3708(342)	0.4205(294)
Dharwad	0.3250(248)	0.4365(158)	0.4548(146)	0.5014(141)	0.5150(153)	0.5288(172)	0.4037(169)	0.4741(132)	0.4904(155)
Dhaulpur	0.3394(217)	0.4554(110)	0.4156(255)	0.1662(527)	0.2205(508)	0.2817(463)	0.2375(468)	0.3169(435)	0.3421(425)
Dhemaji	0.3006(309)	0.4643(092)	0.3970(326)	0.3431(311)	0.3997(295)	0.4472(275)	0.3212(316)	0.4308(231)	0.4213(293)
Dhenkanal	0.3483(193)	0.4304(172)	0.4362(192)	0.3784(283)	0.4861(192)	0.6081(098)	0.3630(241)	0.4574(170)	0.5150(108)
Dhubri	0.2456(443)	0.3890(304)	0.3473(464)	0.2102(493)	0.2352(502)	0.2571(487)	0.2272(477)	0.3025(465)	0.2988(492)
Dhule	0.3851(106)	0.4236(194)	0.4111(270)	0.4241(226)	0.4337(253)	0.4435(283)	0.4041(168)	0.4286(236)	0.4270(279)
Dibang Valley	0.0815(537)	0.1160(539)	0.3373(481)	0.2449(447)	0.2766(435)	0.2922(446)	0.1413(529)	0.1791(539)	0.3139(480)
Dibrugarh	0.2960(322)	0.3648(375)	0.4130(267)	0.5237(120)	0.5273(138)	0.5155(186)	0.3937(188)	0.4386(212)	0.4614(205)
Dima Hasao	0.3443(206)	0.4449(140)	0.4280(218)	0.3661(292)	0.3973(297)	0.4242(307)	0.3550(257)	0.4204(255)	0.4261(282)
Dimapur	0.5595(005)	0.5774(004)	0.5699(007)	0.3841(272)	0.4310(254)	0.4862(231)	0.4636(076)	0.4989(090)	0.5264(093)
Dindigul	0.4073(071)	0.4531(115)	0.4587(139)	0.6242(048)	0.5830(083)	0.5291(171)	0.5042(041)	0.5140(072)	0.4926(150)
Dindori	0.3021(304)	0.3839(321)	0.3946(338)	0.2898(367)	0.3053(397)	0.3201(416)	0.2959(360)	0.3424(387)	0.3554(405)
Doda	0.2361(455)	0.2915(511)	0.3845(375)	0.3896(264)	0.4193(270)	0.4373(293)	0.3033(347)	0.3496(371)	0.4100(311)
Dohad	0.2379(452)	0.3681(365)	0.3375(480)	0.2235(474)	0.2440(490)	0.2641(479)	0.2306(474)	0.2997(471)	0.2985(494)
Dungarpur	0.2592(415)	0.3527(402)	0.3556(444)	0.2225(476)	0.2667(452)	0.3147(420)	0.2401(465)	0.3067(454)	0.3346(440)
East	0.4379(031)	0.4925(039)	0.5549(008)	0.4936(144)	0.5431(128)	0.6014(102)	0.4649(075)	0.5172(065)	0.5777(032)
East District	0.4312(045)	0.5312(013)	0.5378(013)	0.5134(126)	0.6186(063)	0.7622(015)	0.4705(071)	0.5732(013)	0.6403(005)
East Garo Hills	0.3508(185)	0.4781(065)	0.3480(461)	0.2155(490)	0.2352(501)	0.2557(489)	0.2749(396)	0.3353(402)	0.2983(495)
East Godavari	0.3078(285)	0.3590(389)	0.3852(371)	0.6211(050)	0.6477(045)	0.6782(050)	0.4372(109)	0.4822(119)	0.5111(114)
East Kameng	0.1869(504)	0.4172(211)	0.3620(431)	0.0030(539)	0.1355(537)	0.1917(526)	0.0239(539)	0.2378(529)	0.2634(519)
East Khasi Hills	0.4065(072)	0.5225(016)	0.4961(047)	0.2993(351)	0.3017(402)	0.3040(428)	0.3488(270)	0.3970(295)	0.3884(340)
East Siang	0.3766(139)	0.5041(027)	0.4531(150)	0.3612(295)	0.4796(200)	0.5945(108)	0.3688(230)	0.4917(103)	0.5190(102)
Ernakulam	0.3813(121)	0.4018(257)	0.4986(040)	0.7864(005)	0.7541(009)	0.7204(029)	0.5476(011)	0.5505(033)	0.5993(019)
Erode	0.3511(183)	0.3995(268)	0.4861(070)	0.7017(018)	0.7101(018)	0.7187(030)	0.4964(046)	0.5326(045)	0.5911(024)
Etah	0.3182(263)	0.2717(526)	0.4393(183)	0.1843(515)	0.2352(500)	0.2918(448)	0.2422(461)	0.2528(520)	0.3581(397)
Etawah	0.3629(165)	0.3868(312)	0.4668(121)	0.2853(375)	0.3243(366)	0.3675(363)	0.3218(314)	0.3542(362)	0.4142(303)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Faizabad	0.2592(416)	0.3602(386)	0.4213(237)	0.2876(372)	0.3086(388)	0.3302(398)	0.2730(402)	0.3334(406)	0.3730(370)
Faridabad	0.2305(460)	0.1887(538)	0.4668(120)	0.4015(254)	0.4292(255)	0.4563(265)	0.3042(344)	0.2846(496)	0.4615(203)
Faridkot	0.3165(265)	0.4056(248)	0.4234(230)	0.5223(121)	0.5212(143)	0.5178(183)	0.4065(163)	0.4598(163)	0.4682(190)
Farrukhabad	0.2951(324)	0.3541(399)	0.4106(273)	0.2209(478)	0.2568(473)	0.2942(442)	0.2553(439)	0.3015(466)	0.3476(416)
Fatehabad	0.2515(429)	0.3623(382)	0.3988(319)	0.4180(232)	0.4394(246)	0.4610(259)	0.3243(313)	0.3990(294)	0.4288(276)
Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Fatehgarh Sahib	0.2719(385)	0.4393(153)	0.4521(153)	0.5655(086)	0.5827(084)	0.6012(103)	0.3921(189)	0.5059(080)	0.5214(099)
Fatehpur	0.2765(374)	0.3298(456)	0.3627(430)	0.2471(444)	0.2727(442)	0.2988(437)	0.2614(431)	0.2999(470)	0.3292(451)
Firozabad	0.2912(335)	0.3573(392)	0.3786(391)	0.2272(467)	0.2775(432)	0.3361(392)	0.2572(438)	0.3149(438)	0.3567(403)
Firozpur	0.2843(358)	0.4092(237)	0.2708(527)	0.4641(172)	0.4793(201)	0.4949(213)	0.3633(240)	0.4429(203)	0.3661(379)
Gadag	0.3501(188)	0.3884(305)	0.4233(231)	0.4449(202)	0.4446(238)	0.4426(285)	0.3946(186)	0.4156(262)	0.4328(266)
Gadchiroli	0.3221(256)	0.3902(298)	0.4005(315)	0.3800(281)	0.5036(175)	0.6638(061)	0.3499(268)	0.4433(201)	0.5156(107)
Gajapati	0.1930(497)	0.3190(477)	0.3183(507)	0.2838(380)	0.2918(417)	0.2997(435)	0.2340(471)	0.3051(460)	0.3088(486)
Gandhinagar	0.3884(101)	0.4205(203)	0.5196(020)	0.4627(177)	0.5237(142)	0.5921(112)	0.4239(130)	0.4693(143)	0.5547(058)
Ganganagar	0.2973(318)	0.3330(448)	0.3955(332)	0.3874(267)	0.4422(242)	0.5101(195)	0.3393(285)	0.3837(314)	0.4492(237)
Ganjam	0.3125(275)	0.4125(227)	0.4081(281)	0.3882(266)	0.4500(231)	0.5257(176)	0.3483(272)	0.4309(230)	0.4632(201)
Gautam Buddha Nagar	0.2749(377)	0.3498(408)	0.4979(042)	0.3115(337)	0.3051(398)	0.2807(464)	0.2926(364)	0.3267(414)	0.3739(369)
Gaya	0.2214(475)	0.3652(374)	0.3803(382)	0.2669(413)	0.2603(469)	0.2485(497)	0.2430(460)	0.3083(451)	0.3074(487)
Ghaziabad	0.2431(444)	0.3245(467)	0.3551(447)	0.3204(329)	0.3252(365)	0.3255(405)	0.2791(386)	0.3248(417)	0.3400(430)
Ghazipur	0.2606(411)	0.3233(469)	0.4496(160)	0.2869(373)	0.2950(410)	0.2960(439)	0.2734(401)	0.3088(448)	0.3648(382)
Goalpara	0.3004(310)	0.4463(134)	0.3904(351)	0.2802(390)	0.3082(390)	0.3296(400)	0.2901(369)	0.3709(341)	0.3587(395)
Golaghat	0.3055(294)	0.4234(195)	0.4284(216)	0.4471(196)	0.4722(206)	0.4846(235)	0.3696(227)	0.4471(196)	0.4556(218)
Gonda	0.1845(506)	0.3147(481)	0.3524(453)	0.2091(494)	0.2647(456)	0.3270(404)	0.1964(510)	0.2886(492)	0.3395(432)
Gondiya	0.4043(078)	0.4480(126)	0.4671(118)	0.4589(184)	0.5078(164)	0.5679(130)	0.4307(117)	0.4770(126)	0.5150(109)
Gopalganj	0.2029(492)	0.3749(343)	0.4132(266)	0.2849(376)	0.2763(436)	0.2589(485)	0.2405(464)	0.3218(426)	0.3271(457)
Gorakhpur	0.3478(194)	0.3097(491)	0.3437(471)	0.3099(338)	0.3711(325)	0.4473(274)	0.3283(306)	0.3390(396)	0.3921(334)
Gulbarga	0.2421(445)	0.3211(472)	0.4029(305)	0.3525(298)	0.3830(315)	0.4166(312)	0.2921(366)	0.3507(370)	0.4097(312)
Guna	0.2608(410)	0.3248(466)	0.3690(412)	0.2685(407)	0.2751(438)	0.2731(473)	0.2646(423)	0.2989(472)	0.3175(473)
Guntur	0.2709(388)	0.3305(455)	0.3539(450)	0.6705(025)	0.6656(033)	0.6563(068)	0.4262(123)	0.4690(144)	0.4819(170)
Gurdaspur	0.1714(509)	0.4396(151)	0.3829(377)	0.5556(097)	0.5649(107)	0.5731(128)	0.3086(337)	0.4984(091)	0.4684(189)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Gurgaon	0.2116(480)	0.3113(487)	0.4847(074)	0.3178(331)	0.3881(310)	0.4751(245)	0.2593(435)	0.3476(375)	0.4799(173)
Gwalior	0.4323(043)	0.5307(014)	0.4587(138)	0.3490(304)	0.4005(294)	0.4612(258)	0.3885(196)	0.4610(161)	0.4599(210)
Hailakandi	0.3205(257)	0.4899(046)	0.4493(162)	0.2804(388)	0.2754(437)	0.2676(477)	0.2998(354)	0.3673(346)	0.3468(418)
Hamirpur	0.2927(333)	0.3628(381)	0.4051(295)	0.2895(368)	0.3252(364)	0.3649(367)	0.2911(367)	0.3435(384)	0.3844(348)
Hamirpur	0.4506(022)	0.4731(077)	0.4807(082)	0.5925(070)	0.5983(075)	0.6018(100)	0.5167(035)	0.5320(046)	0.5378(077)
Hanumangarh	0.3243(250)	0.3437(427)	0.3897(355)	0.3698(287)	0.2998(405)	0.1123(537)	0.3463(275)	0.3210(428)	0.2092(537)
Harcloi	0.2726(382)	0.3789(335)	0.4022(309)	0.1751(522)	0.2101(518)	0.2479(500)	0.2185(489)	0.2821(500)	0.3158(476)
Harda	0.3771(137)	0.4707(081)	0.4142(261)	0.2611(423)	0.3012(404)	0.3475(384)	0.3138(328)	0.3765(327)	0.3794(357)
Hassan	0.3106(279)	0.3309(454)	0.4110(272)	0.6468(035)	0.6287(058)	0.5969(106)	0.4482(093)	0.4561(172)	0.4953(144)
Haveri	0.3611(171)	0.3977(276)	0.4297(214)	0.4535(192)	0.4914(187)	0.5340(164)	0.4047(165)	0.4421(205)	0.4790(176)
Hingoli	0.3621(168)	0.4318(168)	0.4226(233)	0.3763(284)	0.4045(288)	0.4354(297)	0.3691(229)	0.4179(259)	0.4290(274)
Hisar	0.2049(491)	0.3817(331)	0.4198(242)	0.4557(188)	0.4654(215)	0.4691(250)	0.3056(342)	0.4215(251)	0.4438(248)
Hoogly	0.3746(147)	0.4234(196)	0.4373(188)	0.6375(039)	0.6761(026)	0.7214(028)	0.4887(051)	0.5350(043)	0.5617(048)
Hoshangabad	0.3882(104)	0.4545(111)	0.4637(130)	0.2893(369)	0.3621(332)	0.4469(277)	0.3351(294)	0.4056(278)	0.4552(220)
Hoshiarpur	0.4061(073)	0.4694(083)	0.4747(094)	0.5558(096)	0.5859(082)	0.6200(090)	0.4751(065)	0.5244(055)	0.5425(073)
Howrah	0.3794(128)	0.4422(147)	0.4365(190)	0.5865(071)	0.6148(064)	0.6464(073)	0.4717(069)	0.5214(057)	0.5312(086)
Hyderbad	0.4211(058)	0.4475(130)	0.4955(050)	0.6049(059)	0.6256(061)	0.6488(072)	0.5047(040)	0.5291(050)	0.5670(040)
Idukki	0.3748(146)	0.4184(208)	0.4681(116)	0.7849(006)	0.7775(003)	0.7670(013)	0.5424(016)	0.5704(018)	0.5992(020)
Imphal East	0.4054(075)	0.4849(052)	0.4871(067)	0.463(174)	0.4796(199)	0.4964(210)	0.4333(111)	0.4822(120)	0.4918(153)
Imphal West	0.4269(050)	0.5146(019)	0.5185(021)	0.5526(102)	0.5680(101)	0.5843(116)	0.4857(054)	0.5406(036)	0.5504(062)
Indore	0.2889(341)	0.4788(064)	0.5071(030)	0.4340(213)	0.4710(207)	0.5130(190)	0.3541(259)	0.4749(130)	0.5100(118)
Jabalpur	0.3789(131)	0.4186(207)	0.4589(137)	0.3904(262)	0.4186(271)	0.4510(269)	0.3846(202)	0.4186(258)	0.4549(221)
Jagatsinghapur	0.3904(097)	0.4504(121)	0.4855(072)	0.5087(135)	0.5972(076)	0.7081(035)	0.4456(097)	0.5187(063)	0.5863(027)
Jaintia Hills	0.1882(501)	0.3834(323)	0.2910(519)	0.1249(537)	0.1208(538)	0.1162(536)	0.1533(524)	0.2152(535)	0.1838(538)
Jaipur	0.3103(280)	0.3854(316)	0.4371(189)	0.3296(321)	0.4139(277)	0.5149(187)	0.3198(317)	0.3994(292)	0.4744(181)
Jaipur	0.3782(134)	0.4566(107)	0.4662(124)	0.4459(197)	0.4853(193)	0.5295(170)	0.4106(156)	0.4707(138)	0.4968(141)
Jaisalmer	0.2663(396)	0.3318(452)	0.3086(513)	0.1628(529)	0.2114(515)	0.2640(480)	0.2082(503)	0.2649(513)	0.2854(504)
Jalandhar	0.3195(259)	0.4518(120)	0.4709(107)	0.6145(053)	0.6017(071)	0.5827(117)	0.4431(101)	0.5214(058)	0.5238(096)
Jalaun	0.3291(237)	0.3797(334)	0.4180(249)	0.2936(360)	0.3669(328)	0.4465(278)	0.3108(332)	0.3732(339)	0.4320(268)
jalgaon	0.3913(095)	0.4363(159)	0.4438(174)	0.4621(178)	0.4710(208)	0.4797(239)	0.4252(126)	0.4533(179)	0.4614(204)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Jalna	0.3514(182)	0.4293(175)	0.4151(257)	0.3534(297)	0.3713(324)	0.3884(346)	0.3524(264)	0.3992(293)	0.4015(322)
Jalor	0.2413(448)	0.3129(485)	0.3155(510)	0.1816(518)	0.2610(466)	0.3527(380)	0.2093(501)	0.2858(493)	0.3336(443)
Jalpaiguri	0.3521(179)	0.4748(073)	0.3361(483)	0.4204(230)	0.5273(136)	0.6558(070)	0.3847(200)	0.5004(087)	0.4695(186)
Jammu	0.3887(100)	0.4264(184)	0.4802(084)	0.4568(186)	0.4550(224)	0.4379(292)	0.4213(138)	0.4405(207)	0.4586(213)
Jamnagar	0.2957(323)	0.3250(464)	0.3156(509)	0.5126(128)	0.5124(158)	0.5112(194)	0.3893(194)	0.4080(273)	0.4016(321)
Jaunpur	0.2612(405)	0.3596(387)	0.4145(259)	0.2535(434)	0.3229(369)	0.4057(327)	0.2573(437)	0.3407(390)	0.4101(310)
Jehanabad	0.2487(438)	0.2990(502)	0.3959(329)	0.2781(392)	0.2706(447)	0.2610(483)	0.2630(429)	0.2844(498)	0.3215(464)
Jhabua	0.1444(518)	0.1957(537)	0.2270(538)	0.1433(534)	0.1704(535)	0.1986(523)	0.1438(528)	0.1826(358)	0.2123(535)
Jhajjar	0.1751(508)	0.3806(332)	0.4690(112)	0.4547(190)	0.4820(196)	0.5114(193)	0.2821(382)	0.4283(238)	0.4897(157)
Jhalawar	0.2925(334)	0.3465(417)	0.3450(467)	0.2813(386)	0.3422(349)	0.4128(320)	0.2868(376)	0.3443(381)	0.3774(362)
Jhansi	0.3127(274)	0.3919(295)	0.4375(187)	0.3618(294)	0.4018(290)	0.4480(271)	0.3364(292)	0.3968(296)	0.4428(251)
Jharsugudha	0.3497(189)	0.4293(174)	0.4359(194)	0.4675(169)	0.5055(171)	0.5497(144)	0.4043(167)	0.4659(153)	0.4895(158)
Jhunjhunun	0.3831(116)	0.3835(322)	0.4075(286)	0.3498(302)	0.4172(275)	0.5007(204)	0.3661(235)	0.4000(289)	0.4517(231)
Jind	0.2566(420)	0.3831(325)	0.4031(303)	0.4106(241)	0.4283(256)	0.4446(280)	0.3246(312)	0.4051(280)	0.4233(288)
Jodhpur	0.2761(375)	0.3481(413)	0.3734(403)	0.2649(416)	0.3057(396)	0.3511(382)	0.2704(411)	0.3262(416)	0.3620(389)
Jorhat	0.3321(230)	0.4223(200)	0.4500(158)	0.5562(095)	0.5665(104)	0.5612(137)	0.4298(120)	0.4891(106)	0.5025(131)
Jumai	0.1525(515)	0.3518(406)	0.4047(296)	0.2529(436)	0.2662(454)	0.2796(465)	0.1963(511)	0.3060(457)	0.3364(437)
Junagadh	0.3646(162)	0.4001(263)	0.2989(516)	0.4923(146)	0.5181(150)	0.5469(150)	0.4237(133)	0.4553(176)	0.4043(318)
Jyotiba Phule Nagar	0.2630(402)	0.4243(191)	0.3980(322)	0.2200(480)	0.2527(478)	0.2872(454)	0.2406(463)	0.3274(412)	0.3381(435)
Kachchh	0.3094(281)	0.4055(249)	0.4161(254)	0.3460(308)	0.3783(317)	0.4141(316)	0.3272(308)	0.3917(304)	0.4151(301)
Kaimur	0.2796(368)	0.4167(215)	0.4090(277)	0.1918(510)	0.2125(514)	0.2339(507)	0.2316(473)	0.2975(475)	0.3092(485)
Kaithal	0.2550(422)	0.3695(362)	0.4110(271)	0.4331(216)	0.4062(285)	0.3606(373)	0.3323(297)	0.3874(308)	0.3850(346)
Kalahandi	0.2106(484)	0.3661(372)	0.3632(428)	0.3261(325)	0.3269(363)	0.3254(406)	0.2621(430)	0.3459(377)	0.3438(423)
Kamrup	0.3082(283)	0.3640(378)	0.3752(399)	0.4476(195)	0.4568(223)	0.4593(261)	0.3714(223)	0.4078(274)	0.4151(300)
Kancheepuram	0.4507(021)	0.5173(018)	0.4783(086)	0.6378(038)	0.6324(055)	0.6249(088)	0.5362(020)	0.5720(016)	0.5467(069)
Kandhamal	0.2866(351)	0.4206(202)	0.3916(346)	0.2085(496)	0.2492(483)	0.2944(441)	0.2445(457)	0.3237(421)	0.3395(431)
Kangra	0.4450(026)	0.4711(079)	0.4599(136)	0.6047(060)	0.5604(112)	0.4889(224)	0.5187(034)	0.5138(073)	0.4742(182)
Kannauj	0.2732(380)	0.3842(319)	0.4238(229)	0.2323(464)	0.2690(450)	0.3093(423)	0.2519(444)	0.3215(427)	0.3620(390)
Kanniyakumari	0.4791(011)	0.5022(031)	0.4998(037)	0.7685(010)	0.7631(007)	0.7550(019)	0.6068(001)	0.6191(001)	0.6143(009)
Kannur	0.4222(056)	0.4459(135)	0.5037(035)	0.7395(011)	0.7294(014)	0.7181(031)	0.5587(006)	0.5703(019)	0.6014(017)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Kanpur Dehat	0.3280(243)	0.3318(451)	0.3686(415)	0.2654(414)	0.3087(387)	0.3581(378)	0.2951(361)	0.3201(429)	0.3633(384)
Kanpur Nagar	0.2892(340)	0.3592(388)	0.4716(106)	0.5116(130)	0.4696(209)	0.4040(328)	0.3846(201)	0.4107(269)	0.4365(260)
Kapurthala	0.3185(261)	0.4610(102)	0.4690(113)	0.5853(072)	0.5633(110)	0.5321(166)	0.4318(115)	0.5095(075)	0.4995(135)
Karauli	0.3273(244)	0.3761(340)	0.3688(414)	0.2065(498)	0.2521(480)	0.3029(429)	0.2600(433)	0.3079(452)	0.3342(441)
Karbi Anglong	0.2841(359)	0.4455(137)	0.4216(235)	0.2832(382)	0.2608(467)	0.2425(504)	0.2837(381)	0.3409(389)	0.3197(469)
Kargil	0.3111(277)	0.4173(210)	0.3839(376)	0.2039(501)	0.2497(482)	0.2826(461)	0.2518(445)	0.3228(422)	0.3294(450)
Karimganj	0.2856(354)	0.4936(038)	0.4511(155)	0.2685(408)	0.2838(423)	0.2990(436)	0.2769(391)	0.3742(336)	0.3673(377)
Karlmnagar	0.3154(268)	0.3519(405)	0.3767(395)	0.6371(040)	0.7052(020)	0.7981(006)	0.4483(092)	0.4982(093)	0.5483(065)
Karnal	0.2911(336)	0.3715(356)	0.4363(191)	0.4542(191)	0.4033(289)	0.3226(411)	0.3636(239)	0.3871(310)	0.3752(366)
Karur	0.3817(118)	0.4407(149)	0.4255(223)	0.6506(032)	0.6585(039)	0.6665(056)	0.4983(045)	0.5387(039)	0.5325(082)
Kasaragod	0.4141(065)	0.4116(228)	0.4850(073)	0.6872(021)	0.6679(032)	0.6461(074)	0.5334(027)	0.5243(056)	0.5598(050)
Kathua	0.4426(028)	0.4170(214)	0.3680(418)	0.4619(179)	0.4509(229)	0.4361(295)	0.4522(088)	0.4336(223)	0.4006(326)
Katihar	0.0939(535)	0.3101(489)	0.3297(493)	0.1771(519)	0.1888(529)	0.1999(522)	0.1290(535)	0.2420(526)	0.2567(522)
Katni	0.3597(173)	0.4346(162)	0.4337(205)	0.2751(397)	0.2806(429)	0.2844(458)	0.3146(327)	0.3492(373)	0.3512(411)
Kaushambi	0.2091(485)	0.3144(482)	0.3221(503)	0.2119(491)	0.2013(521)	0.1900(527)	0.2105(499)	0.2516(521)	0.2474(528)
Kendrapara	0.3893(099)	0.4675(086)	0.4775(088)	0.4364(209)	0.5070(166)	0.5922(111)	0.4121(154)	0.4868(115)	0.5317(085)
Kendujhar	0.3019(306)	0.4061(246)	0.3896(356)	0.4266(223)	0.5104(163)	0.6101(096)	0.3589(251)	0.4553(175)	0.4876(163)
Khagaria	0.1393(519)	0.3522(403)	0.3702(408)	0.1957(507)	0.1896(528)	0.1833(529)	0.1651(520)	0.2584(518)	0.2605(520)
Khammar	0.2948(325)	0.3544(397)	0.3597(439)	0.5961(067)	0.6143(066)	0.6291(081)	0.4192(144)	0.4666(149)	0.4757(179)
khandwa	0.2985(315)	0.3667(368)	0.3663(420)	0.3014(349)	0.4194(269)	0.5865(115)	0.2999(352)	0.3921(303)	0.4635(200)
Khargone	0.3027(302)	0.3457(421)	0.3290(496)	0.3325(319)	0.3229(368)	0.2924(445)	0.3173(322)	0.3341(405)	0.3102(484)
Kheda	0.3832(113)	0.4316(169)	0.4339(203)	0.4095(242)	0.4478(234)	0.4889(225)	0.3961(182)	0.4396(211)	0.4606(208)
Kheri	0.2286(465)	0.3394(435)	0.3405(475)	0.2254(471)	0.2357(499)	0.2408(505)	0.2270(478)	0.2828(499)	0.2863(503)
Khordha	0.3495(190)	0.4622(096)	0.4907(057)	0.4607(182)	0.5328(134)	0.6172(092)	0.4012(171)	0.4962(096)	0.5503(063)
Kinnaur	0.4306(047)	0.4477(129)	0.4403(182)	0.4297(218)	0.5731(099)	0.7755(009)	0.4301(118)	0.5065(079)	0.5844(029)
Kishanganj	0.0315(538)	0.3334(447)	0.3699(410)	0.1611(531)	0.1601(536)	0.1588(535)	0.0713(537)	0.2310(532)	0.2423(529)
Koch Bihar	0.3966(087)	0.4960(035)	0.5048(033)	0.3857(269)	0.4982(180)	0.6286(084)	0.3911(190)	0.4971(095)	0.5633(046)
Kodagu	0.3382(220)	0.3798(333)	0.4428(175)	0.6635(028)	0.6680(031)	0.6661(059)	0.4737(067)	0.5037(082)	0.5431(072)
Kohima	0.3704(153)	0.4014(258)	0.4353(196)	0.4072(247)	0.4428(240)	0.4807(237)	0.3883(198)	0.4216(250)	0.4574(215)
Kokrajhar	0.2301(462)	0.4137(222)	0.3951(335)	0.3393(314)	0.3403(350)	0.3275(403)	0.2794(385)	0.3752(332)	0.3597(393)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Kolar	0.3004(311)	0.2627(528)	0.4089(279)	0.5082(137)	0.5465(125)	0.5925(110)	0.3907(192)	0.3789(324)	0.4922(152)
Kolasib	0.5573(006)	0.6061(002)	0.5494(010)	0.3571(296)	0.3923(307)	0.4304(302)	0.4461(096)	0.4876(110)	0.4863(164)
Kolhapur	0.3615(170)	0.4133(223)	0.4576(142)	0.5737(083)	0.6277(059)	0.6926(044)	0.4554(084)	0.5093(076)	0.5630(047)
Kolkata	0.2905(338)	0.3644(377)	0.4349(197)	0.6818(023)	0.7417(012)	0.8078(005)	0.4450(098)	0.5199(060)	0.5927(022)
Kollam	0.3788(132)	0.4226(199)	0.4874(065)	0.7802(007)	0.7703(004)	0.7568(018)	0.5437(015)	0.5705(017)	0.6073(013)
Koppal	0.2889(342)	0.3852(317)	0.3882(360)	0.3325(320)	0.3513(342)	0.3714(359)	0.3099(333)	0.3679(344)	0.3797(356)
Koraput	0.1257(523)	0.2781(522)	0.2806(523)	0.3253(327)	0.2924(416)	0.2527(495)	0.2022(505)	0.2852(494)	0.2663(515)
Kota	0.3623(166)	0.3818(329)	0.4286(215)	0.3824(275)	0.4416(243)	0.5145(188)	0.3722(221)	0.4106(270)	0.4696(185)
Kottayam	0.3754(144)	0.4246(190)	0.4926(053)	0.7887(004)	0.7775(002)	0.7624(014)	0.5441(014)	0.5746(011)	0.6129(010)
Kozhikode	0.4155(063)	0.4614(099)	0.4946(052)	0.7387(012)	0.6898(023)	0.6321(079)	0.5540(008)	0.5642(028)	0.5591(052)
Krishna	0.3061(289)	0.3563(393)	0.3881(361)	0.6852(022)	0.6205(062)	0.5092(196)	0.4580(081)	0.4702(140)	0.4445(245)
Krishnagiri	0.3769(138)	0.3969(278)	0.4054(293)	0.5388(114)	0.5070(165)	0.4435(282)	0.4506(089)	0.4486(195)	0.4240(287)
Kullu	0.4492(024)	0.4842(055)	0.4618(133)	0.5113(131)	0.5364(132)	0.5642(132)	0.4792(063)	0.5096(074)	0.5105(115)
Kupwara	0.1879(502)	0.3359(442)	0.3159(508)	0.4051(250)	0.3718(323)	0.3409(389)	0.2759(395)	0.3534(365)	0.3281(453)
Kurnool	0.2746(378)	0.3406(433)	0.3244(501)	0.4603(183)	0.4914(188)	0.5261(175)	0.3555(256)	0.4091(272)	0.4131(306)
Kurukshetra	0.2775(372)	0.3932(292)	0.4317(209)	0.4934(145)	0.4925(186)	0.4879(228)	0.3700(226)	0.4400(209)	0.4589(211)
Kushinagar	0.2234(474)	0.3481(414)	0.3795(386)	0.2476(443)	0.2750(439)	0.3006(434)	0.2352(470)	0.3094(447)	0.3377(436)
Ladakh	0.2828(363)	0.4095(236)	0.4769(090)	0.3813(277)	0.4129(279)	0.4135(317)	0.3283(307)	0.4112(268)	0.4440(246)
Lahul and Spiti	0.3647(161)	0.3745(344)	0.3814(380)	0.5654(087)	0.6324(056)	0.7061(036)	0.4541(085)	0.4866(116)	0.5189(103)
Lakhimpur	0.3343(228)	0.4807(062)	0.4478(164)	0.3431(312)	0.4048(287)	0.4591(262)	0.3387(288)	0.4411(206)	0.4534(227)
Lakhisarai	0.2069(487)	0.3628(380)	0.3974(324)	0.2373(457)	0.2557(474)	0.2748(469)	0.2216(487)	0.3046(462)	0.3305(448)
Lalitpur	0.2660(398)	0.3898(302)	0.3946(337)	0.1885(513)	0.2313(503)	0.2790(466)	0.2240(485)	0.3003(469)	0.3318(445)
Latur	0.4181(061)	0.4731(076)	0.4586(140)	0.4295(219)	0.4337(252)	0.4344(298)	0.4237(132)	0.4530(180)	0.4463(243)
Lawngtlai	0.4432(027)	0.4246(189)	0.3733(404)	0.2117(492)	0.2197(509)	0.2278(511)	0.3063(339)	0.3054(458)	0.2916(499)
Lohit	0.3056(293)	0.4249(188)	0.2329(537)	0.2424(452)	0.3167(377)	0.3842(350)	0.2721(404)	0.3668(347)	0.2991(491)
Lower Subansiri	0.2052(489)	0.4543(112)	0.5471(011)	0.2468(445)	0.3876(312)	0.5092(197)	0.2250(482)	0.4196(256)	0.5278(092)
Lucknow	0.2666(394)	0.3240(468)	0.5501(009)	0.4062(249)	0.4338(250)	0.4646(253)	0.3291(303)	0.3749(333)	0.5055(126)
Ludhiana	0.2611(408)	0.4242(192)	0.4881(063)	0.5508(104)	0.5649(106)	0.5799(120)	0.3793(212)	0.4896(105)	0.5320(084)
Lunglei	0.4521(018)	0.5203(017)	0.4994(038)	0.3446(309)	0.3876(311)	0.4363(294)	0.3947(185)	0.4491(194)	0.4668(194)
Madhepura	0.1113(528)	0.3183(478)	0.3476(462)	0.2014(503)	0.2139(512)	0.2265(513)	0.1497(526)	0.2609(515)	0.2806(507)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Madhubani	0.1710(510)	0.3495(411)	0.3734(402)	0.2676(410)	0.2766(434)	0.2855(457)	0.2140(497)	0.3110(445)	0.3265(458)
Madurai	0.4638(014)	0.4949(036)	0.4717(103)	0.6163(052)	0.6549(042)	0.6966(043)	0.5347(024)	0.5693(021)	0.5733(038)
Mahamaya Nagar	0.3289(238)	0.3399(434)	0.4960(048)	0.2295(465)	0.2744(440)	0.3219(414)	0.2747(397)	0.3054(459)	0.3996(327)
Maharajganj	0.2133(480)	0.3273(461)	0.3756(398)	0.1828(516)	0.2622(462)	0.3592(376)	0.1975(509)	0.2929(482)	0.3673(376)
Mahbubnagar	0.2176(476)	0.3102(488)	0.3137(512)	0.4119(240)	0.4362(249)	0.4623(256)	0.2994(356)	0.3678(345)	0.3808(354)
Mahendragarh	0.3263(245)	0.4049(253)	0.4164(253)	0.4347(211)	0.4625(217)	0.4905(222)	0.3766(216)	0.4327(225)	0.4519(230)
Mahoba	0.2787(370)	0.3826(327)	0.3927(343)	0.2644(417)	0.3087(386)	0.3595(374)	0.2715(408)	0.3436(382)	0.3758(365)
Mainpuri	0.2986(314)	0.4031(254)	0.4541(148)	0.2625(4219)	0.2600(470)	0.2473(501)	0.2799(384)	0.3237(420)	0.3351(439)
Malappuram	0.4840(010)	0.5439(010)	0.4970(044)	0.5947(068)	0.5810(089)	0.5638(133)	0.5365(019)	0.5621(029)	0.5294(088)
Maldah	0.2819(364)	0.4151(221)	0.3878(363)	0.2948(358)	0.3851(314)	0.4984(207)	0.2883(371)	0.3998(291)	0.4396(253)
Malkangiri	0.0046(539)	0.2910(513)	0.2964(517)	0.2690(405)	0.2431(492)	0.2172(517)	0.0352(538)	0.2660(512)	0.2537(525)
Mamit	0.6239(001)	0.5688(006)	0.4993(039)	0.2983(353)	0.2838(422)	0.2696(476)	0.4314(116)	0.4017(282)	0.3669(378)
Mandi	0.4308(046)	0.4592(103)	0.4473(167)	0.5468(107)	0.6015(073)	0.6665(057)	0.4853(056)	0.5256(053)	0.5460(070)
Mandla	0.3521(178)	0.3936(287)	0.4007(313)	0.3080(340)	0.3567(338)	0.4102(323)	0.3293(302)	0.3747(334)	0.4054(317)
Mandsaur	0.3635(164)	0.3971(277)	0.3942(339)	0.3255(326)	0.4229(264)	0.5411(154)	0.3440(279)	0.4098(271)	0.4619(202)
Mandya	0.2803(367)	0.3028(498)	0.3799(383)	0.6126(056)	0.6327(053)	0.6552(071)	0.4144(148)	0.4377(217)	0.4989(137)
Mansa	0.2397(450)	0.3707(358)	0.3870(366)	0.4627(176)	0.4959(182)	0.5346(163)	0.3330(296)	0.4287(235)	0.4549(223)
Mathura	0.2716(387)	0.3999(265)	0.4180(248)	0.2555(431)	0.2547(475)	0.2442(503)	0.2634(428)	0.3192(432)	0.3195(471)
Mau	0.2982(316)	0.3496(410)	0.4132(265)	0.2768(393)	0.3110(384)	0.3448(387)	0.2873(373)	0.3297(410)	0.3775(360)
Mayurbhanj	0.2498(434)	0.3726(354)	0.4478(165)	0.3901(263)	0.4176(273)	0.4471(276)	0.3121(331)	0.3945(298)	0.4474(241)
Medak	0.2716(386)	0.3535(400)	0.3565(443)	0.4878(154)	0.5124(160)	0.5378(157)	0.3640(238)	0.4256(242)	0.4379(257)
Meerut	0.2297(464)	0.2937(508)	0.3861(369)	0.3080(339)	0.3320(357)	0.3577(379)	0.2660(422)	0.3123(443)	0.3716(374)
Mehsana	0.3817(119)	0.4188(205)	0.4741(096)	0.4887(152)	0.5137(155)	0.5419(153)	0.4319(114)	0.4638(155)	0.5069(121)
Mirzapur	0.2876(347)	0.3784(336)	0.3951(336)	0.2170(484)	0.2521(481)	0.2910(449)	0.2498(449)	0.3088(449)	0.3391(433)
Moga	0.3139(269)	0.4087(240)	0.4252(224)	0.5424(112)	0.5001(177)	0.4334(300)	0.4126(153)	0.4521(183)	0.4293(273)
Mokokchung	0.4976(009)	0.5589(008)	0.4716(105)	0.4887(153)	0.5789(091)	0.6742(052)	0.4931(049)	0.5688(022)	0.5639(045)
Mon	0.1875(503)	0.2984(503)	0.3032(514)	0.2886(370)	0.2799(431)	0.2709(475)	0.2326(472)	0.2890((491)	0.2866(502)
Moradabad	0.2127(481)	0.3227(470)	0.2706(528)	0.2164(486)	0.2388(497)	0.2580(486)	0.2145(495)	0.2776(503)	0.2642(517)
Morena	0.3200(258)	0.4835(056)	0.3959(330)	0.2529(435)	0.3051(399)	0.3621(371)	0.2845(378)	0.3841(313)	0.3786(358)
Morigaon	0.2937(328)	0.4425(144)	0.3744(401)	0.2494(441)	0.2883(420)	0.3225(412)	0.2706(410)	0.3572(357)	0.3475(417)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Muktsar	0.2612(406)	0.3782(337)	0.3938(340)	0.4900(149)	0.4728(204)	0.4456(279)	0.3578(253)	0.4229(247)	0.4189(296)
Mumbai	0.3329(229)	0.4895(047)	0.7234(002)	0.6813(024)	0.7022(021)	0.7252(026)	0.4762(064)	0.5863(005)	0.7243(001)
Mumbai Suburban	0.3051(295)	0.3418(429)	0.3866(367)	0.6132(054)	0.6585(040)	0.7121(034)	0.4325(113)	0.4744(131)	0.5247(095)
Munger	0.2551(421)	0.3957(282)	0.4343(200)	0.2913(366)	0.2909(418)	0.2903(451)	0.2726(403)	0.3393(395)	0.3551(406)
Murshidabad	0.3072(288)	0.4467(133)	0.4079(282)	0.3481(307)	0.4228(266)	0.5119(192)	0.3270(309)	0.4346(222)	0.4570(216)
Muzaffarnagar	0.2279(467)	0.2250(535)	0.3378(479)	0.2608(424)	0.2775(433)	0.2929(444)	0.2438(459)	0.2499(523)	0.3145(479)
Muzaffarpur	0.2106(483)	0.3386(436)	0.3862(368)	0.2409(453)	0.2628(461)	0.2857(456)	0.2252(481)	0.2983(474)	0.3322(444)
Mysore	0.3038(300)	0.3516(407)	0.4105(274)	0.5448(109)	0.5826(087)	0.6267(086)	0.4068(162)	0.4526(181)	0.5072(120)
Nabarangapur	0.0997(532)	0.2822(520)	0.2799(524)	0.2691(404)	0.2616(464)	0.2541(492)	0.1638(522)	0.2717(506)	0.2667(513)
Nadia	0.3312(234)	0.4450(139)	0.4354(195)	0.5146(125)	0.6358(052)	0.7917(007)	0.4128(151)	0.5319(047)	0.5872(026)
Nagaon	0.3024(303)	0.4396(152)	0.3966(327)	0.2938(359)	0.3298(359)	0.3607(372)	0.2981(359)	0.3808(319)	0.3782(359)
Nagapattinam	0.4543(017)	0.5030(028)	0.4871(066)	0.6401(037)	0.6691(030)	0.7018(039)	0.5393(017)	0.5802(007)	0.5847(028)
Nagaur	0.3057(292)	0.3458(420)	0.3628(429)	0.2838(379)	0.3298(358)	0.3831(353)	0.2945(363)	0.3377(399)	0.3728(372)
Nagpur	0.4179(062)	0.4532(114)	0.4981(041)	0.5602(093)	0.5916(080)	0.6277(085)	0.4838(058)	0.5178(064)	0.5592(051)
Nalanda	0.2261(472)	0.3382(438)	0.3772(392)	0.2688(406)	0.2713(446)	0.2734(472)	0.2465(454)	0.3029(464)	0.3212(466)
Nalbari	0.3284(240)	0.4447(143)	0.4465(169)	0.4348(210)	0.5124(159)	0.5816(118)	0.3778(214)	0.4773(125)	0.5096(119)
Nalgonda	0.3075(286)	0.3520(404)	0.3613(433)	0.5203(123)	0.5814(088)	0.6624(064)	0.4000(176)	0.4524(182)	0.4892(160)
Namakkal	0.3798(126)	0.4312(170)	0.4348(198)	0.6206(051)	0.6756(027)	0.7346(023)	0.4855(055)	0.5398(038)	0.5651(043)
Nanded	0.3675(158)	0.4324(166)	0.4208(240)	0.3675(290)	0.4244(263)	0.4872(229)	0.3675(231)	0.4284(237)	0.4528(229)
Nandurbar	0.2894(339)	0.3609(385)	0.3405(474)	0.3489(305)	0.3925(306)	0.4394(290)	0.3178(321)	0.3763(328)	0.3868(344)
Narmada	0.3297(236)	0.3841(320)	0.4028(306)	0.3882(265)	0.4174(274)	0.4476(272)	0.3577(254)	0.4004(287)	0.4246(286)
Narsimhapur	0.4015(080)	0.4129(225)	0.4172(251)	0.3024(348)	0.3738(320)	0.4586(264)	0.3485(271)	0.3929(300)	0.4374(259)
Nashik	0.3850(108)	0.4521(118)	0.4446(173)	0.4167(235)	0.4494(233)	0.4858(232)	0.4005(174)	0.4507(188)	0.4648(197)
Navsari	0.3617(169)	0.3932(291)	0.4684(115)	0.5747(081)	0.5779(092)	0.5807(119)	0.4559(083)	0.4767(127)	0.5216(098)
Nawada	0.1647(512)	0.3410(432)	0.3848(373)	0.2783(391)	0.2945(411)	0.3109(421)	0.2141(496)	0.3169(434)	0.3459(420)
Nayagarh	0.3312(233)	0.4349(161)	0.4346(199)	0.4073(246)	0.4658(214)	0.5305(168)	0.3670(232)	0.4501(191)	0.4802(172)
Neemuch	0.3377(223)	0.3997(267)	0.3901(352)	0.3497(303)	0.4338(251)	0.5352(161)	0.3436(280)	0.4163(261)	0.4569(217)
New Delhi	0.5363(007)	0.6240(001)	0.9385(001)	0.5552(099)	0.5252(140)	0.4656(252)	0.5457(013)	0.5724(014)	0.6611(003)
Nizamabad	0.2723(383)	0.3446(425)	0.3637(427)	0.5538(101)	0.5745(095)	0.5939(109)	0.3884(197)	0.4449(199)	0.4647(198)
North	0.3791(130)	0.4063(245)	0.4881(064)	0.5423(113)	0.5482(124)	0.5541(142)	0.4534(087)	0.4719(133)	0.5200(101)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
North District	0.3713(152)	0.4738(074)	0.4529(151)	0.4048(251)	0.5182(147)	0.6795(049)	0.3877(199)	0.4955(099)	0.5548(057)
North East	0.4116(070)	0.4941(037)	0.5047(034)	0.3925(261)	0.4363(248)	0.4868(230)	0.4019(170)	0.4643(154)	0.4956(143)
North Goa	0.3183(262)	0.4010(259)	0.5214(018)	0.6620(029)	0.6642(035)	0.6655(060)	0.4591(080)	0.5161(067)	0.5891(025)
North Tripura	0.3955(090)	0.4976(033)	0.3688(413)	0.3724(285)	0.3947(303)	0.4179(310)	0.3838(204)	0.4431(202)	0.3926(333)
North24 Parganas	0.3637(163)	0.4061(247)	0.4270(221)	0.5566(094)	0.6549(041)	0.7735(010)	0.4500(091)	0.5157(068)	0.5747(037)
North West	0.3764(140)	0.4859(050)	0.5051(032)	0.4455(200)	0.4820(197)	0.5225(179)	0.4095(157)	0.4839(118)	0.5137(111)
Nuapada	0.1948(494)	0.3739(348)	0.3716(405)	0.3440(310)	0.3458(345)	0.3477(383)	0.2588(436)	0.3596(354)	0.3594(394)
Osmanabad	0.4675(013)	0.4051(251)	0.4139(263)	0.4286(220)	0.4620(219)	0.4987(206)	0.4476(094)	0.4326(226)	0.4543(225)
Pachmahal	0.3409(214)	0.3989(270)	0.3316(489)	0.3376(315)	0.3599(333)	0.3839(351)	0.3393(286)	0.3789(325)	0.3568(402)
Palakkad	0.4043(079)	0.4563(108)	0.4717(104)	0.7103(016)	0.7262(015)	0.7432(020)	0.5359(021)	0.5757(010)	0.5921(023)
Pali	0.2866(350)	0.3382(437)	0.3610(435)	0.2482(442)	0.3017(401)	0.3651(366)	0.2667(420)	0.3195(430)	0.3630(386)
Panchkula	0.2595(413)	0.4127(226)	0.4920(055)	0.5078(138)	0.5065(168)	0.4956(212)	0.3630(242)	0.4572(171)	0.4938(147)
Panipat	0.2460(442)	0.3944(283)	0.4168(252)	0.3961(258)	0.4069(284)	0.4148(315)	0.3122(330)	0.4006(286)	0.4158(299)
Panna	0.3490(192)	0.4075(243)	0.3823(378)	0.1745(523)	0.2436(491)	0.3253(407)	0.2468(453)	0.3151(437)	0.3526(408)
Papumpare	0.4281(048)	0.5728(005)	0.5762(006)	0.3365(316)	0.4150(276)	0.4853(233)	0.3796(211)	0.4876(111)	0.5288(090)
Parbhani	0.3695(155)	0.4483(125)	0.4343(201)	0.3835(274)	0.4014(293)	0.4202(309)	0.3765(217)	0.4242(245)	0.4272(278)
Paschim Champaran	0.1296(520)	0.2993(501)	0.3441(469)	0.2202(479)	0.2159(511)	0.2064(520)	0.1689(518)	0.2542(519)	0.2665(514)
Paschim Mednipur	0.2262(471)	0.4485(124)	0.4666(122)	0.5042(139)	0.5740(096)	0.6587(067)	0.3377(290)	0.5074(077)	0.5544(060)
Patan	0.2963(319)	0.3901(299)	0.4246(226)	0.3488(306)	0.4256(259)	0.5086(199)	0.3215(315)	0.4075(276)	0.4647(199)
Pathanamthitta	0.3504(187)	0.3763(339)	0.4972(043)	0.8185(001)	0.8071(001)	0.7913(008)	0.5356(022)	0.5511(032)	0.6272(006)
Patiala	0.3035(301)	0.4270(183)	0.4457(171)	0.5468(108)	0.5150(151)	0.4748(246)	0.4074(160)	0.4689(145)	0.4600(209)
Patna	0.2414(447)	0.2776(523)	0.3716(406)	0.3281(324)	0.3125(383)	0.2884(452)	0.2814(383)	0.2945(478)	0.3273(456)
Perambalur	0.6174(002)	0.5421(011)	0.6902(003)	0.5816(075)	0.4879(190)	0.3470(385)	0.5992(002)	0.5143(071)	0.4894(159)
Phek	0.3759(142)	0.4480(127)	0.3790(388)	0.2643(418)	0.2445(489)	0.2251(514)	0.3152(325)	0.3309(409)	0.2921(497)
Pilibhit	0.2284(466)	0.3195(474)	0.3480(460)	0.2086(495)	0.2657(455)	0.3351(393)	0.2183(490)	0.2914(487)	0.3415(427)
Porabandar	0.3539(176)	0.3902(297)	0.4274(220)	0.5296(117)	0.5399(129)	0.5482(148)	0.4329(112)	0.4590(164)	0.4841(165)
Prakasam	0.2728(381)	0.3360(441)	0.3292(495)	0.5604(092)	0.5827(086)	0.6073(099)	0.3910(191)	0.4425(204)	0.4471(242)
Pratapgarh	0.3157(266)	0.3883(307)	0.4724(102)	0.2927(361)	0.3381(353)	0.3914(341)	0.3040(345)	0.3623(351)	0.4300(272)
Pudukkottai	0.4224(055)	0.4665(088)	0.4321(207)	0.6479(033)	0.6526(044)	0.6558(069)	0.5231(030)	0.5517(031)	0.5323(083)
Pulwama	0.2500(433)	0.3037(497)	0.3145(511)	0.4611(181)	0.4269(257)	0.3911(342)	0.3395(283)	0.3601(352)	0.3507(413)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Punch	0.2760(376)	0.4769(067)	0.4033(302)	0.3676(289)	0.3961(300)	0.4176(311)	0.3185(319)	0.4347(221)	0.4104(309)
Pune	0.3831(115)	0.4576(105)	0.4948(051)	0.5820(074)	0.5800(090)	0.5752(125)	0.4722(068)	0.5152(069)	0.5335(081)
Purba Champaran	0.1161(527)	0.3258(463)	0.3549(448)	0.2162(488)	0.2082(519)	0.1976(524)	0.1585(523)	0.2605(516)	0.2648(516)
Purba Medinipur	0.2262(470)	0.4723(078)	0.5078(029)	0.50881(134)	0.5649(105)	0.6331(077)	0.3392(287)	0.5165(066)	0.5670(041)
Puri	0.3845(109)	0.4472(131)	0.4734(097)	0.4145(237)	0.5496(122)	0.7054(037)	0.3992(179)	0.4957(098)	0.5778(031)
Purnia	0.1064(529)	0.2875(516)	0.3220(504)	0.2014(502)	0.1919(526)	0.1792(530)	0.1464(527)	0.2349(531)	0.2402(533)
Puruliya	0.3020(305)	0.4099(234)	0.3759(396)	0.4125(239)	0.4549(225)	0.5012(203)	0.3529(261)	0.4318(227)	0.4341(262)
Rae Bareli	0.2484(440)	0.3142(483)	0.3534(451)	0.2707(401)	0.3131(382)	0.3623(370)	0.2593(434)	0.3136(440)	0.3578(400)
Raichur	0.2338(457)	0.3414(431)	0.3492(457)	0.3802(280)	0.3725(322)	0.3595(375)	0.2981(358)	0.3566(358)	0.3543(407)
Raigarh	0.3911(096)	0.4520(119)	0.4728(100)	0.5482(106)	0.5526(120)	0.5558(139)	0.4630(077)	0.4998(088)	0.5126(113)
Raisen	0.4009(082)	0.4327(165)	0.3888(359)	0.2917(365)	0.2972(408)	0.2868(455)	0.3420(282)	0.3586(355)	0.3339(442)
Rajgarh	0.2831(362)	0.3669(366)	0.3610(434)	0.2553(432)	0.3182(374)	0.3918(340)	0.2688(415)	0.3417(388)	0.3761(364)
Rajkot	0.3156(267)	0.3872(311)	0.4095(276)	0.5612(091)	0.5118(162)	0.4638(254)	0.4209(140)	0.4452(198)	0.4358(261)
Rajouri	0.3359(224)	0.4098(235)	0.3913(347)	0.4078(245)	0.4250(260)	0.4491(270)	0.3701(225)	0.4173(260)	0.4192(295)
Rajsamand	0.2936(329)	0.3544(396)	0.3685(417)	0.2605(426)	0.3012(403)	0.3465(386)	0.2766(394)	0.3268(413)	0.3573(401)
Ramanathapurm	0.4513(020)	0.4903(044)	0.4694(110)	0.6442(036)	0.6726(028)	0.7052(038)	0.5392(018)	0.5743(012)	0.5754(035)
Rampur	0.1566(514)	0.2982(504)	0.3305(490)	0.1937(508)	0.2410(495)	0.2946(440)	0.1742(516)	0.2680(508)	0.3120(482)
Rangareddi	0.3968(086)	0.5138(022)	0.5005(036)	0.5317(115)	0.5367(130)	0.5350(162)	0.4593(079)	0.5252(054)	0.5175(104)
Ratlam	0.3829(117)	0.4083(241)	0.3599(438)	0.2879(371)	0.3455(346)	0.4093(325)	0.3320(298)	0.3756(330)	0.3838(350)
Ratnagiri	0.3786(133)	0.4007(262)	0.4511(156)	0.6343(042)	0.7132(017)	0.8103(004)	0.4901(050)	0.5346(044)	0.6046(015)
Rayagada	0.1285(521)	0.2844(518)	0.2915(518)	0.2957(357)	0.2951(409)	0.2920(447)	0.1949(512)	0.2897(488)	0.2917(498)
Rewa	0.3426(211)	0.4272(181)	0.4199(241)	0.2359(459)	0.3280(362)	0.4420(287)	0.2843(379)	0.3743(335)	0.4308(270)
Rewari	0.2884(344)	0.4257(187)	0.4375(186)	0.4514(193)	0.3661(329)	0.1634(534)	0.3608(246)	0.3948(297)	0.2674(512)
Ribhoi	0.3253(247)	0.4769(068)	0.4831(077)	0.1613(530)	0.1814(533)	0.2015(521)	0.2291(476)	0.2941(479)	0.3120(483)
Rohtak	0.2519(427)	0.3991(269)	0.4215(236)	0.4739(165)	0.4847(194)	0.4921(220)	0.3455(277)	0.4398(210)	0.4555(219)
Rohtas	0.2819(365)	0.3984(272)	0.4416(178)	0.2759(396)	0.2908(419)	0.3029(430)	0.2789(387)	0.3403(391)	0.3657(380)
Rup Nagar	0.3288(239)	0.3351(443)	0.4627(131)	0.5847(073)	0.5731(098)	0.5487(146)	0.4385(107)	0.4382(213)	0.5039(129)
Sabarkantha	0.3688(157)	0.4054(250)	0.3219(505)	0.3861(268)	0.4098(282)	0.4343(299)	0.3774(215)	0.4076(275)	0.3739(368)
Sagar	0.3750(145)	0.4561(109)	0.4412(180)	0.2403(454)	0.3062(394)	0.3831(354)	0.3002(351)	0.3737(338)	0.4111(308)
Saharampur	0.2661(397)	0.3341(446)	0.3964(328)	0.2683(409)	0.2927(413)	0.3191(417)	0.2672(418)	0.3127(441)	0.3556(404)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Saharsa	0.1269(522)	0.3167(480)	0.3386(477)	0.2348(460)	0.2262(507)	0.2173(516)	0.1726(517)	0.2677(509)	0.2713(511)
Sahid Bhagat Singh Nagar	0.3355(225)	0.4371(156)	0.4775(089)	0.6038(063)	0.5566(117)	0.4889(226)	0.4501(090)	0.4932(101)	0.4832(167)
Saiha	0.3938(092)	0.4879(049)	0.5172(024)	0.3143(335)	0.3387(351)	0.3643(368)	0.3518(266)	0.4065(277)	0.4341(263)
Salem	0.3842(111)	0.4239(193)	0.4239(228)	0.6042(061)	0.6405(050)	0.6816(047)	0.4818(059)	0.5210(059)	0.5375(078)
Samastipur	0.1774(507)	0.3562(394)	0.3758(397)	0.2324(463)	0.2472(487)	0.2613(482)	0.2030(504)	0.2968(476)	0.3133(481)
Sambalpur	0.3088(282)	0.4452(138)	0.4924(054)	0.4173(234)	0.4926(184)	0.5782(122)	0.3590(250)	0.4683(146)	0.5336(080)
Sangli	0.3807(124)	0.4206(201)	0.4535(149)	0.5761(080)	0.5953(077)	0.6160(093)	0.4683(074)	0.5004(086)	0.5285(091)
Sangrur	0.2611(407)	0.3349(444)	0.4057(292)	0.4779(161)	0.5055(170)	0.5364(158)	0.3533(260)	0.4114(267)	0.4665(195)
Sant Kabir Nagar	0.2172(477)	0.3447(424)	0.3796(384)	0.2163(487)	0.2725(444)	0.3373(391)	0.2168(492)	0.3065(455)	0.3578(399)
Sant Ravidas Nagar	0.2992(313)	0.3612(384)	0.3874(365)	0.2170(485)	0.2704(448)	0.3309(397)	0.2548(441)	0.3125(442)	0.3580(398)
Saran	0.2272(469)	0.3743(345)	0.4184(247)	0.2650(415)	0.2819(426)	0.2963(438)	0.2454(455)	0.3248(418)	0.3521(409)
Sarikakulam	0.2692(391)	0.3224(471)	0.3378(478)	0.5486(105)	0.5568(116)	0.6666(055)	0.3843(203)	0.4237(246)	0.4746(180)
Satara	0.3793(129)	0.4104(232)	0.4506(157)	0.5789(078)	0.5953(078)	0.6124(095)	0.4686(073)	0.4943(100)	0.5253(094)
Satna	0.3808(123)	0.4704(082)	0.4154(256)	0.1894(512)	0.2833(425)	0.3896(343)	0.2685(416)	0.3650(348)	0.4023(320)
Sawai Maghopur	0.2871(348)	0.3621(383)	0.3787(390)	0.2537(433)	0.3103(385)	0.3762(358)	0.2699(413)	0.3352(403)	0.3774(361)
Sehore	0.3469(201)	0.4707(080)	0.3890(358)	0.2328(462)	0.3064(392)	0.3969(337)	0.2842(380)	0.3798(321)	0.3930(332)
Senapati	0.4210(059)	0.51410(020)	0.6521(004)	0.4682(168)	0.4620(218)	0.4546(266)	0.4440(100)	0.4873(113)	0.5444(071)
Seoni	0.3803(125)	0.4276(179)	0.4124(268)	0.3153(333)	0.3963(299)	0.4887(227)	0.3463(276)	0.4117(266)	0.4490(238)
Serchhip	0.5617(004)	0.5573(009)	0.5296(016)	0.3931(260)	0.4455(235)	0.5037(201)	0.4699(072)	0.4983(092)	0.5165(106)
Shahdol	0.2467(441)	0.3026(499)	0.3954(333)	0.2622(421)	0.2836(424)	0.3070(425)	0.2543(442)	0.2929(483)	0.3484(415)
Shahjahanpur	0.2277(468)	0.3127(486)	0.3664(419)	0.1758(521)	0.2273(506)	0.2832(460)	0.2001(507)	0.2666(511)	0.3221(463)
Shajapur	0.3723(151)	0.3930(293)	0.2853(522)	0.2927(362)	0.3686(326)	0.4634(255)	0.3301(300)	0.3806(320)	0.3636(383)
Sheikhpura	0.1918(499)	0.3557(395)	0.4033(301)	0.2262(470)	0.2395(496)	0.2532(493)	0.2083(502)	0.2919(485)	0.3195(470)
Sheohar	0.0969(533)	0.3075(493)	0.3605(436)	0.1983(505)	0.1977(523)	0.1933(525)	0.1386(530)	0.2466(524)	0.2640(518)
Sheopur	0.2313(458)	0.3647(376)	0.3428(472)	0.2210(477)	0.2291(505)	0.2316(509)	0.2261(480)	0.2891(490)	0.2818(506)
Shimla	0.4236(053)	0.4770(066)	0.4844(075)	0.5807(076)	0.6017(072)	0.6247(089)	0.4960(047)	0.5357(041)	0.5501(064)
Shimoga	0.3663(160)	0.3854(315)	0.4422(176)	0.6303(045)	0.5751(094)	0.4936(217)	0.4805(061)	0.4708(137)	0.4672(193)
Shivpuri	0.3423(212)	0.4089(239)	0.3648(425)	0.1817(517)	0.2476(485)	0.3279(401)	0.2494(450)	0.3182(433)	0.3458(421)
Shrawasti	0.0962(534)	0.2165(536)	0.2705(529)	0.1741(524)	0.1935(525)	0.2136(518)	0.1294(534)	0.2047(537)	0.2404(532)
Siddharthnagar	0.1668(511)	0.2887(515)	0.3249(500)	0.1610(532)	0.2019(520)	0.2446(502)	0.1639(521)	0.2414(527)	0.2819(505)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Sidhi	0.2721(384)	0.2951(506)	0.3927(342)	0.2082(497)	0.2312(504)	0.2550(491)	0.2380(467)	0.2612(514)	0.3165(475)
Sikar	0.3992(084)	0.3879(308)	0.3996(317)	0.3281(323)	0.3969(298)	0.4792(240)	0.3619(245)	0.3924(301)	0.4376(258)
Sindhudurg	0.3734(149)	0.3966(279)	0.4649(127)	0.7043(017)	0.7101(019)	0.7127(033)	0.5128(038)	0.5307(048)	0.5755(034)
Sirmaur	0.4229(054)	0.5046(026)	0.4606(135)	0.4370(207)	0.4229(265)	0.3975(336)	0.4299(119)	0.4619(159)	0.4279(277)
Sirohi	0.2838(360)	0.3009(500)	0.2883(520)	0.2272(468)	0.2690(451)	0.3163(419)	0.2539(443)	0.2845(497)	0.3020(489)
Sirsa	0.3039(299)	0.3817(330)	0.4089(278)	0.4804(159)	0.4839(195)	0.4808(236)	0.3821(206)	0.4298(234)	0.4434(250)
Sitamarhi	0.1210(525)	0.2870(517)	0.3276(498)	0.1904(511)	0.2113(516)	0.2330(508)	0.1518(525)	0.2463(525)	0.2763(508)
Sitapur	0.2359(456)	0.3706(359)	0.3970(325)	0.1872(514)	0.2106(517)	0.2356(506)	0.2102(500)	0.2794(501)	0.3059(488)
Sivaganga	0.4319(044)	0.4829(058)	0.4549(145)	0.6289(046)	0.6620(036)	0.6996(041)	0.5212(033)	0.5654(026)	0.5641(044)
Sivasagar	0.2657(399)	0.3920(294)	0.4339(204)	0.4580(185)	0.5212(145)	0.5770(123)	0.3489(269)	0.4520(184)	0.5004(134)
Siwan	0.2145(478)	0.3878(309)	0.4220(234)	0.3358(318)	0.3076(391)	0.2784(467)	0.2684(417)	0.3454(379)	0.3428(424)
Solan	0.4375(034)	0.5024(030)	0.5154(025)	0.5280(118)	0.5364(131)	0.5435(152)	0.4806(060)	0.5191(062)	0.5292(089)
Solapur	0.3815(120)	0.4309(171)	0.4361(193)	0.4634(173)	0.4954(183)	0.5300(169)	0.4205(141)	0.4621(158)	0.4808(171)
Sonbhadra	0.2369(454)	0.3770(338)	0.3787(389)	0.2237(473)	0.2628(459)	0.3063(427)	0.2302(475)	0.3148(439)	0.3406(429)
Sonipat	0.2586(417)	0.4186(206)	0.4418(177)	0.4457(199)	0.4428(241)	0.4358(296)	0.3395(284)	0.4306(232)	0.4388(255)
Sontipur	0.1940(496)	0.3715(355)	0.3794(387)	0.3811(278)	0.3936(304)	0.3977(335)	0.2719(405)	0.3824(316)	0.3885(339)
South	0.4043(077)	0.4664(089)	0.5089(028)	0.4423(204)	0.4664(212)	0.4932(218)	0.4229(135)	0.4664(150)	0.5010(133)
South District	0.3775(136)	0.5062(025)	0.5203(019)	0.4334(215)	0.5763(093)	0.8218(002)	0.4044(166)	0.5401(037)	0.6539(004)
South Garo Hills	0.3048(297)	0.4891(048)	0.5176(023)	0.3076(343)	0.1850(531)	0.0071(539)	0.3062(340)	0.3008(467)	0.0607(539)
South Goa	0.2859(352)	0.3417(430)	0.4970(045)	0.6324(043)	0.6143(065)	0.5911(113)	0.4252(127)	0.4582(169)	0.5420(075)
South Tripura	0.4134(067)	0.4847(053)	0.3361(484)	0.4262(224)	0.4662(213)	0.5092(198)	0.4197(142)	0.4754(129)	0.4137(305)
South 24 Parganas	0.3698(154)	0.4530(116)	0.4340(202)	0.4218(229)	0.5124(156)	0.6258(087)	0.3949(184)	0.4818(121)	0.5211(100)
South West	0.4497(023)	0.4913(042)	0.5320(015)	0.4365(208)	0.4433(239)	0.4476(273)	0.4431(102)	0.4667(148)	0.4880(162)
Sri Potti Sriramulu	0.3058(290)	0.3451(422)	0.3554(445)	0.5936(069)	0.6426(049)	0.6974(042)	0.4261(124)	0.4709(136)	0.4978(138)
Srinagar	0.2526(425)	0.2954(505)	0.3368(482)	0.4186(231)	0.4133(278)	0.3959(338)	0.3252(311)	0.3494(372)	0.3652(381)
Subarnapur	0.3176(264)	0.4154(218)	0.4209(239)	0.4088(243)	0.4394(245)	0.4724(247)	0.3603(247)	0.4273(240)	0.4459(244)
Sultanpur	0.2736(379)	0.3700(361)	0.3203(506)	0.2693(403)	0.3229(370)	0.3869(348)	0.2714(409)	0.3456(378)	0.3520(410)
Sundargarh	0.2936(330)	0.3822(328)	0.4197(243)	0.4220(228)	0.4446(237)	0.4696(249)	0.3520(265)	0.4122(265)	0.4439(247)
Supaul	0.1175(526)	0.3527(401)	0.3659(421)	0.2335(461)	0.2411(494)	0.2482(498)	0.1656(519)	0.2916(486)	0.3014(490)
Surat	0.2844(357)	0.3659(373)	0.4724(101)	0.5101(133)	0.5124(157)	0.5132(189)	0.3809(208)	0.4330(224)	0.4924(151)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Surendranagar	0.3412(213)	0.3979(275)	0.3908(348)	0.3847(271)	0.4452(236)	0.5163(185)	0.3623(244)	0.4209(254)	0.4492(236)
Tamenglong	0.3494(191)	0.4259(186)	0.4053(294)	0.3982(257)	0.4501(230)	0.4993(205)	0.3730(220)	0.4378(215)	0.4498(233)
Tawang	0.2385(451)	0.3750(342)	0.34674(465)	0.2511(438)	0.3734(321)	0.4946(214)	0.2447(456)	0.3742(337)	0.4141(304)
Thane	0.3446(204)	0.4820(060)	0.4007(312)	0.5019(140)	0.5242(141)	0.5486(147)	0.4159(146)	0.5027(083)	0.4689(188)
Thanjavur	0.4375(033)	0.4830(057)	0.4807(081)	0.6968(019)	0.6942(022)	0.6878(046)	0.5522(010)	0.5791(008)	0.5750(036)
The Dangs	0.3762(141)	0.4732(075)	0.4745(095)	0.3008(350)	0.3172(376)	0.3341(394)	0.3364(291)	0.3874(309)	0.3982(329)
The Nilgiris	0.4335(041)	0.4448(141)	0.4733(098)	0.7202(013)	0.7642(006)	0.8160(003)	0.5588(005)	0.5831(006)	0.6214(007)
Theni	0.4374(035)	0.4761(070)	0.4669(119)	0.6231(049)	0.5910(081)	0.5495(145)	0.5220(032)	0.5304(049)	0.5065(123)
Thiruvallur	0.4191(060)	0.5066(024)	0.4690(111)	0.6315(044)	0.6459(047)	0.6613(065)	0.5145(037)	0.5721(015)	0.5569(055)
Thiruvananthapuram	0.3044(298)	0.3739(347)	0.4866(068)	0.7733(008)	0.7667(005)	0.7572(017)	0.4852(057)	0.5354(042)	0.6070(014)
Thiruvarur	0.4486(025)	0.4846(054)	0.4914(056)	0.6879(020)	0.6642(034)	0.6291(082)	0.5555(007)	0.5673(024)	0.5560(056)
Thoothukkudi	0.4731(012)	0.4766(069)	0.4856(071)	0.6009(064)	0.6691(029)	0.7405(021)	0.5332(028)	0.5647(027)	0.5997(018)
Thrissur	0.4219(057)	0.4610(101)	0.4955(049)	0.7695(009)	0.7541(010)	0.7367(022)	0.5698(003)	0.5896(004)	0.6042(016)
Tikamgarh	0.3078(284)	0.3962(281)	0.3751(400)	0.2274(466)	0.2994(406)	0.3863(349)	0.2646(424)	0.3444(380)	0.3807(355)
Tinsukia	0.2672(393)	0.3730(351)	0.3795(385)	0.4396(206)	0.4613(220)	0.4702(248)	0.3427(281)	0.4148(263)	0.4224(290)
Tirap	0.1922(498)	0.3286(459)	0.2148(539)	0.2058(499)	0.2608(468)	0.3097(422)	0.1988(508)	0.2927(484)	0.2579(521)
Tiruchiappalli	0.4347(038)	0.4900(045)	0.4697(109)	0.6554(030)	0.6585(038)	0.6609(066)	0.5338(026)	0.5680(023)	0.5572(054)
Tirunelveli	0.4623(015)	0.5140(021)	0.4889(062)	0.6475(034)	0.6324(054)	0.6132(094)	0.5471(012)	0.5702(020)	0.5475(066)
Tiruvannamalai	0.3958(089)	0.4378(154)	0.4135(264)	0.5672(085)	0.5731(097)	0.5788(121)	0.4738(066)	0.5009(085)	0.4892(161)
Tonk	0.2521(426)	0.3250(465)	0.3575(440)	0.2767(394)	0.3280(361)	0.3890(345)	0.2641(427)	0.3265(415)	0.3729(371)
Toubal	0.3597(174)	0.4337(163)	0.4409(181)	0.3808(279)	0.3958(301)	0.4113(322)	0.3701(224)	0.4143(264)	0.4259(283)
Tuensang	0.2300(463)	0.2936(509)	0.3618(432)	0.2746(398)	0.2858(421)	0.2937(443)	0.2513(446)	0.2897(489)	0.3259(459)
Tumkur	0.3133(270)	0.2572(531)	0.2454(534)	0.5257(119)	0.5599(113)	0.6008(104)	0.4058(164)	0.3795(322)	0.3840(349)
Udaipur	0.2836(361)	0.3170(479)	0.3287(497)	0.2607(425)	0.2811(428)	0.3027(431)	0.2719(406)	0.2985(473)	0.3154(477)
Udhampur	0.2978(317)	0.3588(390)	0.4062(290)	0.4232(227)	0.4250(261)	0.4128(319)	0.3550(258)	0.3905(306)	0.4095(313)
Udupi	0.3756(143)	0.3684(363)	0.4757(091)	0.8128(002)	0.7186(016)	0.5614(136)	0.5525(009)	0.5146(070)	0.5168(105)
Ujjain	0.3404(216)	0.3667(367)	0.3554(446)	0.3194(330)	0.4048(286)	0.5013(202)	0.3298(301)	0.3853(312)	0.4221(291)
Ukhrul	0.3282(241)	0.5275(015)	0.4968(046)	0.3792(282)	0.4196(268)	0.4621(257)	0.3528(263)	0.4705(139)	0.4791(175)
Umaria	0.3382(219)	0.4468(132)	0.4244(227)	0.2574(428)	0.2589(471)	0.2558(488)	0.2950(362)	0.3401(392)	0.3295(449)
Una	0.4516(019)	0.4823(059)	0.4812(080)	0.5613(090)	0.5137(154)	0.4294(303)	0.5035(043)	0.4977(094)	0.4546(224)
Unnao	0.2690(392)	0.3100(490)	0.3474(463)	0.2702(402)	0.2987(407)	0.3300(399)	0.2696(414)	0.3043(463)	0.3386(434)
Upper Siang	0.3130(272)	0.4108(231)	0.3990(318)	0.2919(364)	0.3915(308)	0.4849(234)	0.3023(350)	0.4010(284)	0.4398(252)

Districts	EI_2006	EI_2011	EI_2016	HI_2006	HI_2011	HI_2016	HCI_2006	HCI_2011	HCI_2016
Upper Subansiri	0.2812(366)	0.4492(122)	0.4820(078)	0.1643(528)	0.2458(488)	0.3186(418)	0.2149(493)	0.3323(407)	0.3919(335)
Uttar Dinajpur	0.2527(424)	0.3899(301)	0.3517(454)	0.2984(352)	0.3559(339)	0.4253(306)	0.2746(399)	0.3725(340)	0.3868(345)
Uttar Kannada	0.3850(107)	0.2615(529)	0.2333(536)	0.6131(055)	0.6116(067)	0.6015(101)	0.4859(053)	0.3999(290)	0.3746(367)
Vadodara	0.2869(349)	0.3729(352)	0.3818(379)	0.4688(166)	0.4991(179)	0.5323(165)	0.3668(233)	0.4314(229)	0.4508(232)
Vaishali	0.2239(473)	0.3855(314)	0.3983(321)	0.2613(422)	0.2696(449)	0.2757(468)	0.2419(462)	0.3224(424)	0.3314(446)
Valsad	0.3472(197)	0.4171(212)	0.4487(163)	0.5215(122)	0.5211(146)	0.5185(182)	0.4255(125)	0.4662(151)	0.4823(169)
Varanasi	0.2694(390)	0.3269(462)	0.3874(364)	0.2840(378)	0.3587(336)	0.4520(268)	0.2766(393)	0.3424(386)	0.4185(297)
Vellore	0.4260(051)	0.4811(061)	0.4274(219)	0.5967(066)	0.5983(074)	0.5998(105)	0.5042(042)	0.5365(040)	0.5063(124)
Vidisha	0.3451(202)	0.4405(150)	0.4024(308)	0.2763(395)	0.2732(441)	0.2554(490)	0.3088(335)	0.3469(376)	0.3206(467)
Viluppuram	0.3810(122)	0.4264(185)	0.3880(362)	0.5539(100)	0.5588(115)	0.5638(134)	0.4594(078)	0.4881(109)	0.4677(191)
Virudhunagar	0.4355(037)	0.4759(071)	0.4662(123)	0.6110(057)	0.6256(060)	0.6413(075)	0.5158(036)	0.5457(035)	0.5468(068)
visakhapatnam	0.2853(355)	0.3543(398)	0.3656(423)	0.5636(089)	0.5713(100)	0.5757(124)	0.4010(172)	0.4499(193)	0.4588(212)
Vizianagaram	0.2491(436)	0.3056(495)	0.3253(499)	0.4850(157)	0.5000(178)	0.5122(191)	0.3476(273)	0.3909(305)	0.4082(314)
Wardha	0.3831(114)	0.4182(209)	0.4781(087)	0.5436(110)	0.6459(048)	0.7734(011)	0.4564(082)	0.5198(061)	0.6081(012)
Warnagal	0.3114(276)	0.3702(360)	0.3858(370)	0.5770(079)	0.6405(051)	0.7302(024)	0.4239(131)	0.4870(114)	0.5308(087)
Washim	0.4013(081)	0.4748(072)	0.4545(147)	0.4272(222)	0.4639(216)	0.5055(200)	0.4141(149)	0.4694(142)	0.4793(174)
Wayanad	0.4116(068)	0.4852(051)	0.4804(083)	0.6704(026)	0.6849(024)	0.7001(040)	0.5253(029)	0.5765(009)	0.5799(030)
West	0.3935(093)	0.4800(063)	0.5422(012)	0.4862(156)	0.5055(173)	0.5265(174)	0.4374(108)	0.4926(102)	0.5343(079)
West District	0.3229(254)	0.4915(041)	0.5224(017)	0.3855(270)	0.5181(149)	0.7237(027)	0.3528(262)	0.5046(081)	0.6149(008)
West Garo Hills	0.2516(428)	0.4479(128)	0.4043(297)	0.2047(500)	0.2125(513)	0.2205(515)	0.2269(479)	0.3085(450)	0.2986(493)
West Godavari	0.3238(251)	0.3666(369)	0.3846(374)	0.6350(041)	0.6549(043)	0.6768(051)	0.4535(086)	0.4900(104)	0.5102(117)
West kameng	0.3019(307)	0.4328(164)	0.4148(258)	0.3035(347)	0.3594(335)	0.4086(326)	0.3027(349)	0.3944(299)	0.4117(307)
West Khasi Hills	0.4052(076)	0.4925(040)	0.4145(260)	0.1245(538)	0.1164(539)	0.1067(538)	0.2246(483)	0.2394(528)	0.2103(536)
West Siang	0.3441(207)	0.4534(113)	0.4212(238)	0.3145(334)	0.4228(267)	0.5276(173)	0.3289(304)	0.4378(214)	0.4714(183)
West Tripura	0.4342(040)	0.4908(043)	0.3501(456)	0.5118(129)	0.5665(103)	0.6290(083)	0.4714(070)	0.5273(052)	0.4693(187)
Wokha	0.4568(016)	0.4490(123)	0.4625(132)	0.4021(253)	0.4692(211)	0.5551(141)	0.4286(122)	0.4590(165)	0.5067(122)
Y.S.R	0.3317(232)	0.3665(370)	0.3513(455)	0.6040(062)	0.5827(085)	0.5482(149)	0.4476(095)	0.4621(157)	0.4388(254)
Yamunanagar	0.2646(400)	0.3663(371)	0.4228(232)	0.4892(151)	0.4868(191)	0.4777(243)	0.3598(249)	0.4223(248)	0.4494(235)
Yavatmal	0.3842(110)	0.4447(142)	0.4500(159)	0.4451(201)	0.4884(189)	0.5405(156)	0.4135(150)	0.4660(152)	0.4932(148)
Zunehboto	0.3727(150)	0.4970(034)	0.5062(031)	0.3293(322)	0.4073(283)	0.4964(211)	0.3503(267)	0.4499(192)	0.5013(132)

Appendix 5A.2: District under extreme low and low-level trap in respect of Education, Health and Human Capital Index over time

Education Index	Health Index	Human Capital Index
Agra, Aligarh, Anantang, Araria, Bahraich, Balarampur, Banswara, Bara Banki, Bareilly, Barwani, Belgaum, Budaun, Bulandshahr, Darbhanga, Darjiling, Dharmapuri, Dibang Valley, Doda, Faridabad, Gajapati, Gonda, Gurgaon, Jalor, Jehanabad, Jhabua, Katihar, Kaushambi, Koraput, Madhepura, Mahbubnagar, Malkangiri, Meerut, Mon, Muzaffarnagar, Nabarangapur, Paschim Champaran, Patna, Pulwama, Purnia, Rae Bareli, Rampur, Rayagada, Saharsa, Shahdol, Shahjahanpur, Sheohar, Shrawasti, Siddharthnagar, Sitamarhi, Tuensang, Vizianagaram	Agra, Ajmer, Aligarh, Araria, Ashoknagar, Aurangabad, Baghpat, Bahraich, Balarampur, Banda, Banka Banswara, Bara Banki Bareilly, Barmer, Barwani Begusarai, Bhagalpur Bharatpur, Bhilwara, Bhojpur Bijnor, Budaun, Bulandshahr Buxer, Chhatarpur, Chitrakoot Darbhanga, Darrang, Dausa Dhaulpur, Dhubri,Dibang Valley, Dindori, Dohad, Dungarpur, East Garo Hills East Kameng, East Khasi Hills, Etah, Faizabad, Farrukhabad, Fatehpur, Firozabad, Gajapati Gautam Buddha Nagar, Gaya, Ghaziabad, Ghazipur, Goalpara, Gonda, Gopalganj, Guna, Hailakandi, Harcloi, Jaintia Hills, Jaisalmer, Jehanabad, Jhabua, Jumai, Jyotiba Phule Nagar, Kaimur, Kalahandi, Kandhamal, Kannauj, Karauli, Karbi Anglong, Kargil, Karimganj, Katihar, Katni, Kaushambi Khagaria, Kheri, Kishanganj, Koraput, Kushinagar, Lakhisarai, Lalitpur, Lawngtlai, Madhepura, Madhubani, Mahamaya Nagar, Mainpuri, Malkangiri, Mamit, Mathura Mirzapur, Mon,Moradabad, Morigaon, Munger, Muzaffarnagar, Muzaffarpur, Nabarangapur, Nalanda, Nawada, Panna, Paschim Champaran, Patna, Phek, Pilibhit, Purba Champaran, Purnia, Raisen, Rampur, Rayagada, Ribhoi, Rohtas, Saharampur, Saharsa, Samastipur, Sant Kabir Nagar, Sant Ravidas Nagar, SaranShahdol, Shahjahanpur, Sheikhpura, Sheohar, Sheopur, Shivpuri, Shrawasti, Siddharthnagar, Sidhi, Sirohi, Sitamarhi, Sitapur, Sonbhadra, South Garo Hills, Supaul, The Dangs, Tirap, Tuensang, Udaipur, Umaria, Unnao, Upper Subansiri, Vaishali,Vidisha, West Garo Hills, West Khasi Hills	Aligarh, Araria, Bahraich, Balarampur, Banka, Banswara, Bara Banki, Bareilly, Barmer, Barwani, Begusarai, Bhagalpur, Budaun, Bulandshahr Darbhanga, Dhubri, Dibang Valley, Dohad, East Kameng, Gajapati, Gaya, Harcloi, Jaintia Hills, Jaisalmer, Jhabua, Kaimur, Katihar, Kaushambi, Khagaria, Kheri, Kishanganj, Koraput, Madhepura, Malkangiri, Mon, Moradabad, Muzaffarnagar, Nabarangapur, Nalanda, Paschim Champaran, Purba Champaran, Purnia, Rampur, Rayagada, Ribhoi, Saharsa, Samastipur, Shahjahanpur, Sheikhpura, Sheohar, Sheopur, Shrawasti, Siddharthnagar, Sidhi, Sirohi, Sitamarhi, Sitapur, Supaul, Tirap, Tuensang, West Garo Hills, West Khasi Hills

Aligarh, Araria, Bahraich, Balarampur, Banswara, Bara Banki, Bareilly, Barwani, Budaun, Bulandshahr, Darbhanga, Dibang Valley, Gajapati, Jhabua, Katihar, Kaushambi, Koraput, Madhepura, Malkangiri, Mon, Muzaffarnagar, Nabarangapur, Paschim Champaran, Purnia, Rampur, Rayagada, Saharsa, Shahjahanpur

Appendix 5A.3: Result of local Moran's index across districts overtime

	Human Capital Index			Education Index			Health Index		
Districts	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**
Adilabad	0.144	0.141	0.194**(1)	-0.062	0.036	0.032	0.241	0.498	0.810**(1)
Agra	0.492**(2)	1.054**(2)	0.617	-0.118	0.104	-0.135	0.625**(2)	0.809**(2)	0.803**(2)
Ahmadabad	0.391	0.279	0.477	0.1802	-0.023	0.372	0.216	0.268	0.362
Ahmadnagar	0.515	0.405	0.289	0.617**(1)	0.283	0.168	0.192	0.206	0.186
Aizawl	1.057	1.003	0.471	5.778**(1)	6.093**(1)	2.296**(1)	-0.093	-0.169	-0.235
Ajmer	0.269	0.582**(2)	0.349	0.0068	0.356**(2)	0.164	0.482**(2)	0.489**(2)	0.344
Akola	0.658	0.635	0.524	1.101	0.782	0.635	0.132	0.207	0.244
Alappuzha	2.683**(1)	2.79**(1)	3.166**(1)	-0.08	0.003	1.222**(1)	6.757**(1)	5.456**(1)	3.280**(1)
Aligarh	1.144**(2)	1.946**(2)	1.131**(2)	0.557	1.584**(2)	0.084	1.197**(2)	1.358**(2)	1.295**(2)
Allahabad	0.427	0.522	-0.0045	0.0009	0.117	0.032	0.811	0.594	0.275
Alwar	0.135	0.183	0.2066	0.0087	0.0054	0.035	0.368	0.358	0.305
Ambala	0.103	0.369	0.235	0.086	0.01	0.339	0.699	0.374	0.046
Ambedkar Nagar	0.307**(2)	0.254**(2)	0.031	-0.1079	-0.313**(4)	-0.274	0.719**(2)	0.479**(2)	0.164
Amravati	0.298	0.421	0.648	0.472	0.245	0.303	0.067	0.238	0.556
Amreli	0.426	0.138	-0.0096	0.1011	-0.013	0.091	0.48	0.254	0.065
Amritsar	0.028	0.371	0.542	0.522	-0.541	0.099	0.804	0.776	0.562
Anand	0.293	0.2055	0.296	0.197	0.004	0.183	0.1339	0.141	0.146
Anantapur	0.158	-0.0083	0.027	-0.008	0.793**(2)	0.946**(2)	0.5133	0.223	-0.083
Anantnag	0.184	0.519	0.772	0.704	1.665**(2)	1.713**(2)	-0.045	0.073	0.295
Anugul	0.02	0.175	0.205	0.0095	0.287	0.203	0.0007	0.037	0.105
Anuppur	-0.382	0.549	1.594	-0.318	0.051	0.102	0.0857	0.703	1.891**(2)
Araria	4.396**(2)	3.177**(2)	3.297**(2)	6.497**(2)	1.485**(2)	1.034**(2)	1.691**(2)	2.516**(2)	3.002**(2)
Ashoknagar	-0.078	0.796	1.531	-0.064	-0.0075	0.121	0.652**(2)	1.138**(2)	1.816**(2)
Auraiya	0.1649	0.399	0.087	0.0482	-0.098	0.063	0.674	0.604	0.405
Aurangabad	0.741	0.716	0.762	0.5183	-0.064	-0.027	0.699	1.07	1.351
Aurangabad	0.079	0.113	0.071	0.159	0.379	0.231	0.0002	-0.011	-0.001
Azamgarh	0.476	0.397**(2)	0.0098	0.057	0.124	0.002	0.773**(2)	0.4295**(2)	0.048
Badgam	0.183	0.117	0.526	1.199	0.726	1.683	0.033	-0.0001	0.103
Bagalkot	0.002	0.055	0.1108	0.009	0.119	0.142	-0.0026	0.0301	0.096
Baghpat	0.241	0.4028	0.208	0.31005	0.573	0.013	0.139	0.249	0.348
Bahraich	3.11**(2)	3.261**(2)	2.711**(2)	3.3019**(2)	2.747**(2)	2.191**(2)	1.894**(2)	2.1559**(2)	2.031**(2)
Balaghat	0.135	0.07	0.202	0.9532**(1)	0.255	0.186	-0.075	-0.0636	0.076

	Human Capital Index			Education Index			Health Index		
Districts	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**
Balangir	0.14	0.0142	0.035	0.2414	-0.0138	0.014	0.069	0.0704	0.051
Baleshwar	0.004	0.472	0.533**(1)	-0.208	0.413	0.29	0.076	184	0.345**(1)
Ballia	0.235**(2)	0.498**(2)	0.385**(2)	0.282**(2)	0.293	-0.013	0.172**(2)	0.4006**(2)	0.665**(2)
Balrampur	4.026**(2)	3.732**(2)	2.6102**(2)	4.603**(2)	3.768**(2)	2.593**(2)	2.339**(2)	2.277**(2)	1.839
Banas Kantha	0.134	0.125	0.107	0.008	-0.006	0.211	0.247	0.1665	0.063
Banda	0.781**(2)	0.712**(2)	0.7723**(2)	-0.071	0.0245	0.134	1.299**(2)	1.261**(2)	0.934**(2)
Bangalore Rural	0.456	0.028	0.091	-0.016	1.285**(2)	-0.376**(4)	1.1302**(1)	0.809**(1)	0.375
Bangalore	1.011	0.165	-0.037	0.1148	0.446	-0.172	1.6007	0.79001	0.092
Banka	1.848**(2)	1.279**(2)	1.026	2.523**(2)	0.515	0.099	0.913	1.167**(2)	1.225**(2)
Bankura	0.339	0.811**(1)	0.8293**(1)	-0.005	0.075	-0.018	0.494	0.932**(1)	1.409**(1)
Banswara	1.175**(2)	1.879**(2)	2.1256**(2)	0.473	0.918	1.605**(2)	1.302**(2)	1.57**(2)	1.566**(2)
Bara Banki	1.309**(2)	1.685**(2)	1.107**(2)	0.962**(2)	1.396**(2)	0.656	1.139**(2)	1.215**(2)	1.040**(2)
Bargarh	-0.021	0.079	0.134	0.034	-0.0126	0.021	-0.0038	0.0235	0.096
Baramula	0.269	0.094	0.217	1.3342**(2)	0.456	0.305**(2)	0.0071	0.008	0.140
Baran	0.288	0.5527	0.373	-0.046	0.264	0.265	0.576	0.519	0.352
Barddhaman	0.403	0.8211**(1)	0.886**(1)	0.0925	0.078	-0.007	0.449	0.941**(1)	1.559**(1)
Bareilly	2.178**(2)	2.411**(2)	1.505**(2)	1.8042**(2)	2.358**(2)	1.572**(2)	1.686**(2)	1.546**(2)	1.089**(2)
Barmer	1.115**(2)	1.609**(2)	1.258	-0.039	0.68	1.426**(1)	1.631**(2)	1.399**(2)	0.891
Barpeta	0.063	-0.0011	0.016	0.0327	-0.031	0.133	0.1012	0.0145	-0.032
Barwani	0.029	0.296	0.682	-0.161	0.1972	1.804	0.271	0.3079	0.271
Basti	1.137**(2)	1.161**(2)	0.366	0.578**(2)	0.793	0.055	1.217**(2)	0.959**(2)	0.510**(2)
Bathinda	0.141	0.193	0.072	-0.0102	0.009	0.004	0.439	0.319	0.113
Bauda	-0.017	0.038	0.0027	-0.0014	0.5243	0.105	0.0142	-0.0232	0.058
Begusarai	1.465**(2)	1.217**(2)	1.221**(2)	1.609**(2)	0.057	0.083	0.954**(2)	1.312**(2)	1.536**(2)
Belgaum	-0.123**(3)	-0.475	-0.4736	-0.325	0.235	-0.228	0.376**(2)	0.158**(1)	-0.053**(3)
Bellary	-0.008	-0.0049	0.014	-0.008	0.181	0.136	-0.064	-0.075	-0.042
Betul	-0.007	-0.0335	-0.127	0.031	-0.035	-0.123	0.365	0.102	-0.100
Bhadrak	0.071	0.369	0.316	0.4109	0.395	-0.078	0.017	0.1448	0.408
Bhagalpur	0.222	1.695**(2)	1.502**(2)	2.592**(2)	0.7203**(2)	0.367	1.133**(2)	1.491**(2)	1.606**(2)
Bhandara	2.07**(2)	0.613	1.089**(1)	0.712**(1)	0.1813	0.398	0.099	0.453	1.060**(1)
Bharatpur	0.553	0.904**(2)	0.772**(2)	-0.021	0.023	0.159	1.174**(2)	1.164**(2)	0.920**(2)
Bharuch	0.533	0.094	0.199	0.062	-0.082	0.042	0.195	0.1833	0.141
Bhavnagar	0.108	0.1223	-0.011	0.0877	-0.04	0.02	0.142	0.0986	-0.060
Bhilwara	0.222	-0.784	0.3667	0.231	0.999**(2)	0.563**(2)	0.606**(2)	0.472	0.216

	Human Capital Index			Education Index			Health Index		
Districts	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**
Bhind	-0.509	0.021	0.008	0.263	0.246	0.017	0.481**(2)	0.303	0.099
Bhiwani	0.051	-0.021	-0.042	0.207	-0.032	-0.002	0.0088	-0.0047	-0.042
Bhojpur	0.019	0.512**(2)	0.574	0.377	-0.219	-0.003	0.479	0.769**(2)	1.009**(2)
Bhopal	-0.384	-0.417	-0.653**(4)	0.179	0.116	-0.533	-0.051**(4)	-0.2041**(4)	-0.366**(4)
Bid	0.215	0.063	-0.0075	0.676**(1)	0.326	0.053	0.0011	-0.0051	-0.003
Bidar	0.068	0.065	0.029	0.086	-0.097	-0.009	0.0069	0.021	0.037
Bijapur	0.016	0.004	0.036	-0.049	-0.187	0.133	-0.0066	-0.0446	-0.026
Bijnor	0.806**(2)	1.103**(2)	0.993**(2)	0.267	0.0433**(2)	0.197**(2)	0.911**(2)	1.068**(2)	1.068**(2)
Bikaner	0.314	0.549**(2)	0.5919**(2)	-0.0025	0.254	0.526	0.517	0.4904	0.408**(2)
Bilaspur	1.932**(1)	1.111**(1)	0.489**(1)	1.5703**(1)	0.695	0.752**(1)	1.227**(1)	0.746**(1)	0.162
Birbhum	0.107	0.394	0.3901	0.053	0.199**(1)	-0.004	0.0556	0.268	0.686
Bishnupur	0.276	0.593	0.4625	0.222	1.0887	0.942**(1)	0.1514	0.141	0.110
Bongaigaon	0.353	0.153	0.3116	0.149	0.058	0.065	0.434	0.412	0.374
Budaun	2.563**(2)	2.984**(2)	2.2164**(2)	1.851**(2)	2.326**(2)	1.98**(2)	2.105**(2)	2.053**(2)	1.606**(2)
Bulandshahr	1.119**(2)	1.722**(2)	1.246**(2)	0.8195**(2)	1.362**(2)	0.385	0.982**(2)	1.233**(2)	1.311**(2)
Buldana	0.345	0.197	0.076	0.687**(1)	0.232	0.193	0.028	0.018	0.008
Bundi	0.325	0.544	0.148	0.095	1.074**(2)	0.581	0.454	0.238	0.034
Burhanpur	0.133	-0.107	-0.2503	0.1628	-0.106	0.036	-0.0039	-0.0247	-0.238
Buxar	0.593	0.709**(2)	0.7333**(2)	0.273	-0.059	0.039	0.675	1.021**(2)	1.283**(2)
Cachar	-0.018	0.057	0.0007	0.069**(1)	1.298**(1)	0.226	0.0674	0.0625	0.054
Central	1.588**(1)	1.074**(1)	1.937**(1)	1.318**(1)	-0.2007**(3)	3.06**(1)	0.886	0.826	0.562
Chamba	0.411	0.318	-0.004	0.141	-0.0005	-0.019	0.337	0.1296	-0.052
Champhai	0.749**(1)	0.644**(1)	0.157**(1)	0.429**(1)	5.341**(1)	2.245**(1)	-0.079	-0.161	-0.251
Chamrajnagar	0.536**(1)	-0.013**(3)	0.481**(1)	0.117	0.391	-0.199	2.092**(1)	1.702**(1)	0.855**(1)
Chandauli	0.416**(2)	0.608**(2)	0.2704	-0.404	0.003	0.026	1.031**(2)	0.7815**(2)	0.357**(2)
Chandel	-0.193	0.5001	0.5401	-0.665	0.547**(1)	0.348**(1)	0.074	0.1088	0.093
Chandrapur	0.513	0.651**(1)	1.284**(1)	0.347	0.032	0.233	-0.066	0.449**(1)	1.549**(1)
Changlang	0.695	0.321	0.649	0.442	0.0039	1.251**(2)	0.637	0.4165	0.247
Chennai	3.571**(1)	4.139**(1)	2.348**(1)	1.901**(1)	2.5018**(1)	0.897	3.206**(1)	3.091**(1)	2.371
Chhatarpur	0.813**(2)	0.671**(2)	0.359	0.0028	0.0074	0.035	1.391**(2)	1.054**(2)	0.523**(2)
Chhindwara	-0.46	-0.075	0.131	-2.0005**(3)	0.029	0.312	0.121	-0.029	-0.033
Chikmagalur	0.925**(1)	0.341	0.373	-0.069	0.5003	-0.002	2.125**(1)	1.465**(1)	0.529**(1)
Chitradurga	0.2348	0.011	0.001	-0.0016	0.634**(2)	0.061	0.396	0.319	0.174
Chitrakoot	0.629**(2)	1.219**(2)	1.171**(2)	-0.2965	0.0076	0.557	1.649**(2)	0.1542**(2)	1.106**(1)

	Human Capital Index			Education Index			Health Index		
Districts	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**
Chittaurgarh	0.296	0.586	0.1189	0.034	1.195	0.586	0.425	0.2004	0.013
Chittoor	0.824**(1)	0.363	0.091	0.069	0.096	0.157	1.322**(1)	0.927**(1)	0.372
Churachandpur	0.237**(1)	0.697**(1)	0.499**(1)	0.1886**(1)	1.982**(1)	1.4702**(1)	0.084	0.0919	0.078
Churu	0.053	0.226	0.205	0.078	0.155	0.199	0.25	0.1953	0.118
Coimbatore	3.378**(1)	3.689**(1)	5.092**(1)	1.177**(1)	0.544	2.462	3.854**(1)	4.704**(1)	4.707**(1)
Cuddalore	2.87**(1)	2.301**(1)	1.375**(1)	2.233**(1)	1.219**(1)	0.751**(1)	1.955**(1)	1.787**(1)	1.162
Y.s.r.	0.467	0.197	0.009	-0.044	0.374**(2)	0.897**(2)	1.25**(1)	0.9116**(1)	0.395
Cuttack	0.233	0.567**(1)	1.211**(1)	0.183	0.035**(1)	0.369**(1)	0.097	0.486	1.225**(1)
Dakshin Dinajpur	-0.112	-0.204	-0.222	-0.2918	0.047	-0.173	0.117	-0.235	0.070
Dakshina Kannada	2.475**(1)	1.269**(1)	1.232**(1)	0.348	-0.082	0.506	3.893**(1)	2.71**(1)	1.111**(1)
Damoh	0.298	0.258	0.1001	0.1996	0.1265	-0.017	1.029**(2)	0.627**(2)	0.197
Darbhanga	2.201**(2)	1.938**(1)	1.821**(2)	3.052**(2)	1.26**(2)	0.8102**(2)	1.062**(2)	1.494**(2)	1.71**(2)
Darjiling	-0.055	0.134	0.067	0.184	1.4002**(3)	-0.853	-0.206	0.355	1.784**(1)
Darrang	0.347	0.209	0.471	0.435	0.034	0.5902	0.185	0.262	0.344
Datia	-0.008	0.0387	-0.041	0.6503	0.741	0.087	0.404	0.2119	0.033
Davanagere	0.424	0.148	0.216	0.096	0.096	0.018	0.485	0.421	0.230
Debagarh	-0.028	0.0689	0.031	-0.0095	0.259	0.541	-0.021	-0.048	0.010
Deoria	0.559	0.625**(2)	0.052	0.3877	0.666	0.039	0.526	0.4095**(2)	0.078**(2)
Dewas	0.098	0.0386	0.0058	0.014	0.0036	0.164	0.334	0.1228	-0.002
Dhalai	0.063	0.3521	-0.0016	0.406**(1)	2.811**(1)	-1.335	-0.049	-0.139	-0.244
Dhar	0.536**(2)	0.445**(2)	0.638**(2)	0.291	0.1665	1.545**(2)	0.57**(2)	0.448	0.260
Dharmapuri	0.097**(1)	0.336**(3)	-0.061**(3)	-0.394	0.174	0.044	0.956**(1)	0.624**(1)	0.137**(1)
Dharwad	0.289	-0.0724	-0.1358	0.021	-0.6049	-0.622**(4)	0.415	0.3039	0.151
Dhaulpur	0.785	0.884	0.7649	-0.014	-0.1626	-0.006	1.475**(2)	1.367**(2)	0.979
Dhemaji	0.042	0.1004	-0.0383	0.023	0.553	-0.106	0.061	-0.025	-0.019
Dhenkanal	0.035	0.288	0.523	0.083	0.213	0.151	-0.018	0.1487	0.599
Dhubri	0.642	0.374	0.707	0.1109	-0.108	0.089	0.871	0.9163	0.826
Dhule	-0.09	-0.053	0.006	0.095	0.024	0.016	-0.065	-0.0178	0.021
Dibang Valley	0.923	0.1603	-0.131	0.089	-0.722	0.251	0.686	0.239	-0.226
Dibrugarh	-0.081	0.0525	-0.0042	0.087	-0.082	0.0103	-0.037	0.0445	0.037
Dindigul	2.618**(1)	1.963**(1)	0.839**(1)	1.214**(1)	0.755**(1)	0.411	2.562**(1)	1.749**(1)	0.649**(1)
Dindori	-0.027	0.2802	0.536	-0.108	-0.041	0.0104	0.291	0.4885	0.747
Doda	-0.151	0.0101	0.0804	-0.193	0.377	0.295	-0.017	-0.0015	0.032
Dohad	0.934	1.262**(2)	1.543**(2)	0.659	0.505**(2)	1.543**(2)	0.8172	1.003	1.030

	Human Capital Index			Education Index			Health Index		
Districts	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**
Dungarpur	0.499	0.896	1.051**(2)	0.0728	0.379	1.053**(2)	0.7577	0.839	0.748
Dimapur	-0.019	-0.04	-0.1864	0.128	0.939	0.434	0.0111	-0.0076	-0.067
East	0.939**(1)	0.811	1.443**(1)	1.342**(1)	1.123**(1)	4.509**(1)	0.3055	0.3205	0.218
East	0.462	1.677	2.679**(1)	0.249	0.607	-0.193	0.338	1.403	3.846**(1)
East Garo Hills	0.526	0.748**(2)	2.149**(2)	-0.0601	0.665	0.0904	1.046**(2)	1.531**(2)	1.868**(2)
East Godavari	-0.183	0.106	-0.038	0.093**(2)	0.484	0.384**(2)	1.1114	0.968	0.638
East Kameng	1.524	-0.061	-0.117	0.423	0.153	-0.156	1.335	0.5471	0.098
East Khasi Hills	0.003**(2)	0.1882**(2)	0.8334**(2)	-0.114	1.375	-0.311	1.091**(2)	1.646**(2)	1.973**(2)
East Nimar	-0.01	0.0318	-0.1033	-0.091	-0.0127	0.281	0.1901	0.013	-0.219
East Siang	-0.047	0.151	0.092	-0.076	0.597	-0.123	0.0789	-0.0181	0.161
Ernakulam	3.567**(1)	2.923**(1)	3.122**(1)	0.451	0.017	1.235**(1)	6.375**(1)	5.172**(1)	3.189**(1)
Erode	1.749**(1)	1.554**(1)	2.105**(1)	0.218	-0.0007	0.352	2.962**(1)	3.018**(1)	2.478**(1)
Etah	0.813	1.867**(2)	0.566	-0.0068	1.3886	0.018	1.341**(2)	1.328**(2)	1.046**(2)
Etawah	0.155	0.426**(2)	0.08	-0.011	0.0366	0.068	0.618**(2)	0.5725**(2)	0.41**(2)
Faizabad	0.718**(2)	0.799**(2)	0.425	0.189	0.441	0.315	1.118**(2)	0.931**(2)	0.548
Faridabad	0.103	0.398	0.077	0.211	1.027	0.8804**(1)	-0.0059	-0.005	-0.001
Faridkot	0.187	0.239	-0.024	-0.0014	-0.0017	-0.069	0.531	0.3009	0.070
Farrukhabad	1.136**(2)	1.694**(2)	0.918**(2)	0.161	0.622**(2)	0.021	1.538**(2)	1.537**(2)	1.254**(2)
Fatehabad	0.022	0.005	0.0007	0.437	0.251	0.036	0.0367	0.008	-0.008
Fatehgarh Sahib	0.186	0.553	0.6016	0.156	-0.159	0.274	1.005	0.819	0.479
Fatehpur	0.566**(2)	1.1002**(2)	0.814**(2)	0.118	0.679**(2)	0.298	0.746**(2)	0.8836**(2)	0.867**(2)
Firozabad	0.599	0.1333**(2)	0.5352	0.027	0.553**(2)	-0.099	0.997**(2)	0.989**(2)	0.753**(2)
Firozpur	0.057	0.142	0.0045	0.035	-0.003	-0.27	0.289**(1)	0.146	-0.012
Gadag	0.035	-0.0098	-0.0054	-0.03	0.061	-0.044	0.036	0.004	0.004
Gajapati	0.436	0.3169	0.2446	1.262	1.003	1.368**(2)	-0.061	-0.048	-0.253
Gandhinagar	0.418	0.285	0.4623	0.495	0.062	0.213	0.152	0.236	0.333
Ganganagar	0.015	0.1026	-0.248**(4)	0.036	0.324	0.302**(2)	0.012	-0.0435	-0.292
Ganjam	-0.005	0.0815	0.178	0.0045	-0.0048	0.005	-0.0104	0.584	0.315
Garhchiroli	0.006	0.305	0.851**(1)	0.0315	0.003	-0.019	-0.071	0.4778**(1)	1.651**(1)
Gautam Buddha Nagar	0.058	0.327	-0.0093	-0.0013	0.336	0.523	0.136	0.2118	0.274
Gaya	1.038**(2)	1.171**(2)	1.211**(2)	1.135**(2)	0.359	0.091	-0.6926	1.142**(2)	1.507*(2)
Ghaziabad	0.164	0.325	0.1624	0.1005	0.184	-0.365	0.1679	0.277	0.375
Ghazipur	0.526**(2)	0.827**(2)	0.328	0.179	0.387	-0.035	0.626**(2)	0.708**(2)	0.637**(2)
Goalpara	0.302	0.183	0.492	0.038	0.105	-0.247	0.488	0.493	0.463

	Human Capital Index			Education Index			Health Index		
Districts	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**
Golaghat	0.027	0.099	0.035	-0.0518	0.261**(1)	0.085	-0.0345	-0.029	-0.015
Gonda	2.388**(2)	2.182**(2)	1.271**(2)	2.341**(2)	2.008**(2)	1.146**(2)	1.663**(2)	1.494**(2)	1.023**(2)
Gondiya	0.304	0.375	0.695	0.703	0.2073	0.241	0.0122	0.229	0.630
Gopalganj	1.294**(2)	1.07**(2)	1.056**(2)	1.734**(2)	0.2807**(2)	0.009	0.678**(2)	1.073**(2)	1.377**(2)
Gorakhpur	0.208**(2)	0.728**(2)	0.214	-0.266**(4)	0.921**(2)	0.328	0.608**(2)	0.341**(2)	0.033**(2)
Gulbarga	-0.22	-0.206	-0.029	-0.2803	-0.2004	0.025	-0.0917	-0.08	-0.530
Guna	0.197	0.619	0.711	-0.268	0.0369	0.213	0.544	0.672	0.763
Guntur	0.279	0.203	0.063	0.233	0.875	0.835**(2)	1.686	1.425	0.872
Gurdaspur	-0.365**(3)	0.823**(1)	0.204	-1.124	0.346	-0.175	0.881**(1)	0.646	0.306
Gurgaon	-0.116	-0.0103	0.0671	0.085	0.1535	0.977**(1)	-0.133	-0.019	-0.033
Gwalior	-0.117	-0.1055	-0.056	0.585	1.411	0.028	0.228	0.098	-0.011
Hailakandi	-0.113	-0.074	0.1406	0.078**(1)	2.598**(1)	0.496**(1)	0.392	0.6173	0.778
Hamirpur	2.434**(1)	1.586**(1)	0.696	2.165**(1)	1.106**(1)	0.685	1.428**(1)	1.021	0.388
Hamirpur	0.261	0.443	0.199	0.051	0.266	0.168	0.403	0.4035	0.322
Hanumangarh	0.0036	0.032	0.275	-0.051	0.2658	0.175	-0.0156	-0.0509	-0.057
Haora	0.706	1.518**(1)	1.459**(1)	-0.061	0.269	0.162	1.224**(1)	1.692**(1)	1.962**(1)
Harda	0.123	0.077	0.0132	0.244	0.2802	0.002	0.668	0.381	-0.011
Hardoi	1.031**(2)	1.366**(2)	0.791**(2)	0.31**(2)	0.2315**(2)	0.003	1.125**(2)	1.256**(2)	1.164**(2)
Hassan	0.907**(1)	0.324	0.476**(1)	-0.0046	0.833**(2)	0.012	2.283**(1)	1.828**(1)	0.991**(1)
Mahamaya Nagar	0.665	1.519**(2)	0.3028**(2)	-0.073	1.095**(2)	-0.382	1.103**(2)	1.141**(2)	0.957**(2)
Haveri	0.384	0.1067	0.067	0.203	0.006	-0.057	0.2602	0.2501	0.159
Hingoli	0.084	0.055	-0.0003	0.387	0.361	0.0401	0.007	-0.018	-0.027
Hisar	0.059	-0.017	-0.0568	0.706	0.078	-0.007	0.0592	-0.01204	-0.034
Hoshangabad	0.063	0.004	-0.0838	0.206	0.377	-0.051	0.552**(2)	0.285	0.023
Hoshiarpur	1.116**(1)	1.294**(1)	0.6936	0.2653	0.615	0.528	1.261**(1)	1.0002**(1)	0.443
Hugli	0.956	1.646**(1)	1.722**(1)	0.135	0.152	0.085	1.361**(1)	2.089**(1)	2.676**(1)
Hyderabad	1.634	1.785	1.292	1.102	1.195**(1)	1.4225	1.168	1.017	0.636
Idukki	3.435**(1)	3.034**(1)	2.769**(1)	0.726**(1)	0.214**(1)	0.892**(1)	5.003**(1)	4.383**(1)	2.981**(1)
Imphal East	0.505	0.513	0.393	0.798	1.345	1.558**(1)	0.1206	0.065	0.013
Imphal West	0.237	0.718	0.418	0.2907	1.581	0.786	0.0268	0.0841	0.094
Indore	-0.019	-0.342	-0.443	0.0324	-0.424	-1.308**(4)	-0.132	-0.139	-0.111
Jabalpur	-0.114	-0.057	-0.1072	0.318	0.079	-0.0218	0.0378**(2)	0.035**(2)	0.015
Jagatsinghapur	0.502	1.075	2.053**(1)	0.549	0.441	0.764	0.1864	0.8712	2.076**(1)
Jaintia Hills	0.708	0.741	1.391	-0.348	-0.234**(3)	-0.987	1.219	1.689	1.92**(2)

	Human Capital Index			Education Index			Health Index		
Districts	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**
Jaipur	0.102	0.0416	-0.1775	-0.0161	0.043	-0.092	0.272**(2)	0.0449	-0.144
Jaisalmer	1.193	1.667	1.455	0.116	0.654	1.58**(2)	1.644**(2)	1.4827	0.036
Jajapur	0.222	0.458	0.5829**(1)	0.318	0.365	0.178	0.049	0.2169	0.455**(1)
Jalandhar	0.624	1.109**(1)	0.465	0.0018	0.408	0.224	1.393**(1)	0.9351**(1)	0.365
Jalaun	0.1222	0.185	-0.0073	0.044	0.0245	0.012	0.464	0.249	0.027
Jalgaon	0.031	-0.088	-0.129	0.197	-0.0345	-0.174	-0.074	-0.084	-0.058
Jalna	0.014	-0.028	-0.0531	0.275	0.263	0.002	-0.026	-0.01	0.017
Jalor	0.996	1.196**(2)	0.798	0.1715	0.778	1.305**(2)	1.287**(2)	0.9558**(2)	0.451
Jalpaiguri	-0.002	0.316	0.1053	-0.1126	-0.031	0.518	0.029	0.339	1.002
Jammu	0.0412	-0.067	-0.061	-0.171	-0.235	-0.115	0.062	-0.0016	0.031
Jamnagar	0.298	0.0073	-0.0396	-0.049	0.158	-0.074	0.713	0.396	0.116
Jamui	1.862**(2)	1.209**(2)	0.927**(2)	2.602**(2)	0.419	0.037	0.8815**(2)	1.164**(2)	1.262**(2)
Jaunpur	0.649**(2)	0.556**(2)	0.075	0.217	0.332	0.0005	0.809**(2)	0.507**(2)	0.150
Jhabua	1.285	1.771	1.8903**(2)	0.801	1.233	2.631**(2)	1.136	1.217	1.073
Jhajjar	-0.117	0.076	0.1582	0.0505	-0.101	0.577**(1)	0.0898	0.056	-0.014
Jhalawar	0.195	0.314	0.1985	-0.061	0.237	0.656	0.4938	0.273	0.057
Jhansi	0.066	0.053	-0.049	-0.0067	-0.029	-0.025	0.2108**(2)	0.123**(2)	0.022
Jharsuguda	0.058	0.269	0.4127	-0.057	0.0547	0.138	0.0889	0.211	0.354
Jhunjhunun	-0.002	0.003	0.0091	-0.134	0.0302	0.022	0.0534	0.0038	0.023
Jodhpur	0.697**(2)	0.999**(2)	0.689**(2)	0.0105	0.486	0.598**(2)	0.9707**(2)	0.849**(2)	0.555
Jorhat	0.357	0.619	0.4759	0.091	0.231	0.203	0.305	0.449	0.388
Junagadh	0.539	0.238	-0.07	0.1384	-0.004	0.013	0.5471	0.395	0.175
Jyotiba Phule Nagar	1.175**(2)	1.144**(2)	1.1182**(2)	0.6101**(2)	-0.451**(4)	0.258**(2)	1.148**(2)	1.268**(2)	1.162**(2)
Kachchh	0.089	0.075	0.054	0.127	-0.0402	-0.0114	0.1639	0.132	0.068
Kaimur (bhabua)	0.881	1.036**(2)	0.869	0.145	-0.0621	-0.007	1.2175**(2)	1.391**(2)	1.315**(2)
Kaithal	-0.0003	-0.032	-0.0122	0.409	0.0769	-0.006	0.096	-0.028	0.047
Kalahandi	0.972**(2)	0.598	0.893**(2)	1.924**(2)	0.455**(2)	0.862**(2)	0.258	0.487	0.692
Kamrup	-0.145	-0.007	0.119**(2)	-0.048	-0.33	0.153	-0.2884**(4)	-0.184**(4)	-0.02**(4)
Kancheepuram	2.738**(1)	2.743**(1)	1.2074**(1)	1.6832**(1)	1.821**(1)	0.294	2.184**(1)	1.876**(1)	1.245**(1)
Kandhamal	0	0	0	0	0	0	0	0	0.000
Kangra	1.724**(1)	1.284**(1)	0.3438**(1)	1.215**(1)	0.877**(1)	0.245	1.278**(1)	0.834**(1)	0.165**(1)
Kannauj	0.489	**(2)	0.3998	-0.001	0.072	0.041	0.7922**(2)	0.878**(2)	0.804**(2)
Kanniyakumari	4.101**(1)	3.819**(1)	2.906**(1)	1.426**(1)	0.996	1.275	4.82**(1)	4.248**(1)	2.851**(1)
Kannur	3.446**(1)	2.728**(1)	2.398**(1)	1.087	0.358	1.113	4.213**(1)	3.518**(1)	2.238**(1)

	Human Capital Index			Education Index			Health Index		
Districts	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**
Kanpur Dehat	0.1945	0.487	0.1726	-0.009	0.265	-0.243	0.436	0.427	0.332
Kanpur Nagar	-0.286**(4)	0.0463**(4)	-0.0629**(4)	0.106	0.415	-0.348	-0.726**(4)	-0.291**(4)	0.293**(2)
Kapurthala	0.406	1.007**(1)	0.4129	-0.006	0.362	0.857	1.205**(1)	0.8215**(1)	0.328
Karbi Anglong	0.269	0.2704	0.617	-0.063	0.565**(1)	0.0134	0.526**(2)	0.831**(2)	1.00.(2)
Kargil	-0.124	-0.053	0.0243	0.017	-0.161	0.234	-0.509	-0.435	-0.282
Karimganj	-0.098	-0.009	0.2923	-0.394**(3)	2.135**(1)	0.182	0.395	0.592	0.720
Karimnagar	0.303	0.439	0.649	0.001	0.375	0.317	1.006	1.613**(1)	2.327**(1)
Karnal	-0.046	0.079	0.1633	0.192**(2)	0.271**(2)	-0.052	-0.011	0.0289	0.308
Karur	2.215**(1)	2.143**(1)	1.342**(1)	0.658**(1)	0.399	0.104	2.695**(1)	2.471**(1)	1.796**(1)
Kasaragod	3.048**(1)	1.845**(1)	1.9**(1)	0.904	0.036	0.908	3.768**(1)	2.967**(1)	1.71**(1)
Kathua	-0.015	0.058	-0.0005	-0.717	-0.041	0.158	0.163	0.045	-0.007
Katihar	4.243**(4)	3.486**(2)	3.444**(2)	6.034**(2)	2.103**(2)	1.625	1.836	2.565**(2)	2.928**(2)
Katni	0.179	0.332	0.337	0.247	0.263	0.008	0.7906**(2)	0.833**(2)	0.648
Kaushambi	0.965	1.707**(2)	1.469	-0.058	0.738	0.668	1.191**(2)	1.464**(2)	1.300
Kendrapara	0.391	0.709	1.044**(1)	0.575	0.548	0.475	0.094	0.375	0.886**(1)
Kendujhar	0.023	0.22	0.292	-0.041	0.044	-0.134	0.018	0.137	0.388
Khagaria	2.503**(2)	2.016**(2)	2.088**(2)	3.152**(2)	0.443	0.328	1.351**(2)	1.9304**(2)	2.239**(2)
Khammam	0.126	0.2547	0.136	0.152	0.469	0.542**(2)	1.283**(1)	1.202**(1)	0.888**(1)
Kheda	0.189	0.108	0.092	0.317	0.035	0.011	0.019	0.041	0.069
Kheri	1.776**(2)	2.117**(2)	1.866**(2)	1.154**(2)	0.904**(2)	0.874**(2)	1.568**(2)	1.805**(1)	1.715**(2)
Khordha	0.147	0.61	1.131**(1)	0.118	0.343	0.422	0.0533	0.385	1.01**(1)
Kinnaur	0.984**(1)	1.277**(1)	1.602**(1)	1.435**(1)	0.484	0.145	0.206	1.111**(1)	2.337**(1)
Kishanganj	3.074**(2)	1.905**(2)	2.0425**(2)	5.193**(2)	1.149**(2)	0.926**(2)	0.829	0.967	0.850
Koch Bihar	-0.208	-0.156	-0.753	-0.418	0.561	-1.023	0.0389	-0.1946	-0.301
Kodagu	1.808**(1)	1.329**(1)	1.456**(1)	0.1765**(1)	-0.029	0.276	3.023**(1)	2.633**(1)	1.726**(1)
Kohima	0.173	0.071	0.1265	0.7012**(1)	0.047**(1)	0.357**(1)	-0.0059	-0.0091	-0.005
Kokrajhar	0.155	-0.051	-0.0056	-0.065	0.148	0.064	0.168	0.104	-0.116
Kolar	0.334	-0.125	0.172	-0.0423	1.015	0.007	0.747	0.6335	0.290
Kolasib	0.4537	0.331	0.0071	4.649**(1)	5.825**(1)	1.841**(1)	0.085	0.0867	0.063
Kolhapur	1.035**(1)	0.862	1.196	0.162	-0.101	-0.042	1.454**(1)	1.784**(1)	1.867**(1)
Kolkata	0.822	1.387**(1)	1.963**(1)	-0.181	-0.256	0.073	1.482	2.443**(1)	0.307**(1)
Kollam	3.087**(1)	2.939**(1)	3.106**(1)	0.3227	0.088	1.132**(1)	5.854**(1)	5.019**(1)	3.301**(1)
Koppal	0.01	0.1042	0.172	0.036	0.076	0.13	0.0117	0.096	0.190
Koraput	1.566**(2)	0.9301	1.4162	3.854**(2)	2.329**(2)	2.702**(2)	0.004	0.198	0.552

	Human Capital Index			Education Index			Health Index		
Districts	LMI_2006	LMI_2011	LMI_2016	LMI_2006	LMI_2011	LMI_2016	LMI_2006	LMI_2011	LMI_2016
Kota	-0.13	-0.029	-0.157	-0.115	0.203**(2)	-0.141**(4)	0.075**(2)	-0.055	-0.078
Kottayam	3.362**(1)	3.091**(1)	3.416**(1)	0.284	0.0029	1.178**(1)	6.605**(1)	5.661**(1)	3.735**(1)
Kozhikode	3.73**(1)	3.159**(1)	1.9445**(1)	1.593**(1)	1.241**(1)	1.294**(1)	3.89**(1)	2.905**(1)	1.502**(1)
Krishna	0.785	0.491	0.098	0.021	0.4338	0.275	2.518**(1)	1.819**(1)	0.446**(1)
Krishnagiri	0.801**(1)	0.1745	-0.021	0.121	0.058**(2)	0.047	1.052**(1)	0.525**(1)	-0.047**(3)
Kullu	1.525**(1)	1.2847**(1)	0.877**(1)	1.761**(1)	0.716	0.168	0.663	0.842**(2)	0.918**(1)
Kupwara	0.415	0.166	0.303	1.886	0.685	0.343	0.0046	0.019	0.248
Kurnool	0.007	-0.002	0.051	0.204	0.687**(2)	1.271**(2)	0.196	0.1381	0.027
Kurukshetra	0.0385	0.088	0.019	0.213	0.014	0.071	0.404	0.1501	-0.023
Kushinagar	1.182**(2)	1.169**(2)	0.715	1.019**(2)	0.7603**(2)	0.281	0.922**(2)	0.921**(2)	0.726
Lahul & Spiti	0.562	0.463	0.312	0.429**(1)	-0.259**(3)	-0.176	0.245	0.3643	0.398
Lakhimpur	0.007	0.1502	0.1042	-0.051	0.703	0.278	-0.015	-0.0251	0.004
Lakhisarai	1.349**(2)	1.238**(2)	1.0244**(2)	1.469**(2)	0.358	0.059	0.886**(2)	1.2073**(2)	1.351**(2)
Lalitpur	0.582	0.719	0.6004	-0.189	-0.006	0.014	1.186**(2)	1.083**(2)	0.811
Latur	0.302	0.132	0.0226	0.945**(1)	0.544	0.069	-0.0022	0.0005	-0.005
Lawangtlai	-0.098	-0.263	-0.3105	1.766**(1)	0.5802**(1)	-0.798**(3)	0.5405	0.6004	0.521
Leh (ladakh)	-0.007	-0.0011	-0.0077	-0.094	-0.006	-0.411	0.009	-0.0091	-0.067
Lohit	0.366	0.1119	0.457	0.0704	-0.073	1.478	0.349	0.196	0.108
Lower Subansiri	0.382	0.0304	0.254	-0.3118	1.009**(1)	1.361	0.625	0.086	-0.017
Lucknow	0.214**(2)	0.459**(2)	-0.869**(4)	0.414	1.007**(2)	-1.333	-0.059**(4)	-0.0606**(4)	-0.063**(4)
Ludhiana	0.189	0.649	0.643	0.076	0.012	0.515	1.076**(1)	0.8135**(1)	0.393
Lunglei	0.293	0.1512	0.0321	3.644**(1)	3.35**(1)	1.332**(1)	0.1394	0.1102	0.046
Madhepura	3.453**(2)	2.544**(2)	2.454**(2)	4.948**(2)	1.236**(2)	0.873**(2)	1.501**(2)	2.061**(2)	2.302**(2)
Madhubani	2.267**(2)	1.6001**(2)	1.562**(2)	3.451**(2)	0.854**(2)	0.605**(2)	0.948**(2)	1.342**(2)	1.542**(2)
Madurai	3.011**(1)	2.762**(1)	1.594**(1)	2.175**(1)	1.574**(1)	0.567	2.126**(1)	2.087**(1)	1.605**(1)
Maharajganj	1.801**(2)	1.692**(2)	0.715**(2)	1.318**(2)	1.332**(2)	0.537**(2)	1.486**(2)	1.211**(2)	0.622**(2)
Mahbubnagar	-0.121	-0.108	-0.079	0.388	0.691	0.837	0.057	0.041	0.023
Mahendragarh	-0.048	-0.0202	-0.013	-0.013	-0.003	0.003	-0.0415	-0.032	-0.030
Mahesana	0.152	-0.1229	0.243	0.181	0.011	0.054	0.0236	0.097	0.185
Mahoba	0.513	0.504	0.2804	0.101	0.051	0.025	0.7368	0.643	0.406
Mainpuri	0.547**(2)	0.999**(2)	0.609	0.017	-0.044	0.072	0.9632**(2)	1.177**(2)	1.171**(2)
Malappuram	3.564**(1)	3.274**(1)	1.7239**(1)	2.206**(1)	1.949**(1)	1.154**(1)	2.691**(1)	2.125**(1)	1.213**(1)
Maldah	0.152	-0.021	0.043	0.037	0.114	0.094	0.257	-0.011	0.176
Malkangiri	-0.475	-0.247	0.0198	2.525	1.432	1.631**(2)	-0.701	-0.889	-0.774

	Human Capital Index			Education Index			Health Index		
Districts	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**
Mamit	0.301	-0.025	-0.067	4.688**(1)	4.933**(1)	1.061**(1)	0.211	0.3174	0.340
Mandi	1.943**(1)	1.585**(1)	0.965**(1)	1.892**(1)	1.027**(1)	0.423**(1)	1.032**(1)	1.041**(1)	0.724
Mandla	-0.002	0.034	0.31	0.249	-0.019	-0.0349	0.247	0.1466	0.040
Mandsaur	0.0128	-0.0134	0.069	0.066	0.0143	0.173	0.243	0.0063	0.026
Mandya	0.4036	0.065	0.718**(2)	0.056	1.851**(2)	0.312	1.653**(1)	1.522**(1)	1.084**(1)
Mansa	-0.023	0.0468	0.942	0.3177	0.183	0.049	0.194	0.202	0.174
Marigaon	0.589	0.364	0.125	0.129	0.209	0.022	0.736	0.8414**(2)	0.831**(2)
Mathura	0.671	1.17**(2)	0.169	0.128	-0.0173**(4)	-0.012	0.914**(2)	1.195**(2)	1.312**(2)
Mau	0.344	0.641	0.182	0.063	0.627**(2)	0.003	0.533	0.456	0.288
Mayurbhanj	-0.054	-0.114	0.169	0.171	-0.189	0.173	-0.019	-0.036	-0.049
Medak	0.069	0.1163	0.054	0.0182	0.132	0.161	0.427**(1)	0.497**(1)	0.5**(1)
Meerut	0.671	1.113**(2)	0.544**(2)	0.635	1.296	0.208	0.4822	0.597**(2)	0.613**(2)
Mirzapur	0.746	0.8112	0.385	0.038	0.09	0.079	1.203**(2)	0.9604	0.481
Moga	0.298	0.375	0.001	0.0041	0.038	-0.003	0.807**(1)	0.3844	-0.083
Mokokchung	0.175	0.423	0.546	0.3661	0.4101	0.327	0.022	0.167	0.373
Mon	0.915	0.897	1.019	1.442	1.299	1.789**(2)	0.394	0.474	0.475
Moradabad	1.837**(2)	1.962**(2)	2.106**(2)	0.366**(2)	0.918	2.032**(2)	1.538**(2)	1.649**(2)	1.476**(2)
Morena	0.382	0.171	0.357	0.006	0.257	0.072	0.876**(2)	0.747**(2)	0.475**(2)
Muktsar	0.025	0.03	0.0386	0.045	0.052	0.146	0.269	0.0775	0.009
Mumbai	1.196	1.777	2.8009	0.071	-0.035	0.945	2.187	2.284	1.999
Mumbai Suburban	0.816	1.024**(1)	1.413**(1)	-0.056	-0.919**(3)	-0.681**(3)	1.628**(1)	1.788**(1)	1.644
Munger	1.073**(2)	0.917	0.879**(2)	1.117**(2)	0.028	-0.118	0.739**(2)	1.109**(2)	1.329**(2)
Murshidabad	-0.066	0.226	0.245	-0.0134	-0.271	0.001	-0.098	-0.016	0.421**(1)
Muzaffarnagar	0.546	1.206	0.709	0.573	1.656	0.121	0.392	0.6115	0.79**(2)
Muzaffarpur	1.685**(2)	1.519**(2)	1.239**(2)	1.9108**(2)	0.686**(2)	0.228	1.034**(2)	1.336**(2)	1.426**(2)
Mysore	0.567**(1)	0.3903	0.7438**(1)	-0.015	0.448	0.002	1.528**(1)	1.576**(1)	1.288**(1)
Nabarangapur	2.059	1.516	2.131**(2)	4.144**(2)	1.906	2.575**(2)	0.394	0.885	1.390
Nadia	0.469	1.377**(1)	1.74**(1)	0.067	0.228	0.042	0.607	1.581**(1)	3.013**(1)
Nagaon	0.188	0.054	0.223	0.055	0.233	0.031	0.2319	0.283	0.319
Nagaur	0.231	0.446	0.216	0.0081	0.077	0.098	0.506**(2)	0.365	0.155
Nagpur	0.421	0.7104	1.232**(1)	0.503	0.312	0.724	0.046	0.488	0.975**(1)
Nalanda	1.076**(2)	1.363**(2)	1.183**(2)	1.205**(2)	0.843**(2)	0.199	0.704**(2)	1.1005**(2)	1.379**(2)
Nalbari	-0.032	-0.0017	-0.1196	-0.031	-0.205	-0.343	-0.021	0.0323	0.108
Nalgonda	0.282	0.292	0.241	0.0222	0.288	0.385	0.867**(1)	1.066**(1)	1.067**(1)

	Human Capital Index			Education Index			Health Index		
Districts	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**
Namakkal	1.994**(1)	2.185**(1)	1.808**(1)	0.596	0.275	0.149	2.398**(1)	2.77**(1)	2.62**(1)
Nanded	0.07	0.0865	0.056	0.222	0.144	0.0007	-0.054	-0.0032	0.053
Nandurbar	0.059	0.088	0.1517	0.0072	0.074	0.5111	0.0999	0.068	0.026
Narmada	0.015	-0.0141	-0.0132	-0.0249	0.0603	-0.00001	-0.022	-0.0207	-0.016
Narsimhapur	0.002	0.0329	-0.0054	0.2955	0.096	0.0092	0.429**(2)	0.1834	-0.005
Nashik	0.285	0.246	0.1344	0.447	0.438	0.188	0.047	0.0497	0.041
Navsari	0.374	0.237	0.2975	0.191	-0.034	0.498	0.292	0.1666	0.018
Nawada	1.611**(2)	1.155**(2)	0.9496**(2)	2.314**(2)	0.567	0.144	0.731**(2)	1.013**(2)	1.15**(2)
Nayagarh	0.034	0.248	0.3392	0.034	0.357	0.161	0.004	0.075	0.253
Neemuch	0.03	-0.0778	-0.0867	-0.079	-0.013	0.249	0.216	-0.023	-0.054
Sri Potti Sriramulu Nellore	0.726**(1)	0.603	0.3209	-0.0301	0.0511	0.405	1.621**(1)	1.673**(1)	1.330
New Delhi	1.98**(1)	1.631	2.599**(1)	3.047**(1)	2.935	11.49**(1)	0.6288	0.434	0.040
Nizamabad	0.139	0.1756	0.147	-0.0146	0.1527	0.297	0.518	0.651	0.682**(1)
North	0.641	0.4533	0.7383**(1)	0.498	0.072	1.163**(1)	0.354	0.3448	0.271
North	0.222	1.449**(1)	2.759**(1)	0.4399	1.773**(1)	0.878**(1)	0.0131	0.614	2.914**(1)
North 24 Parganas	0.9001**(1)	1.493**(1)	2.007**(1)	0.205	0.0415	0.052	1.142**(1)	2.215**(1)	3.469**(1)
Dima Hasao	-0.0344	-0.079	0.023	-0.096	0.318	-0.065	-0.145	0.1541**(2)	0.165**(2)
North East	0.118	0.0243	0.168	0.221	-0.112	1.093	-0.0044	0.0019	-0.019
North Goa	0.946**(1)	0.324	0.516	0.0016	-0.041**(4)	-1.062	2.284**(1)	1.881**(1)	1.145
North Tripura	0.021	0.0079	0.154	1.064**(1)	2.861**(1)	-0.704**(3)	0.093	0.1676	0.226
North West	-0.015	0.051	0.167	-0.2302	-0.149	0.662	0.055	0.0262	0.025
Nuapada	0.307	0.072	0.092	0.807	0.075	0.184	0.0603	0.074	0.052
Osmanabad	0.371	0.084	0.0586	0.866	0.031	-0.003	0.029	0.032	0.030
Palakkad	0.357**(1)	3.629**(1)	0.322**(1)	1.425**(1)	0.988**(1)	1.192**(2)	3.825**(1)	3.942**(1)	3.362**(1)
Pali	0.669**(2)	1.057**(2)	0.6583**(2)	0.0538	0.756**(2)	0.766**(2)	0.988**(2)	0.8200**(2)	0.472**(2)
Panch Mahals	0.041	0.173	0.5179	-0.069	-0.0005	0.933**(2)	0.203	0.2507	0.252
Panchkula	0.1075	0.491	0.402	-0.399	0.209	1.018	0.525	0.303	0.071
Panipat	0.131	0.035	0.0644	0.498	0.049	-0.004	0.0018	0.047	0.154
Panna	0.769	0.7502	0.4861	0.0738	0.043	0.035	1.679**(2)	1.276**(2)	0.652
Papum Pare	-0.391**(4)	-0.363	-0.219	-1.249**(4)	1.192	0.64	0.402**(2)	0.0493	-0.081
Parbhani	0.108	0.0604	-0.0026	0.468**(1)	0.476	0.091	0.0013	0.0051	0.009
Pashchim Champaran	2.418**(2)	2.0766**(2)	1.8033**(2)	3.069**(2)	1.16	0.494	1.241**(2)	1.656**(2)	1.823**(2)
Pashchim Medinipur	-0.043	0.9719**(1)	1.129**(1)	-0.045	0.321	0.264	0.4322	0.759**(1)	1.11**(1)
Patan	-0.0164	0.0005	0.047	-0.035	-0.012	0.005	0.0314	0.0008	0.027

	Human Capital Index			Education Index			Health Index		
Districts	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**
Pathanamthitta	3.292**(1)	2.862**(1)	3.419**(1)	0.283	-0.178	1.195**(1)	6.4472**(1)	5.587**(1)	3.729**(1)
Patiala	0.0522	0.2366	0.1021	0.086	-0.071	0.08	0.588	0.288	0.033
Patna	0.704**(2)	1.294**(2)	1.045**(2)	0.903**(2)	0.819	0.141	0.414**(2)	0.829**(2)	1.242**(2)
Perambalur	3.5001**(1)	1.644**(1)	0.646**(1)	3.537**(1)	1.586	1.061	1.609**(1)	0.568**(1)	-0.87**(3)
Phek	-0.112	-0.472	-0.964	0.444	0.904**(1)	-0.793**(3)	0.0117	-0.056	-0.171
Pilibhit	1.692**(2)	1.877**(2)	1.1235**(2)	1.083**(2)	1.421**(2)	0.952**(2)	1.533**(2)	1.37**(2)	0.901**(2)
Porbandar	0.497	0.1896	-0.088	0.0461	0.051	-0.191**(4)	0.689	0.4613	0.199
Prakasam	0.167	0.1279	0.025	0.2004	0.806**(2)	1.321**(2)	1.029**(1)	0.992**(1)	0.771**(1)
Pratapgarh	0.417**(2)	0.5266**(2)	-0.004**(4)	0.0019	0.134**(2)	-0.588**(4)	0.6826**(2)	0.572**(2)	0.326**(2)
Pudukkottai	3.109**(1)	2.946**(1)	1.5187**(1)	1.696**(1)	1.266**(1)	0.191	2.728**(1)	2.566**(1)	1.934**(1)
Pulwama	0.039	0.3139	0.7763	0.842**(2)	1.971**(2)	2.582**(2)	0.091**(1)	-0.0049	0.174
Punch	0.097	-0.006	0.0744	0.387	-0.664	0.156	-0.031	0.004	0.054
Pune	1.0608**(1)	1.0502**(1)	0.7484	0.527	0.525	0.435	0.9003	0.778	0.516
Purba Champaran	2.974**(2)	2.4013**(2)	2.361**(2)	4.242**(2)	1.203	0.596	1.315**(1)	1.944**(2)	2.353**(2)
Purba Medinipur	-0.047	1.226**(1)	1.445**(1)	-0.208	0.836**(2)	0.681	0.415	0.754	1.162**(1)
Puri	0.237	0.796	1.697**(1)	0.296	0.341	0.531	0.039	0.609	1.793**(1)
Purnia	3.592**(2)	2.809**(2)	2.812**(2)	**(2)	1.541**(2)	1.201**(2)	1.539**(2)	2.149**(2)	2.429**(2)
Puruliya	0.017	0.2842	0.058**(1)	0.011	0.061	-0.149	0.069	0.203	0.385**(1)
Rae Bareli	0.698**(2)	1.048**(2)	0.549**(2)	0.464	1.161**(2)	0.35	0.669**(2)	0.655**(2)	0.483
Raichur	0.058	0.1291	0.289	0.245	0.361	0.625	0.0049	0.048	0.129
Raigarh	1.196**(1)	1.274**(1)	1.19**(1)	0.37	0.358	0.832**(1)	1.2731**(1)	1.182**(1)	0.867**(1)
Raisen	0.011	0.0789	0.0565	0.732**(1)	0.369**(1)	-0.094	0.479	0.471	0.316
Rajouri	-0.061	0.036	0.0194	-0.1034	0.183	0.055	-0.0125	0.0015	0.010
Rajgarh	0.239	0.269	0.211	-0.111	-0.006	0.451	0.6126	0.377	0.111
Rajkot	0.295	0.1076	0.0031	-0.0009	0.028	0.041	0.4194	0.209	0.015
Rajsamand	0.513	0.909**(2)	0.5616	0.113	0.743**(2)	0.551**(2)	0.7277**(2)	0.6649**(2)	0.453
Ramanathapuram	3.156**(1)	0.3097**(1)	2.0401**(1)	2.191**(1)	1.496**(1)	0.504	2.332**(1)	2.571**(1)	2.368**(1)
Rampur	2.685**(2)	2.6138**(2)	1.9242**(2)	2.628**(2)	2.371**(2)	2.243**(2)	1.824**(2)	1.729**(2)	1.287**(2)
Rangareddy	0.241	0.2681	0.261	-0.251	-1.029	-0.507	0.437	0.415	0.296
Ratlam	0.121**(2)	0.2968**(2)	0.387**(2)	-0.256	-0.113**(4)	1.036**(2)	0.626**(2)	0.397**(2)	0.137
Ratnagiri	1.673**(1)	1.577**(2)	2.09**(1)	0.498	0.008	0.336	1.979**(1)	2.515**(1)	2.682**(1)
Rayagada	0.814	0.6999	0.7715	2.228**(2)	1.535	1.901**(2)	0.051	0.207	0.017
Rewa	0.556	0.3972**(2)	-0.0171	0.101	-0.079	-0.033	1.373**(2)	0.817**(2)	0.087**(2)
Rewari	-0.053	0.022	-0.4094	0.203	-0.134	0.132	-0.072	0.041	-0.101

	Human Capital Index			Education Index			Health Index		
Districts	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**
Ri Bhoi	0.839	1.1163**(2)	1.464**(2)	-0.0019	0.715	-0.271	1.433**(2)	1.905**(2)	2.075**(2)
Rohtak	0.01	0.068	0.0551	0.7015**(2)	-0.0003	0.021	0.131	0.078	0.022
Rohtas	0.646**(2)	0.654**(2)	0.6003**(2)	0.245	-0.001	0.255	0.785**(2)	1.034**(2)	1.133**(2)
Rupnagar	0.895**(1)	0.378**(1)	0.66142**(1)	0.091	-0.825**(3)	0.645**(1)	1.299**(1)	0.871**(1)	0.313
Sabar Kantha	-0.0455	-0.00318	0.1505	0.069	-0.026	0.469	0.0291	0.037	0.033
Sagar	0.228	0.258**(2)	0.1567**(2)	0.3103	0.184	-0.098	0.97**(2)	0.775**(2)	0.431**(2)
Saharanpur	-0.002	0.3059	0.2895	0.092	0.44	0.0015	-0.067	0.175	0.468
Saharsa	2.786**(2)	2.121**(2)	2.227**(2)	4.149**(2)	1.0224**(2)	0.817**(2)	1.164**(2)	1.754**(2)	2.107**(2)
Saiha	0.0004	0.0005	-0.0264	1.33**(1)	1.4003	0.453	0.424	0.494	0.467
Salem	1.604**(1)	1.15**(1)	0.9273**(1)	0.622**(1)	0.0329	0.074	1.824**(1)	1.723**(1)	1.183**(1)
Samastipur	1.856**(2)	1.1571**(2)	1.5103**(2)	2.312**(2)	0.537**(2)	0.341	1.042**(2)	1.438**(2)	1.638**(2)
Sambalpur	0.016	0.231	0.386	-0.0039	0.191	0.453	0.016	0.1015	0.252
Sangli	0.83	0.5701	0.579	0.257	-0.055	-0.041	0.899**(1)	0.928**(1)	0.811**(1)
Sangrur	0.004	0.0248	0.162	0.369	-0.031	-0.026	0.3186	0.286	0.202
Sant Kabir Nagar	1.093	1.105**(2)	0.446	0.488	0.695**(2)	0.245	1.155**(2)	0.892	0.456
Sant Ravi Das Nagar(bhadohi)	0.786	0.8824	0.299	0.093	0.351	0.088	1.121	0.826	0.375
Saran (chhapra)	0.836**(2)	0.806**(2)	0.7101**(2)	0.944**(2)	0.189	-0.007	0.553	0.8601	1.094**(2)
Satara	1.296**(1)	1.031**(1)	1.049**(1)	0.551**(1)	0.083	0.344	1.244**(1)	1.256	1.053**(1)
Satna	0.603**(2)	0.463**(2)	0.241**(2)	0.1043	-0.199	-0.002	1.509**(2)	1.086	0.424**(2)
Sehore	0.1023	0.063	0.088	0.212	0.416	0.105	0.679	0.393	0.093
Senapati	0.211	0.377	0.3346	0.395	1.444**(1)	1.733	0.031	0.0175	-0.001
Seoni	-0.007	0.006	0.068	0.269	0.1286	-0.015	0.1125	0.00114	0.030
Serchhip	1.112	0.937	0.6147	6.309**(1)	5.483**(1)	2.404**(1)	0.0023	0.0028	0.005
Shahdol	0.418	1.0809	0.859**(2)	-0.369	-0.022	0.061	0.796**(2)	1.005**(2)	1.153**(2)
Shahid Bhagat Singh Nagar	0.813**(1)	0.957**(1)	0.523**(1)	0.027	0.241	0.751**(1)	1.567**(1)	0.9125**(1)	0.162
Shahjahanpur	1.953**(2)	2.298**(2)	1.37**(2)	0.986**(2)	1.403**(2)	0.666**(2)	1.901**(2)	1.768**(2)	1.293**(2)
Shajapur	0.083	0.1204	0.2253	0.088	0.006	1.293	0.5223**(2)	0.204	-0.008
Sheikhpura	1.733**(2)	1.402**(2)	1.107**(2)	**(2)	0.4623	0.056	1.008**(2)	1.328**(2)	1.433**(2)
Sheohar	3.882**(2)	3.025**(2)	2.768**(2)	5.607**(2)	1.798	0.821	1.644**(2)	2.281**(2)	2.611**(2)
Sheopur	0.832	0.842	0.966	-0.156	-0.162	0.486	1.212**(2)	1.235	0.953
Shimla	1.488	1.685	1.037	1.648**(1)	1.271	0.902	0.624	1.0406	1.430
Shimoga	1.379**(1)	0.367	0.175	0.253	0.135	-0.082	1.995**(1)	1.143**(1)	0.176
Shivpuri	1.165	1.283	1.297**(2)	-0.289	-0.073	0.74**(2)	1.619	1.6233**(2)	1.185**(2)
Shrawasti	4.152**(2)	4.079**(2)	3.002**(2)	5.271**(2)	4.775**(2)	3.267	2.126**(2)	2.279**(2)	2.007**(2)

	Human Capital Index			Education Index			Health Index		
Districts	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**
Sivasagar	0.00009	0.049	-0.11	0.096	0.006	-0.174	0.036	0.0722	0.054
Siddharth Nagar	2.311**(2)	2.322**(2)	1.246**(2)	1.844**(2)	1.999**(2)	1.055**(2)	1.821**(2)	1.564**(2)	0.987
Sidhi	0.844	1.122	0.4196	-0.042	-0.0281	0.021	1.355**(2)	1.1503	0.632
Sikar	-0.017	0.0387	-0.0011	0.382	0.0339	0.029	0.175	0.042	0.004
Sindhudurg	1.333	1.021	1.498**(1)	0.066	0.0156	0.105	2.391**(1)	2.4702**(1)	2.103**(1)
Sirmaur	0.159	0.2039	-0.0045	-0.279	0.102	0.402	0.1224	-0.0077	-0.054
Sirohi	0.578	1.041**(2)	0.981**(2)	0.093	0.92	1.856**(2)	0.868**(2)	0.758	0.488
Sirsa	0.0099	-0.0034	-0.047	0.057	0.105	0.0225	0.174	0.055	-0.035
Sitamarhi	3.034**(2)	2.525**(2)	2.153**(2)	4.152**(2)	1.712**(2)	0.919	1.442**(2)	1.859**(2)	1.959**(2)
Sitapur	1.621**(2)	1.89**(2)	1.318**(2)	0.988**(2)	0.471**(2)	0.126	1.420**(2)	1.641**(2)	1.567**(2)
Sivaganga	2.955**(1)	3.031**(1)	1.3186**(2)	1.889**(1)	1.52**(1)	0.387	2.312**(1)	2.466**(1)	2.19**(1)
Siwan	0.628	0.548	1.8295**(1)	0.962	0.099	-0.005	0.271	0.606	0.893
Solan	1.288**(1)	1.105**(1)	0.5543	1.057	0.949	1.142**(1)	0.771**(1)	0.585**(1)	0.299
Solapur	0.485**(1)	0.308	0.7614**(1)	0.443	0.069	0.094	0.2378	0.2417	0.202
Subarnapur	-0.003	0.07	0.257	-0.001	0.133	0.04	-0.0047	0.0065	0.025
Sonbhadra	0.938	0.925**(2)	0.068	0.089	0.004	0.019	1.224**(2)	1.199**(2)	0.929**(2)
Sonipat	0.02	0.02	0.719	0.395	-0.011**(3)	0.123	0.032	0.0052	0.003
Sonitpur	0.496**(2)	0.064	0.0149	0.247	-0.284	0.019	0.082**(2)	0.131	0.182
South	0.253	0.0916	0.141	0.468	0.156	3.177**(1)	0.039	0.023	-0.001
South	0.251	1.546**(1)	0.593**(1)	0.221	1.043	0.554	0.103	1.0536**(1)	4.237**(1)
South 24 Parganas	0.338	1.031**(1)	0.3163**(1)	-0.006	0.259	0.144	0.186**(1)	0.8663**(1)	1.833**(1)
South Garo Hills	0.435**(2)	1.465**(2)	1.339**(1)	-0.0288	1.425	-0.546	0.827**(2)	2.649**(2)	4.857**(2)
South Goa	0.895	0.3248	6.237**(2)	-0.139	0.259	-0.632	2.373**(1)	1.837**(1)	1.000
South Tripura	0.442	0.6703	0.6314	0.948	1.425**(1)	-0.309	0.049	0.0732	0.089
South West	0.509	0.446	-0.036	0.646	0.852	3.795**(1)	0.1264	0.058	-0.022
Srikakulam	-0.302	-0.135	0.691**(1)	0.634**(2)	0.979	1.194**(2)	-0.4806	-0.4853	-0.727
Srinagar	0.099	0.315	-0.3539	0.846**(2)	1.843**(2)	1.662**(2)	0.034	0.0058	0.156
Sultanpur	0.578**(2)	0.528**(2)	0.547	0.182	0.223	0.246	0.776**(2)	0.563**(2)	0.244
Sundargarh	0.005	0.0302	0.3403	-0.021	-0.123	0.036	0.0182	0.389	0.047
Supaul	3.162**(2)	1.951**(2)	2.026**(2)	4.902**(2)	0.745**(2)	0.663**(2)	1.202**(2)	1.718**(2)	1.986**(2)
Surat	0.175	0.123	0.353	-0.123	0.008	0.3604	0.389	0.2945	0.157
Surendranagar	0.046	0.048	0.069	0.053	-0.0005	-0.0077	-0.03	0.0396	0.111
Tamenglong	0.1225	0.251	0.1368	0.235	0.511**(1)	-0.185**(3)	0.0002	0.036	0.038
Tawang	1.843**(2)	0.363	0.1448	0.7186	-0.1332	0.369	1.5208**(2)	0.434	-0.251

	Human Capital Index			Education Index			Health Index		
Districts	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**
Thane	0.561**(1)	0.8545**(1)	0.309**(1)	0.187	0.461	-0.098	0.563**(1)	0.5401**(1)	0.428**(1)
Thanjavur	3.541**(1)	3.3118**(1)	1.989**(1)	1.912**(1)	1.481**(1)	0.701	3.156**(1)	2.867**(1)	2.042**(1)
The Dangs	-0.054	-0.0627	-0.066	0.3077	0.137	0.018	-0.177	-0.186	-0.160
The Nilgiris	3.106**(1)	2.902**(1)	3.067**(1)	1.197**(1)	0.38	0.785**(1)	3.595**(1)	3.8951**(1)	3.469**(1)
Theni	2.886**(1)	2.181**(1)	1.0161**(1)	1.644**(1)	1.019	0.549	2.484**(1)	1.779**(1)	0.791**(1)
Thiruvallur	2.275**(1)	2.491**(1)	1.258**(1)	1.001**(1)	1.013	0.118	2.244**(1)	2.123**(1)	1.606**(1)
Thiruvananthapuram	2.812**(1)	2.851**(1)	3.0266**(1)	-0.184**(3)	-0.428**(3)	1.139**(1)	5.271**(1)	4.646**(1)	3.162**(1)
Thiruvarur	3.866**(1)	3.419**(1)	2.026**(1)	2.236**(1)	1.723**(1)	1.087	3.313**(1)	2.805**(1)	1.722**(1)
Thoothukkudi	3.244**(1)	3.047**(1)	2.3033**(1)	2.727**(1)	1.569**(1)	0.874	2.025**(1)	2.435**(1)	2.336**(1)
Thoubal	0.1006	0.071	-0.026**(3)	0.184	0.597**(1)	0.508**(1)	-0.047	-0.086	-0.111
Thrissur	3.99**(1)	3.6705	3.272**(1)	1.351**(1)	0.78**(1)	1.536**(1)	4.877**(1)	0.439**(1)	3.147**(1)
Tikamgarh	0.663	0.5145	0.256	0.025	0.0012	0.031	1.084**(2)	0.762	0.298
Tinsukia	0.028	-0.011	0.0288	0.173	-0.084	0.492**(2)	-0.135	-0.071	-0.011
Tirap	0.491	0.241	0.381	0.973	0.502	1.425	0.048	0.0427	0.092
Tiruchirappalli	3.046**(1)	2.721**(1)	1.507**(1)	0.185**(1)	1.359**(1)	0.686**(1)	2.525**(1)	2.231**(1)	1.513**(1)
Tirunelveli	3.555**(1)	3.191**(1)	2.147**(1)	1.585**(1)	0.893	1.061**(1)	3.533**(1)	2.985**(1)	1.886**(1)
Tiruvannamalai	1.339**(1)	0.886**(1)	0.2803	0.634	0.162	0.0003	1.212**(1)	0.907**(1)	0.443
Tonk	0.391	0.527	0.1951	0.057	0.531	0.279	0.533**(2)	0.369	0.142
Tuensang	-0.09	-0.4201	-0.2351	-0.408	-1.1803	-0.132	0.1524	0.026	-0.167
Tumkur	0.355	-0.0887	-0.2016	0.0049	2.024**(2)	0.398	0.947**(1)	0.875**(1)	0.585
Udaipur	0.494	1.083**(2)	0.9061**(2)	0.1015	1.09**(2)	1.322**(2)	0.727**(2)	0.723**(2)	0.541
Udhampur	0.025	-0.0023	0.0123	-0.094	0.174	0.006	0.0404	-0.0008	0.032
Udupi	2.616**(1)	0.765	0.4052	0.364	0.311	-0.206	4.364**(1)	2.597**(1)	0.518
Ujjain	0.052	0.031	0.016	0.0305	-0.095	0.495	0.2559	0.047	-0.019
Ukhrul	0.002	0.183	0.111	0.0302	1.765	1.229**(1)	0.0032	0.005	-0.006
Umaria	0.143	0.4377	0.7217**(2)	0.1008	0.007	-0.008	0.593	0.856**(2)	1.115**(2)
Una	2.066**(1)	1.066**(1)	0.2142**(1)	1.7011**(1)	0.771	0.756**(1)	1.272**(1)	0.589**(1)	-0.103
Unnao	0.441	0.889	0.383	0.275	1.09	-0.183	0.4103	0.5077	0.520
Upper Siang	0.308	0.026	0.0065	0.0185	-0.104	0.035	0.4089	0.0531	0.022
Upper Subansiri	0.918	-0.2016	-0.2775	0.1861	0.592	0.958	1.1602	0.174	-0.357
Uttar Dinajpur	0.705**(2)	0.211	-0.2008	0.9003**(2)	0.082	0.81**(2)	0.335	0.14	-0.014
Uttara Kannada	1.145**(1)	-0.043	-0.351	0.078	0.896	-0.997	1.7763**(1)	1.282**(1)	0.543
Vadodara	-0.0039	-0.1016	-0.087	0.0313	0.141	0.253	-0.1544	-0.169	0.154
Vaishali	1.123**(2)	1.071**(2)	1.011**(2)	1.214**(2)	0.175	0.091	0.759	1.084**(2)	1.287**(2)

	Human Capital Index			Education Index			Health Index		
Districts	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**	**LMI_2006**	**LMI_2011**	**LMI_2016**
Valsad	0.546	0.512	0.316	0.1938	0.1704	0.161	0.5204	0.398	0.216
Varanasi	0.559**(2)	0.648**(2)	0.0623	0.1103	0.531	0.027	0.745**(2)	0.4215**(2)	0.016
Vellore	1.977**(1)	1.648**(1)	0.5256	1.127**(1)	0.806	0.035	1.622**(1)	1.257**(1)	0.678
Vidisha	0.043	0.321	0.7366	0.249	0.131	0.007	0.498	0.7424	1.054**(2)
Viluppuram	1.513**(1)	0.977**(1)	0.3192**(1)	0.885**(1)	0.258	-0.31007**(3)	1.231**(1)	0.944**(1)	0.500
Virudunagar	2.94**(1)	2.683**(1)	1.7139**(1)	1.955**(1)	1.319**(1)	0.608**(1)	2.263**(1)	2.203**(1)	1.742**(1)
Visakhapatnam	-0.462	-0.269	-0.2176	0.572**(2)	0.857**(2)	0.94**(2)	0.189	-0.035	-0.201
Vizianagaram	0.006	0.0765	0.1467	0.956	1.642	1.686**(2)	0.1704	0.019	-0.097
Warangal	0.419	0.5329	0.6326	0.0108	0.278	0.305	1.228**(1)	1.751**(1)	2.293**(1)
Wardha	0.932**(1)	1.202**(1)	2.1456**(1)	0.695**(1)	0.175	0.727	0.4022	1.117	2.234**(1)
Washim	0.372	0.395	0.265	0.812	0.766**(1)	0.322	0.0368	0.069	0.109
Wayanad	2.501**(1)	2.372**(1)	1.9077**(1)	0.841	0.286	0.505	3.032**(1)	2.797**(1)	2.03**(1)
West	0.557	0.663	0.9787**(1)	0.4001	0.553	2.151**(1)	0.3629	0.334	0.251
West	0.0145	0.986	2.357**(1)	0.015	0.425	-0.169	-0.0368	0.6704	3.363**(1)
West Garo Hills	0.924	1.135**(2)	2.89664**(2)	0.129	0.557	0.022	1.255**(2)	2.047**(2)	2.75**(2)
West Godavari	0.886	0.6799	0.4129	-0.0133	0.289	0.231	2.365**(1)	2.124**(1)	1.376
West Kameng	0.743**(2)	0.1141	0.135	0.199**(2)	-0.079*(1)	0.00002	0.7443**(2)	0.3859	0.183
West Khasi Hills	0.508	1.2306	3.1059**(2)	0.268	1.345	-0.001	1.292	2.203**(2)	3.037**(2)
West Nimar	0.086	0.7926	0.3382	0.0278	0.155	0.928	0.1482	0.1885	0.121
West Siang	0.119	0.032	-0.135	-0.075	0.673**(1)	0.054	0.4117	0.007	0.048
West Tripura	0.463	0.7919	-0.0241	0.992	2.245**(1)	-0.161	-0.0046	-0.068	-0.142
Wokha	0.4336	0.442	0.5515	1.092	0.663**(1)	0.426	0.0081	0.1336	0.346
Yavatmal	0.357	0.4223**(1)	0.5195**(1)	0.478**(1)	0.251	0.1722	0.0755	0.224	0.461**(1)
Zunheboto	0.003	0.0386	0.0012	0.516	0.657	0.135	0.089	0.019	-0.016
Yamunanagar	0.013	0.0168	-0.029	0.094	-0.014	0.037	0.178	0.0254	-0.035
Jind	0.0148	-0.0019	-0.0005	0.4445**(2)	0.048	-0.017	0.0306	0.0025	0.006
Dausa	0.371	0.5423	0.3531	-0.0375	-0.062	0.107	0.918**(2)	0.752**(2)	0.420
Karauli	0.647	0.8226	0.6966	0.019	-0.103	0.204	1.378**(2)	1.205**(2)	0.792**(2)
Sawai Madhopur	0.389	0.533	0.2473	-0.027	0.199	0.202	0.737	0.536	0.239
Jehanabad	0.753	1.578**(2)	1.256**(2)	0.752	1.527	0.149	0.558	1.039	1.495**(2)
Nagappattinam	3.438**(1)	3.365**(1)	2.2116**(1)	2.178**(1)	1.731**(1)	0.893	2.724**(1)	2.7115**(1)	2.179**(1)

CHAPTER-6

Concluding Observations and Policy Implications

6.1 Conclusions:

I have focused on convergence in human capital index (along with its two components like Education and Health) both at the aggregate as well as at the disaggregate level in India. My research study on convergence of human capital is comprehensive in nature; my research considers all the standard methods of convergence of human capital at the disaggregate level with a view to explore the chronic low-level trap of human capital. I think earlier studies do not consider this issue specifically, therefore, I believe that the results of convergence of human capital will certainly carry some policy relevance in India at the disaggregate level.

First two chapters, examine the presence of convergence in education and health respectively. In chapter 2, I have considered education as human capital. First, I have constructed the education index and on the basis of this index, I have examined the presence of convergence using both parametric and non-parametric approaches. I have also explored the determinants of convergence as well as determinants of club convergence. I have used per capita education expenditure, per capita health expenditure, and social and physical infrastructure as the determinants of convergence. The study shows that there exists absolute beta (β)convergence and conditional beta(β)convergence in terms of education index. In general, dispersion has a fluctuating trend but, if we compare the dispersion for initial and terminal time points then there exists sigma convergence across the states. Inequality based approach also suggests the presence of convergence across the states. All the inequality measurements show a decreasing trend irrespective of different parts of the distribution. Non-parametric approach shows that there exists polarization in NFHS 1. In NFHS 2, the distribution transformed into stratification with more states falling in lower class, and few states fall in middle and upper class. But in NFHS 3, again we have the polarized distribution just like NFHS 1. In the terminal time point, there exists polarization and the number of states in higher class is found to be increased. The Kernel density estimation reveals the presence of club convergence. The dynamics of the distribution indicates the presence of within distribution transition of states. To capture that transitional pattern, I have used the Transitional Probability Matrix (both short run and long run) which show that most of the states are clustering towards lower class; it can be observed that out of 26 states only three states (viz. Uttar Pradesh, Bihar and Rajasthan) are found to be in extreme lower trap. If we consider low class with this extreme low class, then out of 26 states 11 states fall in chronic trap. Along with these parametric and non-parametric approaches, I have used spatial analysis to examine the presences of club convergence. From this analysis, we can observe that how does space matter towards formation of clubs across states. Spatial analysis also reveals the presence of lower trap or clubs based on the average value. Therefore, geographical location plays an important role towards formation of clubs or clusters. Compared to mean value of education index, in this study, out of 26 states only 7 states are found to be stable in low-low clustering for four time points. All these seven states are also belonging to low and extreme low trap based on transitional probability matrix. But, not all the states are significantly dependent to their neighboring states. The result of SAR model and SEM model suggest that there exist both direct and indirect impact of spatial dependency across the states in respect of education index. Direct impact appears as significant whereas most of the indirect impacts are found to be insignificant. Therefore, both non-parametric and spatial analysis supports the presence of club convergence or chronic trap across 26 states for four time points.

In Chapter 3, I have examined the presence of convergence in of health. Initially, only education was the component of human capital, but in recent days researchers consider both health and education simultaneously to define the human capital. Chapter 3, has focused on health dimension along with three sub dimensions. Here, I have found the presence of both absolute and conditional beta(β) convergence. Each conditional variable (viz. per capita education expenditure, per capita health expenditure, physical infrastructure and social infrastructure) has a positive impact on growth of health over time. The States are experiencing sigma divergence (in the long run) but sigma convergence (in the long run), at the same time, inequality-based approach suggests the presence of convergence over time.

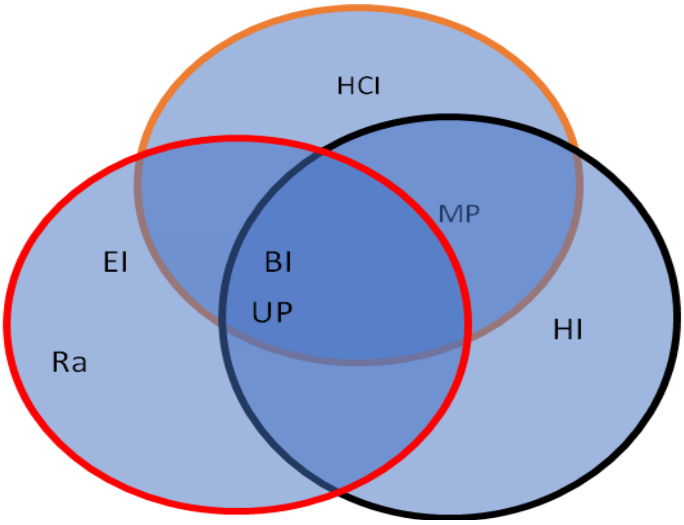
The Kernel density estimation shows that there exists stratification in initial time point, in next time point it has converted to polarization. In NFHS 3 and 4, the distribution is neither polarization nor unimodal. Most of the states are converging towards middle or higher class. For health index, Transitional Probability Matrix shows that most of the states are either moving to middle or higher class. Out of 26 states, only three states (viz. Bihar, Uttar Pradesh and Madhya Pradesh) are found to stable in extreme low trap for four time points. If we increase the range of the class(10-50), then the number of states under chronic low-level trap will increase to seven states. Spatial analysis reveals that these states are located in similar region and they have positive spatial autocorrelation among themselves. This means that a state is influenced by its neighbors both directly as well as indirectly. The states like Rajasthan, Bihar and Uttar Pradesh are in chronic trap in terms of education index whereas in terms of health index, Bihar, Madhya Pradesh and Uttar Pradesh are found to be in chronic trap. So, there is an overlapping situation. If we consider both extreme low and low class (10-50), then number of states falling in overlapping region has increased. In that situation, Assam, Orissa, Madhya Pradesh, Rajasthan, Bihar and Uttar Pradesh are in overlapping area.

In chapter 4, I have constructed the human capital index which is a composite index comprising of education and health index. I find both absolute and conditional convergence of human capital index (HCI). I have considered lagged per capita education and health expenditure along with the availability of infrastructure as conditional variables. I have considered both social as well as physical infrastructure index. All these conditioning variables have a positive and significant impact on growth in education index, health index and human capital index.

Dispersion-based approach clearly shows the presence of convergence of human capital index. Both education index and health index have sigma convergence in the long run; human capital index is a composite of education and health, thus, the human capital index has a decreasing trend of dispersion. This is because human capital is non-decreasing over time. unlike physical capital, if a state attains a level of education or health status at time t, in the next time (t+1), the value of health and education generally show a positive growth.

Inequality results shows that all these three indices experience a decreasing trend in inequality. The states are also experiencing convergence based on inequality measurement approach. However, inequality is sensitive to higher part of the distribution and it is higher for all indices. For all the indices, inequality sensitive to lower or middle part of the distributions are found to be more or less equal. The results of non-parametric approach suggest that the states are converging towards middle class or middle value. But, in terms of health and education index, we have the result of polarization across states. So, even though first two time points experience the presence of clubs but in terminal time point we fail to identify the clubs or class. Transitional Probability Matrix (TPM) helps us to identify the within distributional variation over time. First short run TPM shows that from middle class states are divided into two classes (low and middle), in similar way, we can classify the difference between middle and higher class. This short run TPM is the reflection of second Kernel density estimation. In similar way, we can identify the relationship between Kernel density estimation and TPM for third and terminal time points. From the intra distributional transition, it can be observed that Bihar, Madhya Pradesh and Uttar Pradesh are in extreme low-level trap. Here, also we can check the chronic trap based on extreme low and low-level trap (10-50). In this situation, states like Bihar, Rajasthan, Uttar Pradesh, Madhya Pradesh, Assam, Orissa and Meghalaya are in chronic low-level trap. Again, we can observe the presence of overlapping states in terms of education, health and human capital index. If we focus only on the extreme low class(10-30), then out of 26 states only three states are there in the common trap. Following figure shows the common overlapping trap in terms of education, health and human capital index across states based on extreme lower trap.

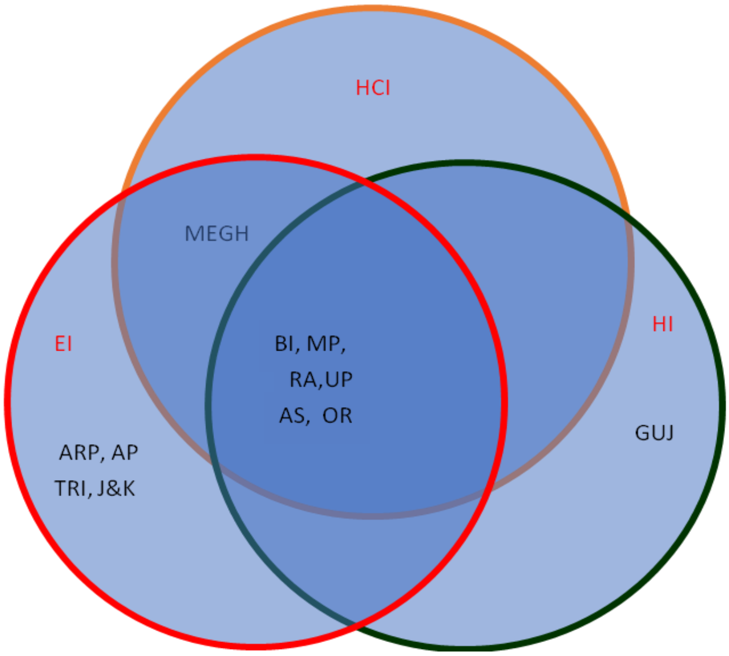
Figure-6.1: Trap based on extreme low-level (10-30) status of Education, Health and Human Capital Index



Circle with red border shows the trap od states in respect to education index. As we have found that Rajasthan, Bihar and Uttar Pradesh are in extreme low-level trap in terms of education index; Madhya Pradesh, Bihar and Uttar Pradesh are in extreme low-level trap in terms of health index (shown in circle with black border). The circle with orange border shows the trap of human capital index. Comparing this Venn diagram, it can be observed that only two states are common in all trap. The states are Bihar and Uttar Pradesh.

Extension of the limit of the trap (10-50) shows that the number of states in common overlapping region has increased from two to six for four time points.

Figure-6.2: Trap based on Extreme low and Low-level (10-50) class of Education, Health and Human Capital Index



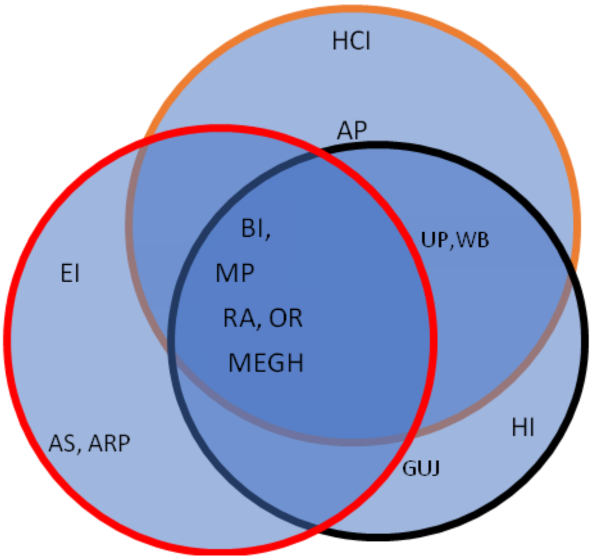
The above diagram shows that number of states falling in the overlapping trap is higher than earlier figure. Again, the circle with red border shows the trap in terms of education index based on both extreme low and low class (10-50); circle with black border represents the trap in respect to health index whereas the circle with orange border represents the trap in terms of human capital index. Here, the states like Bihar, Uttar Pradesh, Madhya Pradesh, Rajasthan, Assam and Orissa are found to be in trap in terms of education, health and human capital index.

Spatial analysis shows that out of 26 states, only 7 states are forming low-low clustering in respect to education index, 8 states are forming low-low clustering in terms of health index and 8 states are in low-low clustering in terms of human capital index. Among these states, 6 states (like, Bihar, Madhya Pradesh, Uttar Pradesh, Rajasthan, Assam and Orissa) are in chronic low level trap in terms of education, health and human capital index for four time points. Therefore, from chapter 2, 3 and 4, we can observe that among 26 states few states are in extreme low level chronic trap in respect of all the indices.

Results of SAR and SEM model state that there exists both direct and indirect neighborhood impact across the states in respect of education, health and human capital index. The SAR and SEM model identify the presence causality across the states through direct and indirect impact (of space) for both dependent and independent variables. Indirect impact can be defined as the neighbors of neighbors or independent variables of the neighbors. But, in all the models, direct impacts appear as significant whereas most of the indirect impacts are found to be insignificant.

I have already found the overlapping trap in respect of education, health and human capital index based on non-parametric approach. In similar way, I have identified the overlapping trap on the basis of spatial analysis. In the following diagram, circle with red border represents the low-low (L-L) clustering in terms of education index, circle with black border shows the low-low (L-L) clustering in terms of health index and circle with orange border define the low-low (L-L) clustering of human capital index. Not all the states are found to be significant in this clustering, though, I have used only the general clustering to identify the stability in lower clustering based on spatial analysis.

Figure-6.3: Trap based on Spatial Analysis



In the above figure, there are seven states in low-low (L-L) clustering in terms of education index. In respect to health and human capital index out of 26 states, only eight states are there in the low-low (L-L) clustering. Out of these states, only five states are common in all traps based on spatial dependency. These five states are Bihar, Madhya Pradesh, Rajasthan, Orissa and Meghalaya. All the states under low-low (L-L) clustering in terms of education index are already exist in chronic low level trap (10-50) obtained from non-parametric approach. The states like Bihar, Uttar Pradesh and Rajasthan are creating extreme low level trap. Now, in the above figure, Uttar Pradesh is missing in low-low (L-L) trap in terms of education index because over time, Uttar Pradesh becomes an outlier (lower states surrounding with higher states). Under health trap, all these existing states are already forming extreme low and low-level trap (10-50). Similarly, for human capital index, out of 8 states, 6 states are forming extreme low and low (10-50) clustering. This comparison between spatial analysis and non-parametric approach shows that there exists some spatial influence towards formation of clubs or traps.

In chapter 5, I have done the same analysis but at the sub-national level where districts are considered as unit of analysis. As I have mentioned earlier that in this chapter to cover the maximum number of district as well as to keep the consistency with state level analysis, here, I have started the analysis from 2005-06 to 2015-16. For this district level analysis, finally, I have 539 districts and three time points (2006, 2011, 2016). Due to unavailability of data pertaining to education and health dimensions, I have considered only few variables from each dimension to construct education, health and human capital index across 539 districts for three time points. The empirical analysis shows that districts are having higher health index value compared to education index value. The mean as well as dispersion of health index are found to be higher than that of education index. Initially, the variation was high for education index but for next two time points, the variation has decreased and it is lower than the health index. Interestingly, all the indices have a fluctuating trend in SD. So, there exists sigma divergence across districts in terms of education, health and human capital index. The education, health and human capital index experience the absolute beta convergence but at the same time we find sigma divergence. In state level analysis, there exist absolute beta convergence in respect to all indices. Inequality based approach shows that inequality sensitive to all parts of the distribution decreased over time. In respect to health index, inequality sensitive to lower part of the distribution has a fluctuating trend, whereas inequality sensitive to middle and upper part of the distribution has decreased. In terms of human capital index, inequality sensitive to lower, middle and upper part of the distribution are found to be fluctuating. Thus, we can say that districts are converging only in terms of education index. Non-parametric approach shows that in terms of education index, the districts are converging towards lower part of the distribution whereas districts are converging towards lower middle or upper middle classes in terms of health and human capital index. Both short run and long run TPMs for education index show that districts are found to be more mobile towards lower classes. Both health and human capital index have an even distributional pattern over time. The TPM shows that in the long run districts are converging towards lower classes whereas in terms of health index districts are converging at the higher level. The long run stationary distribution reveals that districts are converging towards middle class or middle values in respect of HCI. Analysis of variance also support that the classifications of these arbitrary classes is significant, moreover, it provides an indication about mobility or stability over time. Non-parametric analysis reveals that out of 539 districts, only few districts are found in chronic low-level trap based on education, health and human capital index respectively. Only two districts are there in chronic low-level (ranging 10-30) trap in terms of education index whereas out of 539 districts, only three districts are in chronic lower-level trap in terms of health index. Surprisingly, none falls in the chronic trap in terms of human capital index. The number of districts in low level trap has increased if we extend the range (10-50) for defining our trap. Since, both the Kernel plots and TPMs show that districts are concentrating towards low, lower middle and upper middle. Due to this type of concentration, I have few districts under extreme low class (10-30). After extending the range from 10-30 to 10-50, the number of districts in chronic low-level trap in terms of education index has increased to 51, in terms of health index and human capital index the number of districts under chronic trap has increased to 141 and 62 respectively. Comparing all these traps, out of 539 districts, only 28 districts are found to be common in all traps (education, health and human capital index). All these districts are belonging to those states which are also poor in terms of education health and human capital index obtained from our state level analysis.

In terms of education index, states like Rajasthan, Bihar and Uttar Pradesh are in chronic extreme low-level trap. Out of 51 districts, 17 and 11 districts are belonging to Uttar Pradesh and Bihar respectively; rests of the districts are from the states belonging to lower class (30-50). In terms of health index, state like Bihar, Uttar Pradesh and Madhya Pradesh are in chronic extreme low-level trap. Out of 141 districts, 46 districts are from Uttar Pradesh, 36 districts are from Bihar and 15 districts are from Madhya Pradesh. In terms of Human Capital Index, states like Bihar, Uttar Pradesh and Madhya Pradesh are in chronic extreme low level trap. Out of 62 districts, 17 districts are from Uttar Pradesh, 21 districts are from Bihar and only 4 are from Madhya Pradesh. Therefore, based on chronic low and low-level trap (range 10-50), most of the districts belong to those states which are already in extreme low-level trap in terms of education, health and human capital index.

In earlier analysis, I have compared state level analysis with the districts level analysis. Instead of considering 23 years for observing chronic trap of states, here, I can also take the presence of chronic trap for last 10 years also (NFHS 3 to NFHS 4). Since the district level analysis covers 10 years for exploring convergence as well as club convergence along with chronic low-level trap, I also consider 10 years for district level analysis for comparison. To make an consistent comparison between states and district level analysis, I have deliberately considered the trap of states in terms of Education, Health and Human Capital Index from NFHS 3 to NFHS 4. The results of chronic trap of states during NFHS 3 to NFHS 4 are more or less similar to the trap obtained from the time period NFHS 1 to NFHS 4. In terms of education index, Bihar, Rajasthan, Assam, and Uttar Pradesh are in extreme low level trap whereas Bihar, Rajasthan, Assam, Uttar Pradesh, Madhya Pradesh, Arunachal Pradesh, Orissa, Meghalaya, West Bengal, Nagaland, Tripura, Gujarat, Andhra Pradesh and Jammu & Kashmir are in extreme low and low-level trap (10-50). In terms of health and human capital index, Bihar, Madhya Pradesh and Uttar Pradesh are in extreme low trap (10-30) during the time period NFHS 3 to NFHS 4. Based on health index, Bihar, Uttar Pradesh, Madhya Pradesh, Assam, Orissa, Rajasthan, Gujarat are in extreme low and low-level trap (10-50); states like Bihar, Madhya Pradesh, Uttar Pradesh, Assam, Rajasthan, Orissa, West Bengal Gujarat and Meghalaya are in extreme low and low-level trap (10-50) based on human capital Index. Considering only extreme low trap (10-30), only Bihar and Uttar Pradesh are found to be common in all the traps, but with an extending range (10-50), states like Bihar, Madhya Pradesh, Uttar Pradesh, Assam, Rajasthan, Orissa, Gujarat are in extreme low and low-level trap. This analysis also suggests that most of the districts belong to Bihar, Uttar Pradesh and Madhya Pradesh.

The similar result can be obtained from the spatial analysis where the spatial dependency among the districts is more prominent compared to state level analysis. Now, the result can be compared with chronic low and low-level trap (10-50) obtained from non-parametric analysis. This comparison will help us to understand the role of space towards club formation. In terms of education index, out of 539 districts, only 51 districts are there in extreme low and low-level trap (10-50) for three time points; however, on low-low cluster, there exists only 24 districts. Now, comparing these two traps and clusters, it can be observed that 16 districts are common in two analyses. These districts are Araria, Bahraich, Balrampur, Bareilly, Buduan, Darbhanga, Gonda, Koraput, Madhepura, Pulwama, Purnia, Rampur, Saharsa, Shahajahanpur, Shrawasti and Siddhartnagar. Most of the districts belong to Uttar Pradesh. So, the space does have an impact on few districts towards club formation.

Similarly, I have found the presence of spatial dependency towards club formation across districts for three time points. From the non-parametric analysis, I have found that out of 539 districts, 141 districts are in extreme low and low-level trap (10-50) over time period. Spatial analysis shows that only 82 districts are forming low-low clustering. Comparing these two results, it can be found that 69 districts are found to be common in these two analyses. They are in extreme low and low-level trap (10-50) and they are found to be space dependent.

Similar to education and health index, I have examined the overlapping situation for human capital index at the district level also. There were 62 districts in extreme low and low-level trap (10-50) obtained from non-parametric analysis whereas spatial analysis shows that only 64 districts are forming significant low-low clustering over the time period. The comparison shows that only 35 districts are found to be common. Clubs with these 35 districts are found to be space dependent.

Now, the ultimate discussion is based on consistency of results obtained from state and district level analysis. In both the analysis, I have tried to explore the convergence and the presence of chronic low- level trap in terms of human capital index. The study of state level and district level analysis are different in two aspects. First one is due to variables, second one is due to time period. Despite these differences, we have some consistency result from these two analyses. In both state and districts level analysis, we have the result of absolute beta convergence in terms of education, health and human capital index. Dispersion based approach also suggests the presence of sigma divergence across the states as well as districts over the time. So, there exists a co-movement in the state and district level analysis in terms of convergence analysis based on neoclassical approach. Inequality based approach also provides similar results of convergence both for states as well districts. The most important comparisons are found in the presence of chronic low-level trap and spatial dependency across states and districts.

Chronic low-level trap:

I have considered 26 Indian states and 539 districts towards examining the club convergence and chronic low-level trap over time. From chapter 2, 3 and 4, I have found that out of 26 states only three states fall in chronic extreme low-level trap in terms of education, health and human capital index. State like Bihar, Madhya Pradesh and Rajasthan are found in extreme low-level trap (10-30) in terms of education index, state like Bihar, Uttar Pradesh and Madhya Pradesh are found in extreme low trap (10-30) in terms of health and human capital index. However, if we define the low-level trap (10-50), the number of states increase in traps in respective indices.

In districts level analysis, I have found the presence of extreme low and low-level trap in terms education, health and human capital index. Most of the districts, fall in trap and the districts are belonging to Bihar, Uttar Pradesh, Madhya Pradesh and Rajasthan. These states were already in extreme low and low-level trap (10-50). This comparison shows that due to poor performance of districts these states are falling in the low-level trap.

Similarly, the spatial analysis shows that states under extreme low and low-level trap are located in the same region (Central portion of India). The results of GMI and LMI show that states have insignificant spatial dependency over time whereas, the regression-based approach under spatial analysis shows that states are having spatial influence over time.

Now, in district level analysis, districts are more spatial dependent than that of states. It may be due small size of districts and they are found to be more homogenous to their neighbors districts.

Now, out of 26 states, Bihar and Uttar Pradesh are in extreme low-level trap (10-30) in all indices and Bihar, Uttar Pradesh, Madhya Pradesh, Rajasthan, Orissa and Assam are extreme low and low-level trap (10-50). These six states are also located in similar region though GMI and LMI provide insignificant results about the spatial dependency.

Health and education both are the components of Multidimensional Poverty Index (MPI) or other development index like HDI. Study on those indices suggest that these states (falling in extreme low-level trap (10-30)) are found to be poor in respect to MPI (NITI Aayog 2021). The report of NITI Aayog (2021) is based on NFHS 4 which shows that out of 36 states (states like Bihar, Jharkhand, Uttar Pradesh, Madhya Pradesh, Meghalaya, Assam, Chhattisgarh, Rajasthan, Orissa, Nagaland and Arunachal Pradesh) manifest a higher proportion of multidimensionally poor. This is an aggregate assessment of poverty. In disaggregate level also these states are poor or backward. There are three different dimensions under MPI; these are health education and standard of living. In terms of health outcome (or status like nutrition, child mortality, maternal health), Bihar, Uttar Pradesh, Madhya Pradesh, Jharkhand, Chhattisgarh, Rajasthan are in a bad position compared to national range. Not only health, in terms of education also, these states are considered as deprived states in India. In terms of mean years of schooling and school attendance, states like Bihar, Uttar Pradesh, Madhya Pradesh, Jharkhand, Rajasthan, Arunachal Pradesh, Meghalaya are deprived. I have considered these two dimensions in different ways to define human capital (a positive index) across states. In my study, I have found Bihar, Uttar Pradesh, Madhya Pradesh are backward and they are in chronic trap at aggregate as well as at the disaggregate level. Not only states, I have found a consistency ….results with the analysis given by NITI Aayog (2021). According to my analysis, most of the districts under low level trap in respect to education, health and human capital are belonging to Bihar, Uttar Pradesh, Madhya Pradesh and Rajasthan. There are 51 districts fall in the extreme low and low-level education trap (10-50). Out of this, 17 districts are from Uttar Pradesh, and 11 districts are from Bihar. Most of these districts are also multidimensionally poor. Similarly, out of 141 districts under health trap, most of the districts are multidimensionally poor. As a result, districts falling in human capital trap are also deprived.

6.2 Policy Implication:

I strongly believe that the results of the convergence study of human capital have some important policy options both for state and districts level. The six major states (viz. Bihar, Uttar Pradesh, Madhya Pradesh, Rajasthan, Orissa and Assam) roughly account 50% of India's population and more than 50% of India's future demographic dividend largely depends on the performance of these major states. Since health and education have been considered as two important components of human capital, therefore, if health and education of the mass remain poor, effective human capital formation will be disturbed. Therefore, in order to reap the benefits of demographic return, a major investment in human capital especially in those backward states (in respect of health, education) is urgently needed. Not only in states, districts of India are also found backward in terms of human capital. These poor districts are belonging to poorer states of India. Indian states as well as districts are heterogeneous in respect of population size, age–sex composition of the population, socioeconomic characteristics, concentration of backward community, etc. Therefore, uniform development policy to pull out backward states (as well as districts) is difficult to implement; rather each of the state should also develop separate plans for themselves based on their priorities considering the goal of MDGs and SDGs. Following Sachs (2005), Bloom and Canning (2007), we can conclude that with limited resources, the largest health gains may be achieved by focusing on five major states near the threshold of trap, where marginal changes in health status can have large effects on these states' chances of escaping the 'low-level health trap'. It is estimated that about 1.6 billion people are living in multidimensional poverty (in which health is an important component) across the world, and nearly 440 million of them are in eight large Indian states; the eight Indian states that have a similar number of poor as in 25 African countries are Bihar, Jharkhand, MP, UP, Chhattisgarh, Odisha, Rajasthan and West Bengal (OPHI 2017). Poor health as well as education are interlinked with multidimensional poverty; but our public health expenditure is extremely low across all the countries in the world; it is about one percent of our GDP! As a result of such a low public spending in health and due to high out of pocket expenditure (85.6% according to the World Bank is among the highest in the world), nearly 60 million people are pushed further into poverty and consequently into the chronic poverty trap from that they are unable to escape. Therefore, keeping in mind the joint dependency of education, health and poverty as argued by Sala-i-Martin (2005), we can suggest that our poverty eradication programs should be tied up with the ongoing education and health programs for getting rid of the low level health trap. In India, the health sectors are the state's responsibility and education sector is the joint responsibility but, how the poorer states will invest in healthcare as well as education if revenue is insufficient! In a democratic setup like India, we must address the issue of social justice, equity and balanced regional development especially in respect of public health outcomes. This may be achieved if more development grants aiming to eradicate poverty are allowed to poorer states. Implementing an incentive compatible transfer of development grant is extremely difficult in India's federal setup. Government of India has been trying to reduce the regional inequality as well as trying to achieve the inclusive growth via several policies. In 2006, government of India has adopted Backward Region Grant Fund(BRGF) to reduce the regional imbalance in terms of physical and social infrastructures. There were 27 states and 250 districts under this grant fund. According to this fund, initially, each district will get 10 crores along with fund based on 50% of population and area share. Similarly, in 2013, Ministry of Finance has constructed a composite index known as under development index to identify the actual backward state as well as districts. To construct this index, they used 10 different indicators; out of these 10 indicators, there exist both input as well as output variables, at the same time they have used equal weights for each indicator. This will mislead the index construction as well as fund allocation. Similar to the Backward

Regional Grant Fund, here also they have used area and population share as a thumb rule of fund allocation.

However, 14th Finance Commission, Government of India has initiated some bold steps toward allocating more grants to backward areas with a view to achieve inclusive growth (Government of India 2018). The Finance Commission has identified 115 most backward districts (scattered around all the five states as revealed from our study) in India. Eradication of mass human deprivation in respect of health, education and basic amenities of those backward districts is being undertaken through target driven approach along with the existing development programs. All centrally sponsored schemes granted more funds to those districts identified as backward. We have to wait for getting the desired results of such affirmative measures of development. Government can focus on disaggregate level (specific indicators under health and education dimension) to improve the human capital of each state. Government should take required policy to the states as well as districts which are in trap in terms of education index, health index and human capital index. Government may focus on the determinants of convergence (PCEE, PCHE, physical and social infrastructure). Government may consider the spillover impact of space (through neighbouring effect) based both dependent and independent factors of human capital for policy options.

Based on my results, I would like to give my suggestion towards policy implementation. Compared to all these indices, states are more derived in education index than health and human capital index. Both Central and state government may focus on education dimension. I have already identified the significant education indicators using PCA. Therefore, Government may focus on those educational inputs or process variables. It is found that out of 26 states only Bihar and Uttar Pradesh are deprived in respect of education, health and human capital index. Therefore, both Central and state government may implement some effective policies for these two states. Number of deprived districts in respect of health index is higher compared to education and human capital index. Thus, state governments can give more emphasis on health dimension. Since, health index consists of infant survival rate and lower total fertility rate, therefore, the state governments may follow policy related to reproductive and child programme.

6.3 Limitations:

The present study has some limitations. We have arbitrarily chosen five groups while formulating the TPM of Markov process; number of states (Districts) belonging to low level trap might change if we could consider large number of groups. Since, here I have only 26 states, this is why, I have considered only 5 arbitrary classes. I have started the districts-level analysis from 2006 instead of 1993. Since in 1993, the number of districts was very low compared to Census 2011. Thus, the district level analysis only has focused on NFHS 3 to NFHS 4. Due to inadequate data for districts level analysis, I have considered only few indicators from each dimension of human capital.

There are only few states as well districts in the extreme low trap (10-30) in terms of education index, health index and human capital index. If I use panel logit to examine the determinants of chronic extreme low-level trap then that would be a biased panel logit. This is why I have skipped panel logit analysis.

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Appendix 1A: Data of Education Indicators of 26 Indian states (NFHS 1 to NFHS 4)

	Literacy Rate				Complete Years to High School				Complete years to Above High School			
States	NFHS_1	NFHS_2	NFHS_3	NFHS_4	NFHS1	NFHS2	NFHS3	NFHS4	NFHS1	NFHS2	NFHS3	NFHS4
Andhra Pradesh	44.09	60.5	64.1	67.7	10.3	8	9.95	13.15	4.4	6.6	9.2	15.85
Arunachal Pradesh	41.59	54.3	60.65	67	6.9	6.3	4.2	10	2.4	6.6	7.9	14.2
Assam	52.89	63.3	68.25	73.2	7.3	5.9	7.3	8.2	3.1	6.35	8.6	12.15
Bihar	38.48	47	55.4	63.8	9.3	7.25	7.5	8.55	4.3	5.6	6.45	10.2
Delhi	75.29	81.7	84	86.3	20	14.65	13.85	14.85	14.3	24.65	29.6	30.15
Goa	75.51	82	84.7	87.4	19	15.65	17.3	19.9	8.2	16.35	20.1	24.35
Gujarat	61.29	69.1	74.2	79.3	12.4	9.6	9.4	11.45	5	10.25	10.45	16.55
Haryana	55.85	67.9	72.25	76.6	12.9	11.9	12.65	14.5	4.2	9.75	11.5	22.7
Himachal Pradesh	63.86	76.5	80.15	83.8	12.6	15.75	18.95	18.1	3.3	9.6	16.15	24.35
Jammu & Kashmir	51.3411	55.5	62.1	68.7	12.6	8.6	10.8	12.65	4.8	6.9	11.75	17.25
Karnataka	56.04	66.6	71.1	75.6	11.4	10.85	10.95	16.5	4.6	10.2	12.15	18.95
Kerala	89.81	90.9	92.4	93.9	14.6	19.85	15.8	19	4.8	12.35	16.6	29
Madhya Pradesh	44.2	63.7	67.15	70.6	7.6	4.15	4.85	7.7	3.6	7.75	8.7	12.15
Maharashtra	64.87	76.9	79.9	82.9	12	8.2	12.1	13.5	5.6	9.2	14.1	20.15
Manipur	59.89	70.5	75.2	79.9	14.6	9.85	10.2	13.15	8.5	14.15	17.65	22.45
Meghalaya	49.1	62.6	69.05	75.5	7.9	5.05	6.15	10.05	2.1	4.85	9.25	13.4
Mizoram	82.27	88.8	90.2	91.6	13.1	7.55	8.9	11.6	3	7.95	10.7	15.95
Nagaland	61.65	66.6	73.35	80.1	15.1	7.05	7.15	10.85	2.7	6.4	8.1	13.45
Odisha	49.09	63.1	68.3	73.5	7.4	6.3	6.05	9.9	3.3	5.9	7.2	10.75
Punjab	58.51	69.7	73.2	76.7	15.2	15.35	15.15	16.9	3.7	11.2	12.95	23.45
Rajasthan	38.55	60.4	63.75	67.1	6.9	6.25	4.95	8.2	2.8	5.9	7.65	14.1
Sikkim	56.94	68.8	75.5	82.2	3.552055	6.2	7.25	12.05	2.328082	6.55	10.35	17.6
Tamil Nadu	62.66	73.5	76.9	80.3	12.1	10	11.05	15.75	4.4	8.75	13.6	23.1
Tripura	60.44	73.2	80.5	87.8	6.5	4.925	6.85	9.6	3.8	3.85	7	11.5
Uttar Pradesh	41.6	56.3	63	69.7	9.5	6.25	6.45	8.2	3.8	8.15	9.25	16.5
West Bengal	57.7	68.6	72.85	77.1	7.9	5.85	6.35	9.3	5.3	7.4	9.25	12.65

	GER to Middle School				GER to Higher Secondary School				GER to Higher Education			
States	NFHS_1	NFHS_2	NFHS_3	NFHS_4	NFHS_1	NFHS_2	NFHS_3	NFHS_4	NFHS_1	NFHS_2	NFHS_3	NFHS_4
Andhra Pradesh	55.9	45.7	74.32	81.33	22.74176	23.6161	48.93	67.835	4.56286	5.035675	14.32	30.8
Arunachal Pradesh	49.7	65.8	72.54	130.13	22.92216	25.12545	42.55	75.72	2.989439	3.028595	7.13	28.7
Assam	62.1	69.3	37.73	93.05	28.89661	31.05097	32.08	58.2	5.656624	7.531158	6.77	15.4
Bihar	37.1	34.8	30.42	107.89	20.94822	18.67956	16.02	56.995	7.258047	9.913443	5.695	14.3
Delhi	78.5	81	85.94	128.12	42.10167	85.41699	52.52	92.355	13.98054	18.96149	46.86	45.4
Goa	99.4	79.7	38.74	98.74	91.31912	76.96184	56.52	90	11.53701	10.5989	13.17	27.6
Gujarat	73	68.4	49.91	95.73	30.42298	25.11736	39.5	58.78	9.78266	8.078989	12.22	20.7
Haryana	63	65.9	41.45	92.39	34.4178	25.57482	42.22	71.905	6.479931	6.369435	11.195	26.1
Himachal Pradesh	110.8	78.2	109.27	104.36	38.26871	43.50269	131.51	101.305	4.761681	10.64671	14.185	32.5
Jammu & Kashmir	65.1	64.4	71.55	70.2	26.41211	19.95065	63.88	62.705	4.435219	5.167219	7.765	24.8
Karnataka	61	67.6	56.54	93.37	31.69601	35.96509	45.19	61.54	7.601983	0.893492	13.745	26.1
Kerala	105	95.4	77.14	95.39	37.71259	43.55397	64.63	90	3.466198	6.111517	12.005	30.8
Madhya Pradesh	71.9	64.9	71.28	94.02	16.37454	33.45021	37.64	62.87	4.281123	5.303097	13.48	19.6
Maharashtra	81.8	86.3	80.74	99.24	39.38809	34.96022	56.78	78.88	9.634279	10.12541	13.74	29.9
Manipur	60.9	70.5	64.57	129.89	54.6948	42.2367	49.43	80.51	10.92971	18.37153	12.655	34.2
Meghalaya	40.1	52.7	42.62	135.89	22.46558	21.14357	35.71	65.31	3.525005	4.694767	13.965	20.8
Mizoram	73	70.6	88.84	134.78	36.71567	39.39079	41.91	82.35	1.753827	7.814445	11.36	24.1
Nagaland	69.9	65.6	76.35	102.28	23.29781	20.32752	24.07	54.025	2.137961	2.342603	9.49	14.9
Odisha	60.2	53.4	49.43	94.26	33.54325	35.72294	42.82	79.61	3.389484	4.741036	9.275	19.6
Punjab	74	65	54.96	98.38	33.16025	27.92976	39.76	78.625	5.571761	6.721675	12.04	27
Rajasthan	53.3	52.7	63.6	91.34	23.38496	20.46811	34.32	67.685	1.784352	3.857954	7.27	20.2
Sikkim	54.1	59.8	76.38	150.61	27.30106	21.37884	34.76	94.005	2.319936	2.319936	15.5	37.6
Tamil Nadu	100.1	93.6	106.46	94.03	32.22233	36.40582	63.79	87.975	5.506869	6.008884	16.36	44.3
Tripura	84.2	54.7	84.23	127.97	35.32128	34.33149	39.86	80.975	3.324779	3.922337	6.51	16.9
Uttar Pradesh	55.6	40	41.96	75.08	26.0283	19.05213	35.9	64.265	4.287273	6.945128	9.175	24.5
West Bengal	106.9	47.1	66.17	105	30.10776	19.52028	35.46	67.55	5.248044	5.707873	8.165	17.7

Appendix 1B: Data of Health Indicators of 26 Indian states (NFHS 1 to NFHS 4)

	Infant Survival Rate				Well-Nourishment				Lower Total Fertility Rate				NON-ANEMIC			
States	NFHS 1	NFHS 2	NFHS 3	NFHS 4	NFHS 1	NFHS 2	NFHS 3	NFHS 4	NFHS 1	NFHS 2	NFHS 3	NFHS 4	NFHS 1	NFHS 2	NFHS 3	NFHS 4
Andhra Pradesh	929.6	934.2	943	965	67.09	71.533	72.3	73.17	0.386	0.4444	0.5	0.5556	50.066	50.2	37.3	40
Arunachal Pradesh	960	936.9	939	977	65.1	80.433	69.633	77.97	0.235	0.3968	0.3333	0.4762	32.428	37.5	49.5	56.8
Assam	911.3	930.5	934	952	62.2	66.833	67.8	72.27	0.283	0.4329	0.4167	0.4545	17.918	30.3	30.7	54
Bihar	910.8	927.1	938	952	51.57	56.967	53.8	62.33	0.25	0.2865	0.25	0.2941	33.241	36.6	32.6	39.7
Delhi	934.6	953.2	960	969	67.77	72	72.1	75.07	0.331	0.4167	0.4762	0.5556	65.179	59.5	55.7	45.7
Goa	968.1	963.3	984.5	987	72.4	80.067	78.433	78.07	0.526	0.565	0.5556	0.5882	60.212	63.6	62	68.7
Gujrarat	931.3	937.4	950	966	60.93	65.033	61.667	65.27	0.334	0.3676	0.4167	0.5	54.392	53.7	44.7	45.1
Haryana	926.7	943.2	958	967	69.83	70.033	65.2	71.8	0.251	0.3472	0.3704	0.4762	64.563	59.5	43.9	37.3
Himachal Pradesh	944.2	965.6	964	966	61.76	66.067	68.533	79.6	0.337	0.4673	0.5	0.5263	65.313	59.5	57	46.5
Jammu & Kashmir	954.6	935	955	968	66.63	71.633	74.867	81.3	0.319	0.369	0.4167	0.5	39.25	41.3	48	50.6
Karnataka	934.6	948.5	957	973	60.23	66.5	67.033	67.5	0.351	0.4695	0.4762	0.5556	55.094	57.6	48.8	55.2
Kerala	976.2	983.7	985	994	77.5	80.033	78.9	82.83	0.5	0.5102	0.5263	0.625	79.109	77.3	67.2	65.7
Madhya Pradesh	914.8	913.9	930	949	54.71	58.033	51.667	63.13	0.256	0.3021	0.3226	0.4348	44.06	45.7	44.1	47.5
Maharashtra	949.5	956.3	962	976	59.03	63.1	66.733	68	0.35	0.3968	0.4762	0.5263	51.278	51.5	51.6	52
Manipur	957.6	963	970	978	75.83	77.667	77.733	83.5	0.362	0.3289	0.3571	0.3846	66.857	71.1	64.3	73.6
Meghalaya	935.8	911	955	970	61.6	67.967	55.133	70.67	0.268	0.2188	0.2632	0.3333	40.279	36.7	53.8	43.8
Mizoram	985.4	963	966	960	76.13	75.833	77.1	84.6	0.435	0.346	0.3448	0.4348	43.961	52	61.9	75.2
Nagaland	982.8	957.9	962	970	75.4	77.5	74.233	81.13	0.307	0.2653	0.2703	0.3704	57.262	61.6	64.45	72.1
Orissa	887.9	919	935	960	59.07	59.1	64.9	70.37	0.342	0.4065	0.4167	0.4762	31.459	37	38.9	49
Punjab	946.3	942.9	958	971	64.73	75	76.4	79.03	0.342	0.4525	0.5	0.625	66.468	58.6	62	46.5
Rajasthan	927.4	919.6	935	959	65.27	61.9	65.333	67.07	0.275	0.2646	0.3125	0.4167	48.625	51.5	46.9	53.2
Sikkim	952.99	956.1	966	970	79.61	80.967	77.433	80.67	0.308	0.3636	0.5	0.8333	25.709	38.9	40.5	65.1
Tamil Nadu	932.3	951.8	970	980	66.51	71.333	72.367	76.47	0.403	0.4566	0.5556	0.5882	44.122	43.5	46.8	45
Tripura	924.2	932.2	949	973	62.57	58.603	66.7	78.27	0.375	0.3922	0.4545	0.5882	21.12	27.48	34.9	45.5
Uttar Pradesh	900.1	913.3	927	954	55.13	60.567	62	65.43	0.207	0.2506	0.2632	0.3704	52.745	51.3	50.1	47.6
West Bengal	924.7	951.3	952	972	61.38	65.4	66.6	71.87	0.342	0.4367	0.4348	0.5556	36.979	37.3	36.8	37.5

	Body Mass Index				Life Expectancy at Birth			
States	NFHS 1	NFHS 2	NFHS 3	NFHS 4	NFHS 1	NFHS 2	NFHS 3	NFHS 4
Andhra Pradesh	58.336	58.70605	54.55	50.45	61.8	62.5	65.3	69.6
Arunachal Pradesh	59.582	57.88831	76.25	71.9	65.048	61.6289	62.952	70.157
Assam	55.026	58.44645	57.55	63.75	55.7	57.3	60	65.5
Bihar	55.98	57.43401	54.4	59.95	59.3	59.5	64.4	68.7
Delhi	58.862	60.65954	63.15	54.65	63.5939	67.2226	68.323	74.2
Goa	61.73	61.21768	55.85	54.2	69.3841	68.3492	71.86	72.777
Gujarat	57.505	58.73201	49.8	52.35	61	64.1	65.8	69.5
Haryana	57.849	59.27068	54.75	65.95	63.4	64.1	67	69.4
Himachal Pradesh	59.77	61.50324	58.15	57.6	65.4279	66.2	69.6	72.3
Jammu & Kashmir	60.419	59.05651	62.25	63.4	66.7379	63.9869	70	73.5
Karnataka	58.589	59.72498	52.25	58.7	62.5	64.4	66.5	69.1
Kerala	62.178	63.03488	57.25	60.45	72.9	71.7	73.9	75.1
Madhya Pradesh	55.799	55.32476	52.4	59.35	54.7	56.6	60.2	65.4
Maharashtra	59.693	60.48431	51.95	55.1	64.8	65.5	68.6	72.2
Manipur	60.251	60.61411	73.2	67.15	66.3973	67.1309	68.978	71.074
Meghalaya	58.615	56.3372	80.05	77	63.0961	58.498	65.31	69.24
Mizoram	62.353	60.70497	77.2	71.2	70.6417	67.3143	67.537	68.454
Nagaland	62.912	60.11438	78.15	73.05	71.7683	66.1222	65.965	69.633
Odisha	55.753	57.47944	55.15	60.15	56.5	58	61.2	67.6
Punjab	59.842	59.57571	54.2	59.15	67.2	66.4	68.9	72.5
Rajasthan	57.596	56.79799	53.85	61.5	59.1	61.7	64.9	68.3
Sikkim	59.17	59.6471	74.65	64.85	64.2159	65.179	69.24	70.288
Tamil Nadu	58.641	60.14683	54.55	56.95	63.3	64.4	67.5	71.4
Tripura	57.466	59.24472	54.75	66.75	60.7774	64.3668	66.751	70.157
Uttar Pradesh	55.085	56.30475	54.6	59.9	56.8	59.1	61.3	64.8
West Bengal	57.81	59.86776	54.4	62.35	62.1	63.7	67.7	70.8

Appendix 1C: Data of Education Indicators of 539 Districts (2006, 2011 and 2016)

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
Andhra Pradesh	Sarikakulam	87.9	97.7	91.49	71.1	82.4	85.47	55.3	62.3	65.3
	Vizianagaram	99.1	97.1	93.13	65.4	82.1	82.3	51.1	59.5	63.1
	visakhapatnam	84.1	100.7	94.97	66.6	77.7	83.28	60	67.7	71
	East Godavari	79.2	99.8	97.03	68.1	83.6	87.33	65.6	71.4	73.88571
	West Godavari	72.5	97.2	94.38	61.4	81.3	86.32	73.5	74.3	74.64286
	Krishna	76.2	94	92.72	58.4	77.8	82.99	68.8	74.4	76.8
	Guntur	74.3	95.1	91.35	52.6	73.8	78.8	62.5	68	70.35714
	Prakasam	95.3	101.2	91.68	56.7	71.3	73.65	57.4	63.5	66.11429
	Sri Potti Sriramulu	84.9	95.4	91.24	63.1	73.4	77.93	65.1	69.2	70.95714
	Y.S.R	107.1	98.7	92.38	77.4	82.2	76.67	62.8	67.9	70.08571
	Kurnool	111.6	99.2	94.49	69.2	72.7	73.67	53.2	61.1	64.48571
	Anantapur	94.4	93.7	92.23	77.3	78.2	79.73	56.1	64.3	67.81429
	Chittoor	88.6	93.9	89.54	76.2	81.5	83.68	66.8	72.4	74.8
	Mahbubnagar	112	93.2	98.24	72.9	67.9	76.1	44.4	56.1	61.11429
	Rangareddi	134.5	113.1	136.11	101.8	93.7	117.25	66.2	78.1	83.2
	Hyderbad	109.9	117.8	137.66	87.9	93.1	116.78	78.8	81	81.94286
	Medak	109.6	100.3	101.45	78.8	78.9	85.73	51.7	62.5	67.12857
	Nizamabad	106.7	105.6	108.37	79.9	82	88.36	52	62.3	66.71429
	Adilabad	118.1	115.8	113.65	91.9	80.7	86.42	52.7	61.6	65.41429
	Karlmnagar	128.6	104.4	107.27	90.8	87.7	90.18	54.9	64.9	69.18571
	Warnagal	108.7	110.4	114.85	87.8	84.3	87.71	57.1	66.2	70.1
	Khammar	94.3	105.6	99.23	83.5	83.1	81.55	56.9	65.5	69.18571
	Nalgonda	104.8	103.4	102.11	86.2	81	83.46	57.2	65.1	68.48571
Arunachal Pradesh	Tawang	138.5	130	102.73	47.7	70.4	79.01	47.3	60.6	66.3
	West kameng	110.6	120.5	124.9	54.6	83.8	92.36	60.8	69.4	73.08571

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	East Kameng	237.5	108.5	109.98	71.3	62.3	62.97	40.6	62.5	71.88571
	Papumpare	170.1	175	174.25	84.7	130.6	134.61	69.3	82.1	87.58571
	Upper Subansiri	225	175	198.53	75.8	101.2	116.68	50.3	64	69.87143
	West Siang	140	158.8	135.92	80.6	107.1	98.68	59.5	67.6	71.07143
	East Siang	158.9	162.7	115.35	93.6	134.1	110.64	60.7	73.5	78.98571
	Upper Siang	184.7	145.5	142.11	88.7	117.6	110.09	49.8	59.9	64.22857
	Chanalang	117.8	108	109.12	59.9	84.1	96.46	51.3	61.9	66.44286
	Tirap	123.6	110.3	56.21	57	75.5	42.91	41.7	52.2	56.7
	Lower Subansiri	103.4	175	168.07	58.1	100.2	102.5	44.8	76.3	89.8
	Dibang Valley	13.7	106.9	111.27	6.6	76.3	58	58.9	64.8	67.32857
	Lohit	123.6	144.2	37.6	74.2	97.2	31.25	56.1	70.4	76.52857
Assam	Kokrajhar	71.3	122	118.18	66	96.7	80.3	51.6	66.6	73.02857
	Dhubri	127.2	132.2	115.08	59.1	95.7	78.64	48.2	59.4	64.2
	Goalpara	109.6	123.6	112.01	69	88	80.61	58	68.7	73.28571
	Barpeta	103.8	103.7	98.91	69.2	86.4	73.95	56.2	65	68.77143
	Morigaon	101.8	103.7	99.91	66.2	80.3	74.68	58.5	69.4	74.07143
	Nagaon	104.8	104.2	100.83	56.1	81.9	75.2	61.7	73.8	78.98571
	Sontipur	38.7	98.8	102.55	37.3	74	74.18	59	70	74.71429
	Lakhimpur	86	109.8	109.51	73.4	105.2	97.04	68.6	78.4	82.6
	Dhemaji	73.6	112.6	109.35	71.2	106.5	98.88	64.5	69.1	71.07143
	Tinsukia	74	94.1	101.15	55.2	54.1	73.99	61	70.9	75.14286
	Dibrugarh	71.2	101.4	107	54.6	79.1	81.92	69	76.2	79.28571
	Sivasagar	41.6	106.7	105.75	48.6	87.3	83.08	74.5	81.4	84.35714
	Jorhat	70.2	101.5	105.06	62	91.4	89.76	76.3	83.4	86.44286
	Golaghat	71.7	109.1	105.55	60.2	90.3	86.2	69.4	78.3	82.11429
	Karbi Anglong	91.2	117	108.61	70.4	85.4	84.13	57.7	73.5	80.27143
	Dima Hasao	91.3	114.7	102.83	81.5	103.7	82.54	67.6	79	83.88571

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Cachar	91.6	116.8	106.73	63	89.5	81.74	67.8	80.4	85.8
	Karimganj	67.4	123.2	119.15	58.5	92.6	80.91	66.2	79.7	85.48571
	Hailakandi	119.5	127	125.67	72.2	106.7	85.64	59.6	75.3	82.02857
	Bongaigaon	91.5	110.5	114.38	70.9	84.1	86.23	59.3	70.4	75.15714
	Kamrup	60.9	103.4	101.48	59	91	81.04	74.2	72.8	72.2
	Nalbari	79.3	105.6	108.02	79.8	90.6	87.84	67.2	79.9	85.34286
	Darrang	79.1	106.8	103.68	58.5	73.6	62.58	55.4	64.6	68.54286
Bihar	Paschim Champaran	91.8	86.4	111.87	22.1	43.8	68.07	38.9	58.1	66.32857
	Purba Champaran	87	89	108.8	23	60.3	77.09	37.5	58.3	67.21429
	Sheohar	90.8	91.5	121.42	20.9	50.9	82.76	35.3	56	64.87143
	Sitamarhi	80.6	91.7	116.28	24.1	51.1	80.91	38.5	53.5	59.92857
	Madhubani	108.4	95.5	109.74	33.8	69.6	85.62	42	60.9	69
	Supaul	92	93.5	108.79	23.5	63.8	78.07	37.3	59.7	69.3
	Araria	83.1	96	119.02	25.4	49.9	65.63	35	55.1	63.71429
	Kishanganj	80.5	108.7	120.07	15.8	61.3	77.05	31.1	57	68.1
	Purnia	96.5	94.2	118.2	18.9	49.4	75.37	36.1	52.5	59.52857
	Katihar	84	97.3	110.37	25.3	62.9	79.17	35.1	53.6	61.52857
	Madhepura	101.2	104.4	114.73	24.1	62.2	95.39	36.1	53.8	61.38571
	Saharsa	84.7	99.6	118.29	22.4	58.3	83.07	39.1	54.6	61.24286
	Darbhanga	82.9	89.2	108.89	27.4	56.1	78.89	44.3	58.3	64.3
	Muzaffarpur	109.1	90.3	103.58	32.7	60.8	84.59	48	65.7	73.28571
	Gopalganj	98.9	88.1	116.16	36.5	60.1	88.81	47.5	67	75.35714
	Siwan	92.4	88.8	104.86	30.5	67.4	88.26	51.6	71.6	80.17143
	Saran	96.5	91	114.26	38.7	67.3	93.44	51.8	68.6	75.8
	Vaishali	101.8	87.9	96.53	38	71.3	89.72	50.5	68.6	76.35714
	Samastipur	93.2	95.7	101.02	28.5	62.4	83.56	45.1	63.8	71.81429
	Begusarai	110.6	95.6	110.65	24.8	62.5	86.11	48	66.2	74

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Khagaria	80.1	93	107.58	22.9	66.7	83.2	41.3	60.9	69.3
	Bhagalpur	89	89.5	103.77	23.9	60.2	82.66	49.5	65	71.64286
	Banka	83.4	97	107.96	18.9	66.5	85.08	42.7	60.1	67.55714
	Munger	82.4	92.2	112.59	42.8	69	95.33	59.5	73.3	79.21429
	Lakhisarai	94.3	90.7	114.17	41.9	65	89.36	48	65	72.28571
	Sheikhpura	88.7	84.4	114.88	26.6	58.4	89.02	48.6	66	73.45714
	Nalanda	90.7	81.9	103.24	35.6	52.9	81.85	53.2	66.4	72.05714
	Patna	73.9	68.4	89.18	28.6	49.3	73.49	62.9	72.5	76.61429
	Bhojpur	99.2	88	112.39	37.8	66.2	93.95	59	72.8	78.71429
	Buxer	92.5	97.8	110.12	46.7	75.8	100.9	58.8	71.8	77.37143
	Kaimur	118.7	89.5	99.95	55.6	68.1	90.28	55.1	71	77.81429
	Rohtas	91.3	86.6	108.57	51.2	70.3	95.81	61.3	75.6	81.72857
	Aurangabad	97	99.5	118.3	38.6	69.7	102.2	57	72.8	79.57143
	Gaya	102	91	105.75	35.6	54.9	77.5	50.4	66.4	73.25714
	Nawada	73.6	90.1	122.5	22.3	51.4	90.37	46.8	61.6	67.94286
	Jumai	87.3	108.3	127.68	24	66.4	91.54	42.4	62.2	70.68571
	Jehanabad	98.6	93.5	101.8	40.3	66.6	92.52	55.3	68.3	73.87143
Delhi	North West	70	115.4	123.51	82.9	107.2	119.19	80.6	84.7	86.45714
	North	93.4	93	112.45	64.9	88.4	103.02	80.1	86.8	89.67143
	North East	102.8	114.3	126.07	91.1	110.7	122.14	77.5	82.8	85.07143
	East	95.5	130.4	141.24	93.9	120.3	131.27	84.9	88.8	90.47143
	New Delhi	139.4	175	386.25	148.9	315.9	358.91	83.2	89.4	92.05714
	Central	109.5	104.3	99.76	66.3	116.2	123.64	79.7	85.3	87.7
	West	70.9	127.6	135.5	86.9	115.3	132.49	83.4	87.1	88.68571
	South West	117.6	120.2	130.2	87.6	105.1	118.84	83.6	88.8	91.02857
	South	84.9	107.5	114.36	86.3	103.2	120.49	82	87	89.14286
Goa	North Goa	47	116.6	120.98	58.6	113.8	117.65	83.6	88.9	91.17143

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	South Goa	38.9	115	115.81	53.2	107.2	113.91	80.1	85.5	87.81429
Gujrat	Kachchh	98.4	106.1	99.47	78.5	83.5	101.37	59.8	71.6	76.65714
	Banaskantha	121.6	105	95.82	95.3	81.5	96.24	51	66.4	73
	Patan	90	107.6	95.49	69.9	86.1	102.91	60.4	73.5	79.11429
	Mehsana	87.8	110.3	100.8	87.8	95.4	107.26	75.2	84.3	88.2
	Sabarkantha	99.8	104.3	57.73	101.9	90.2	56.1	66.6	76.6	80.88571
	Gandhinagar	85.3	120.2	119.35	90.8	109.1	122.92	76.6	85.8	89.74286
	Ahmadabad	64.3	99	100.48	65.4	83.8	98.32	79.5	86.7	89.78571
	Surendranagar	103.7	106.2	85.58	97.1	88.1	87.13	61.6	73.2	78.17143
	Rajkot	61.2	105.3	84.49	63.9	94	80.13	74.2	82.2	85.62857
	Jamnagar	67.7	94.2	59.9	65.3	79.3	56.54	66.5	74.4	77.78571
	Porabandar	86.5	106.9	98.85	90.4	96.4	98.86	68.6	76.6	80.02857
	Junagadh	92.8	105.2	48.7	98.3	95.6	50.56	67.8	76.9	80.8
	Amreli	87.1	101.4	93.54	91.7	89.5	92.4	66.1	74.5	78.1
	Bhavnagar	95.1	106.7	79.58	90.4	90.9	82.07	66.2	76.8	81.34286
	Anand	93.9	109	102.14	90.6	102.9	104.11	74.5	85.8	90.64286
	Kheda	95.9	99.8	84.99	94.2	99.3	86.87	72	84.3	89.57143
	Pachmahal	104.3	102.2	63.55	100.5	89.4	65.5	60.9	72.3	77.18571
	Dohad	119.2	97	89.65	88.2	75.1	78.51	45.2	60.6	67.2
	Vadodara	59.4	99	71.64	53.9	85.3	72.25	70.8	81.2	85.65714
	Narmada	98.5	96.7	92.18	99.6	82.6	87.88	59.9	73.3	79.04286
	Bharuch	72	107.6	104.31	76.8	94.9	101.36	74.4	83	86.68571
	The Dangs	158.3	135.4	121.83	101.6	84.7	102.97	59.7	76.8	84.12857
	Navsari	74.8	107.1	100.58	81.4	97	101.42	75.8	84.8	88.65714
	Valsad	88.8	101.2	100.64	79.8	86	94.5	69.2	80.9	85.91429
	Surat	52	89.5	99.38	50.4	80.8	95.77	74.6	86.7	91.88571
Himachal Pradesh	Chamba	134.2	102.4	95.97	108.9	96	103.97	62.9	73.2	77.61429

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Kangra	106.5	96.6	97.11	106.8	96.4	96.14	80.1	86.5	89.24286
	Lahul and Spiti	88.8	99.1	87.13	80.2	85.2	75.74	73.1	77.2	78.95714
	Kullu	127.2	110.7	106.48	125.7	102.3	109.59	72.9	80.1	83.18571
	Mandi	109.1	98.9	94.39	112.3	98.1	98.64	75.2	82.8	86.05714
	Hamirpur	103.2	99	102.18	105.5	98.8	99.81	82.5	89	91.78571
	Una	108.5	103.7	105.97	109.7	97	102.01	80.4	87.2	90.11429
	Bilaspur	102.9	102.4	101.75	108.2	95.1	102.78	77.8	85.7	89.08571
	Solan	111.3	117.6	125.7	110.3	103.7	117.79	76.6	85	88.6
	Sirmaur	117.3	109.7	104.79	121.1	98.9	106.66	70.4	80	84.11429
	Shimla	100.5	114.7	113.26	97.5	99.9	108.71	79.1	84.6	86.95714
	Kinnaur	115.3	113.5	99.63	106.4	101.7	97.68	75.2	80.8	83.2
Haryana	Panchkula	50.5	118.2	122.58	37.7	93.6	104.9	74	83.4	87.42857
	Ambala	41.8	105.7	103.3	38.8	104	101.13	75.3	82.9	86.15714
	Yamunanagar	57.3	97.4	94.35	39.1	91.9	92.2	71.6	78.9	82.02857
	Kurukshetra	58.6	105.2	98.54	50.3	100.5	104.36	69.9	76.7	79.61429
	Kaithal	70.6	104.3	99.9	55.4	97.1	100.86	59	70.6	75.57143
	Karnal	68.9	95.3	103.99	56.8	84.9	101.42	67.7	76.4	80.12857
	Panipat	52	87.1	93.7	37.1	78.1	91.17	69.2	77.5	81.05714
	Sonipat	49.3	102.4	97.21	40.4	92.9	97.58	72.8	80.8	84.22857
	Jind	67.6	101.2	90.12	48.4	96.4	96.39	62.1	72.7	77.24286
	Fatehabad	71.4	99.6	98.42	55.6	94.2	98.24	58	69.1	73.85714
	Sirsa	92.8	122.5	102.22	73.9	97.6	100.86	60.6	70.4	74.6
	Hisar	53.4	102.2	92.46	36.1	92.9	98.23	57.24145	73.2	80.03938
	Bhiwani	61.4	108.6	91.86	43.2	100.7	95.7	67.4	76.7	80.68571
	Rohtak	48.5	98.7	89.24	35.6	93.3	91.81	73.7	80.4	83.27143
	Jhajjar	32.3	102.2	97.52	35	92.1	97.5	57.01704	80.8	90.9927
	Mahendragarh	79.7	100.8	89.85	67.8	90	88.84	69.9	78.9	82.75714

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Rewari	53.4	96.6	92.17	50.4	86.9	95.68	75.2	82.2	85.2
	Gurgaon	60.2	102.3	101.61	20.6	81.9	97.96	62.9	84.4	93.61429
	Faridabad	50.7	93.4	103.82	27.5	77.4	97.47	70	83	88.57143
Jammu & Kashmir	Kupwara	92.1	64.3	65.48	60.3	54	53.26	43.2	66.9	77.05714
	Badgam	85.1	60.7	54.55	70.4	61	52.51	42.5	58	64.64286
	Ladakh	706	111	111.88	56.2	102.6	103.44	65.3	80.5	87.01429
	Kargil	100.4	88.5	85.26	73.1	80.99	75.15	60.8	74.5	80.37143
	Punch	123.6	104	105.86	75.8	84.9	86.06	51.2	68.7	76.2
	Rajouri	131.4	103.9	107.95	89.5	83.3	86.29	58	68.5	73
	Kathua	104.9	97.3	101.47	86.8	90.7	91.15	85.6	73.5	68.31429
	Baramula	86.1	105.2	106.44	64.2	84.1	81.24	45.4	66.9	76.11429
	Srinagar	68.2	72.6	67.68	52.5	66.9	68.28	59.8	71.2	76.08571
	Pulwama	101.8	70.3	63.13	75.7	71.9	68.38	49.6	65	71.6
	Anantang	88.3	51.4	52.55	68.3	51.3	49.86	46.5	64.3	71.92857
	Doda	102.2	92.2	99.54	72	85.2	84.9	47.9	66	73.75714
	Udhampur	113.6	97.3	100.92	80.5	94.5	93.13	55.2	69.9	76.2
	Jammu	93.5	111.5	115.13	82.1	100.1	103.32	77	84	87
Karnataka	Belgaum	59	48.6	59	38.5	32	29.21429	64.2	73.9	78.05714
	Bagalkot	93.8	102.4	101.91	101.8	83.6	94.03	57.3	69.4	74.58571
	Bijapur	113.7	118.7	111.02	115.7	89.9	90.96	57	67.2	71.57143
	Bidar	105.4	127.8	117.9	102.6	95.1	92.35	60.9	71	75.32857
	Raichur	87.8	102.8	101.32	74.4	76.4	86.51	48.8	60.5	65.51429
	Koppal	93.9	96	99.06	95.9	79.6	91.81	54.1	67.3	72.95714
	Gadag	84.7	104.9	102.14	99.7	95.3	95.73	66.1	75.2	79.1
	Dharwad	64.4	101.9	107.34	75.3	92	99.73	71.6	80.3	84.02857
	Uttar Kannada	77.4	42.3	27.25714	95.2	31.9	4.771429	76.6	84	87.17143
	Haveri	85.1	101	97.62	102	90.1	95.55	67.8	77.6	81.8

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Bellary	103.7	101.1	102.33	106.7	81.4	93.35	57.4	67.9	72.4
	Chitradurga	78.5	99.4	95.18	94.4	91.7	94.16	64.4	73.8	77.82857
	Davangere	82.4	107.2	103.58	97.4	94.4	97.14	67.4	76.3	80.11429
	Shimoga	74.7	101.3	102.96	89.5	93.9	96.64	74.5	80.5	83.07143
	Udupi	63.4	104	104.59	86.4	101.8	104.26	81.3	86.3	88.44286
	Chikmagalur	54.1	100.3	100.07	64.5	91.3	93.14	72.2	79.2	82.2
	Tumkur	63.5	50.3	44.64286	82	36	16.28571	67	74.3	77.42857
	Bangalore	63.1	65.6	66.67143	67.3	47.2	38.58571	83	88.5	90.85714
	Mandya	61.5	92.8	90.62	78.2	88.6	88.11	61	70.1	74
	Hassan	64.1	97.1	98.07	73.7	90.8	89.32	68.6	75.9	79.02857
	Dakshin Kannada	72.3	103.6	104.58	91.1	102.7	105.02	83.3	88.6	90.87143
	Kodagu	62.1	100.4	100.76	69.4	91.3	94.55	78	82.5	84.42857
	Mysore	68.7	98.9	100.83	82.5	93.7	95.78	63.5	72.6	76.5
	Chamarajanagar	99.9	96.4	94.15	117.4	89	88.25	50.9	61.1	65.47143
	Gulbarga	88.4	112.8	114.72	74.8	83.8	93.33	50	65.7	72.42857
	Kolar	67.9	95.6	96.22	83.1	86	88.58	62.8	74.3	79.22857
	Bangalore Rural	63.5	97.4	103	80.7	85	95.63	64.7	78.3	84.12857
Kerala	Kasaragod	74.8	94.3	102.01	95.3	88.9	102.19	84.6	89.9	92.17143
	Kannur	65	100.5	101.26	89.5	99.7	104.04	92.6	95.4	96.6
	Wayanad	77.5	103.7	101.76	89.3	98.1	102.2	85.2	89.3	91.05714
	Kozhikode	65.2	95.9	98.42	85.8	97.1	100.17	92.2	95.2	96.48571
	Malappuram	93.6	101.7	99.7	117.2	100.6	104.13	89.6	93.6	95.31429
	Palakkad	69.9	94.6	98.05	93.3	97.2	101.15	84.3	88.5	90.3
	Thrissur	67	94.9	98.26	88.2	97.9	100.73	92.3	95.3	96.58571
	Ernakulam	52.7	98.9	101.1	73.6	99.1	99.85	93.2	95.7	96.77143
	Idukki	56.4	91.8	95.87	74.9	90.7	90.69	88.7	92.2	93.7
	Kottayam	50.4	97.1	98.77	67.8	95.6	97.92	95.8	96.4	96.65714

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Aloppuzha	34.4	84.3	94.7	48.9	95.9	97.34	93.4	96.3	97.54286
	Pathanamthitta	42.4	99.2	100.25	62.9	98.1	96.82	94.8	96.9	97.8
	Kollam	52.1	94.5	98.55	76.4	94.6	99.08	91.2	93.8	94.91429
	Thiruvananthapuram	36.9	98.5	99	51.5	96.1	100.23	89.3	92.7	94.15714
Maharastra	Nandurbar	96.4	93.8	97.03	82.5	65.4	79.29	55.8	63	66.08571
	Dhule	95	102.1	104.96	98.4	80.5	95.04	71.6	74.6	75.88571
	jalgaon	89.6	108.8	103.58	93.6	92.4	102.95	75.4	79.7	81.54286
	Buldhana	95.6	105	99.23	99.4	95.3	104.54	75.8	82.1	84.8
	Akola	89.9	102.5	98.45	91.3	94.9	103.39	81.4	87.6	90.25714
	Washim	100.5	105.1	97.95	100.6	95.6	103.82	73.4	81.7	85.25714
	Amravati	84.8	106.8	101.91	90.5	95.7	102.44	82.5	88.2	90.64286
	Wardha	71.8	105.5	101.88	87.7	98.2	102.89	80.1	87.2	90.24286
	Nagpur	79	111.1	108.48	96.1	102.7	107.56	84	89.5	91.85714
	Bhandara	78.2	104.2	100.66	95.8	96.6	100.98	78.5	85.1	87.92857
	Gondiya	82.4	105.4	100.46	99.6	94.8	101.55	78.6	85.4	88.31429
	Gadchiroli	91.3	105.8	100.64	96.7	84.1	92.67	60.1	70.6	75.1
	Chandrapur	78.4	104.6	100.97	93.3	95.1	102.9	73.2	81.4	84.91429
	Yavatmal	94.7	108.1	100.27	89.7	93.2	103.18	73.6	80.7	83.74286
	Nanded	99.1	101.4	98.05	95.3	78.9	91.31	67.8	76.9	80.8
	Hingoli	103.6	103.8	95.3	93.2	80.9	97.56	66.3	76	80.15714
	Parbhani	102	108.3	103.28	103.2	86.6	104.28	66.1	75.2	79.1
	Jalna	92.3	103.7	95.8	102.6	83	100.41	64.4	73.6	77.54286
	Aurangabad	74.7	110	111.3	69.6	91.9	110.98	72.9	80.4	83.61429
	Nashik	89.3	100.8	101.93	92.2	86.2	96.95	74.4	81	83.82857
	Thane	74.7	108.3	77.9	55.8	92.1	72.59	80.7	86.2	88.55714
	Mumbai Suburban	1.1	109	105.19	87.9	26.2	29.9	86.9	90.9	92.61429
	Mumbai	86.4	95.1	108.4	26.2	333.4	346.01	86.4	88.5	89.4

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Raigarh	85.4	106.9	108.11	91.5	95.7	104.11	77	83.9	86.85714
	Pune	76.7	106.3	109.79	82	98.5	109.56	80.5	87.2	90.07143
	Ahmednagar	84.5	106.1	99.87	94.4	93.8	105.63	75.3	80.2	82.3
	Bid	100.5	108.4	105.56	113.8	89.7	107.35	68	73.5	75.85714
	Latur	105.7	111.1	108.87	120.9	94.3	108.35	71.5	79	82.21429
	Osmanabad	136.2	99.3	91.45	162.6	84.7	96.4	69	76.3	79.42857
	Solapur	88.8	106.9	101.53	102.5	93.6	102.16	71.2	77.7	80.48571
	Satara	74.2	99.3	95.97	88.3	92.4	97.54	78.2	84.2	86.77143
	Ratnagiri	79.7	105.6	97.12	93.4	99.4	100.75	75	82.4	85.57143
	Sindhudurg	71.3	103.9	96.99	80.3	97.5	100.39	80.3	86.5	89.15714
	Kolhapur	73.6	103	101.37	79	95.9	102.49	76.9	82.9	85.47143
	Sangli	77	103.2	101.21	92	94.6	100.33	76.6	82.6	85.17143
Meghalaya	West Garo Hills	109.5	141.2	107	61.8	95.9	86.75	50.7	68.4	75.98571
	East Garo Hills	131.3	127.6	79.5	88.9	85.2	50.98	60.6	75.5	81.88571
	South Garo Hills	149.5	163	160.93	57.6	113.4	127.72	55	72.4	79.85714
	West Khasi Hills	166.1	145.3	104.82	89.4	79.7	65.92	65.1	79.3	85.38571
	Ribhoi	103.5	132.9	149.67	61	73.1	93.36	65.7	77.2	82.12857
	East Khasi Hills	115.9	116.5	123.81	80.1	89.8	103.8	76.1	84.7	88.38571
	Jaintia Hills	59.1	108.3	73.62	35.1	63.8	50.93	51.9	63.3	68.18571
Manipur	Senapati	249.2	175	294.3	77.6	137.3	148.95	59.8	75	81.51429
	Tamenglong	179.4	175	124.1	53	62.6	75.09	59.2	70.4	75.2
	Churachandpur	102.5	150	132.95	51.2	95.8	101.27	70.6	84.3	90.17143
	Bishnupur	129.9	131.7	134.88	74.1	98.4	99.43	67.6	76.4	80.17143
	Toubal	126.5	110	114.8	69.4	86.3	91.79	66.4	76.7	81.11429
	Imphal West	119.8	129	131.08	78.6	99.7	112.15	80.2	86.7	89.48571
	Imphal East	125.2	132.2	126.54	73.4	97.7	102.53	75.4	82.8	85.97143
	Ukhrul	112.8	172.9	147.22	29	86.7	93.31	73.1	81.9	85.67143

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Chandel	83.5	154.4	126.47	14	69.7	88.78	56.2	70.9	77.2
Madhya Pradesh	Sheopur	140.1	130.9	104.89	45.2	97.9	89.94	46.4	58	62.97143
	Morena	111.5	154.4	101.95	53.1	112.6	86.79	64.7	72.1	75.27143
	Bhind	123	123.3	108.8	82.4	107.5	101.75	70.5	76.6	79.21429
	Gwalior	156.7	175	119.96	100.9	183.4	100.88	69.4	77.9	81.54286
	Datia	133.8	126.7	99	72.5	109.1	97.79	71.8	73.5	74.22857
	Shivpuri	151.4	127.4	102.69	72.3	105.7	99.55	58.9	63.7	65.75714
	Tikamgarh	132.1	133.4	112.15	72	95.5	102.75	55.7	62.6	65.55714
	Chhatarpur	140.7	134.3	110.85	68.3	104.2	107.24	53.3	64.9	69.87143
	Panna	142.9	132.1	107.23	71	89.3	100.88	61.4	66.1	68.11429
	Sagar	124.2	114.2	100.29	80.2	100.5	103.13	67.7	77.5	81.7
	Damoh	131.3	118.1	99.31	81.2	97.1	98.01	61.8	70.9	74.8
	Satna	135.5	117.5	97.99	93.1	103.9	97.86	64.6	73.8	77.74286
	Rewa	134	123.6	99.96	68.6	95.1	97.92	62	73.4	78.28571
	Umaria	126.5	117.3	94.07	88.9	90.3	101.44	59.1	73.6	79.81429
	Neemuch	113.1	107.7	95.6	61.5	92.3	91.65	66.2	71.8	74.2
	Mandsaur	114.1	110.2	99.79	66.8	92.7	92.83	70.3	72.8	73.87143
	Ratlam	150.6	111.4	101	66.6	84.2	83.82	67.2	68	68.34286
	Ujjain	105.3	111.1	101.17	52.6	104.8	91.49	70.9	67.3	65.75714
	Shajapur	121.8	113.8	60	65.2	87.5	54.52	70.9	70.2	69.9
	Dewas	117.1	120.9	98.04	69.1	92.5	92.3	60.9	70.5	74.61429
	Dhar	124.3	113.9	94.1	46.5	78.8	75.16	52.5	60.6	64.07143
	Indore	62.5	123.3	131.67	42.4	122.3	118.07	75.2	82.3	85.34286
	Khargone	104.6	110.5	91.69	50.8	82.2	80.86	63	64	64.42857
	Barwani	133.2	104	79.83	49.6	66.3	51.54	41.5	50.2	53.92857
	Rajgarh	127.6	114.2	105.09	61	87.9	89.49	53.7	62.7	66.55714
	Vidisha	134.8	113.4	94	71.7	93.3	94.94	61.8	72.1	76.51429

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Bhopal	149.7	127.7	126.37	84.6	102.5	106.73	74.6	82.3	85.6
	Sehore	129.2	111.7	97.56	71.2	99.7	87.67	63.1	71.1	74.52857
	Raisen	136.9	104.7	94.94	72.2	91.5	87.3	72.2	74.3	75.2
	Betul	127.6	110.3	95.71	86.7	101.8	101.33	66.4	70.1	71.68571
	Harda	134.5	130.7	96.67	79.1	109.9	100.03	66.5	74	77.21429
	Hoshangabad	127.5	137.4	111.51	78.9	115.2	122.68	70	76.5	79.28571
	Katni	133	120.9	102.28	78.5	102.3	109.59	63.6	73.6	77.88571
	Jabalpur	99.1	114.1	103.35	73.4	102	101.92	75.7	82.5	85.41429
	Narsimhapur	111.8	107.9	98.39	73.6	110.9	104.3	77.7	76.8	76.41429
	Dindori	135.4	116.7	99.53	73.4	96	109.07	54.2	65.5	70.34286
	Mandla	144.9	112.2	94.85	84.9	106.5	111.27	59.6	68.3	72.02857
	chhindwara	117.4	109.7	96.36	80	106	106.17	34.7	72.2	88.27143
	Seoni	135.9	108.1	93.6	86.2	111.3	105.42	65.6	73	76.17143
	Balaghat	147.4	113.6	97.5	95.3	109.3	103.39	68.7	78.3	82.41429
	Guna	94.4	130.4	104.23	36.8	99.9	93.49	59.5	65.1	67.5
	Ashoknagar	176.46	123.4	100.66	91.19667	95	96.63	68.48151	67.9	67.65078
	Shahdol	74.1	110.3	95.81	46.1	100.7	103.07	58.7	68.4	72.55714
	Anuppur	149.26	110.2	93.46	103.4267	98.2	95.96	70.97651	69.1	68.29578
	Sidhi	119.3	118.8	99.49	65.8	97.4	99.61	52.3	66.1	72.01429
	Jhabua	144	121.4	102.66	36.4	63.9	60.77	36.9	44.5	47.75714
	khandwa	101.9	112.9	95.86	54.6	83.3	87.44	61.8	67.5	69.94286
	Burhanpur	127.57	103	92.47	67.44333	74	76.81	63.63568	65.3	66.01328
Mizoram	Mamit	187.4	155.5	136.38	230.7	86.6	92.88	79.1	86	88.95714
	Kolasib	149.3	170.1	145.35	122.6	128.2	102.07	91.3	94.5	95.87143
	Aizawl	107.2	140.8	118.18	168.2	126.9	106.22	96.5	98.5	99.35714
	Champhai	126.2	147.9	118.55	95.6	126.8	101.8	91.2	93.5	94.48571
	Serchhip	137.6	129.3	113.35	122.3	108.4	101.59	95.1	98.8	100.3857

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Lunglei	117.4	159	128.59	87.7	87.2	90.94	84.2	89.4	91.62857
	Lawngtlai	176.2	151.8	125.88	129.3	79.6	79.82	64.7	66.4	67.12857
	Saiha	77.7	157	135.44	84.3	113.5	101.3	82.2	88.4	91.05714
Nagaland	Mon	118.3	106.9	100.04	52.7	51.7	55.64	41.8	56.6	62.94286
	Mokokchung	155.9	147.1	100.21	93.4	131	81.97	83.9	92.7	96.47143
	Zunehboto	120.5	148.1	135.45	73.7	77.6	83.75	69.3	86.3	93.58571
	Wokha	159.7	120.8	121.39	67.1	70	71.73	80.5	87.6	90.64286
	Dimapur	221.7	172.1	162.58	137.8	126.7	131.96	76.8	85.4	89.08571
	Phek	112.9	95.4	83.43	77.9	68.6	66.73	70.6	79.1	82.74286
	Tuensang	97.2	109.8	82.32	48.4	59.1	53.71	50.6	73.7	83.6
	Kohima	101.1	86.9	88.3	68.7	76.1	82.76	74.5	85.6	90.35714
Orissa	Bargarh	101.7	110.4	100.24	52.1	95.6	99.2	64	75.05	79.78571
	Jharsugudha	108.3	108.3	104.21	58.4	87.8	96.07	70.7	78.2	81.41429
	Sambalpur	94.4	106.6	104.02	48.9	87.8	96.95	67.3	86.85	95.22857
	Debagarh	126.3	112.5	92.99	47.7	88.9	95.13	60.4	73.1	78.54286
	Sundargarh	96.5	105.8	109	42.8	80.1	90.41	64.9	74.1	78.04286
	Kendujhar	124.5	107	108.49	50.2	73.2	83.49	59.2	69	73.2
	Mayurbhanj	120.4	153.8	149.94	41.1	107.3	125.77	51.9	64	69.18571
	Baleshwar	120	102.4	113.7	56.9	85.7	98.7	70.6	80.7	85.02857
	Bhadrak	132.9	115.4	107.89	60.9	95	102.93	73.9	72.5	71.9
	Kendrapara	118.5	104.8	107.45	60.4	92	98.68	76.8	85.9	89.8
	Jagatsinghapur	112.8	106.6	109.88	58.9	98.8	100.48	79.1	87.1	90.52857
	Cuttack	96.2	93.1	100.84	46.4	82.1	91.77	76.7	84.2	87.41429
	Jaipur	132.3	113	114.88	58.8	91.8	101.62	71.4	80.4	84.25714
	Dhenkanal	111.4	100.7	99.1	59.3	89.6	93.14	69.4	79.4	83.68571
	Anugul	121.4	106.3	107.9	51.8	85.8	94.7	68.8	79	83.37143
	Nayagarh	102.9	101.9	96.6	48.6	92.8	96.7	70.5	79.2	82.92857

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Khordha	91.1	103.2	112.27	46.8	90	101.27	79.6	87.5	90.88571
	Puri	111.7	103.7	106.74	58.7	91.2	100.01	78	85.4	88.57143
	Ganjam	127.7	104.8	101.86	49.6	87.8	92.12	60.8	71.9	76.65714
	Gajapati	141.7	116.9	113.48	48	62.9	73.73	41.3	54.3	59.87143
	Kandhamal	153.2	120.1	124.87	49.7	79.3	82.63	52.7	65.1	70.41429
	Baudh	137.1	105.7	98	57.4	93.8	92.67	57.7	83.3	94.27143
	Subarnapur	108.9	103.4	96.72	61.8	91.4	97.69	62.8	74.4	79.37143
	Balangir	121.1	114.8	108.07	47	88.3	100.65	55.7	65.5	69.7
	Nuapada	140.4	132	108.57	41.7	95.8	104.59	42	58.2	65.14286
	Kalahandi	119.3	115.8	108.33	40.4	81.6	89.87	45.9	60.2	66.32857
	Rayagada	126.6	106.4	111.96	37	57	61.68	36.1	50.9	57.24286
	Nabarangapur	129.1	104.4	105.63	33.5	64.5	72.95	33.9	48.2	54.32857
	Koraput	133.4	101.4	105.78	35.4	54.1	63.08	35.7	49.9	55.98571
	Malkangiri	138.4	111.3	116.33	30.7	56.3	60.6	30.5	49.5	57.64286
Punjab	Gurdaspur	27.8	77	76.96	15.6	69.2	71.62	73.8	81.1	84.22857
	Kapurthala	63.8	120.1	116.62	64.4	107.7	107.68	73.9	80.2	82.9
	Jalandhar	57.6	114.4	115.68	60.8	101.3	104.86	78	82.4	84.28571
	Hoshiarpur	90.7	112.3	111.7	85.5	101.5	100.86	81	85.4	87.28571
	Sahid Bhagat Singh Nagar	61.4	101.6	118.8286	72.2	103.6	117.0571	76.4	80.3	81.97143
	Fatehgarh Sahib	58.9	110.9	105.86	38.2	99.9	101.92	73.6	80.3	83.17143
	Ludhiana	48	110.2	125.18	36.7	92	108.15	76.5	82.5	85.07143
	Moga	92.5	118.5	107.36	70.1	96.5	109.23	63.5	71.6	75.07143
	Firozpur	86.3	50.7	49.51	60.5	42.9	45.67	60.7	69.9	73.84286
	Muktsar	76.5	110.9	104.98	59	90.9	102.59	58.2	66.8	70.48571
	Faridkot	96	119.9	110.24	76.4	100.3	107.73	62	70.7	74.42857
	Bathinda	99.3	112.5	106.3	79.7	97.4	105.71	61.2	69.6	73.2
	Mansa	75.7	117.9	107.98	67.6	97.5	109.53	52.4	62.8	67.25714

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Patiala	66	114.2	110.93	62.7	103	107.51	69.8	76.3	79.08571
	Amritsar	59.1	110.3	116.61	43.5	94	103.94	67.3	77.2	81.44286
	Rup Nagar	59.8	108.3	106.88	64.8	103	101.47	78.1	83.3	85.52857
	Sangrur	68.6	110.5	106.04	58.7	98	102.62	60	68.9	72.71429
Rajasthan	Ganganagar	85.8	107.9	108.45	56.4	82.3	91	64.7	70.3	72.7
	Hanumangarh	101.4	107.9	111.37	73.8	85.2	91.92	63.1	68.4	70.67143
	Bikaner	125.9	104.2	98.1	53.5	69.3	75.93	56.9	65.9	69.75714
	Churu	103.4	105.9	104.01	67.8	79.7	89.14	66.8	67.5	67.8
	Jhunjhunun	100.1	108.4	103.32	86.1	87.7	95.1	73	74.7	75.42857
	Alwar	112.2	109.2	103.25	70.3	83.9	88.57	61.7	71.7	75.98571
	Bharatpur	124.3	102.8	93.92	73	79.6	83.94	63.6	71.2	74.45714
	Dhaulpur	142.3	116.1	122.67	69.1	88.3	89.26	60.1	70.1	74.38571
	Karauli	116.8	108.1	107.65	61.2	82.7	83.29	63.4	67.3	68.97143
	Sawai Maghopur	112.9	109.8	105.57	59.3	83.2	88.61	56.7	66.2	70.27143
	Dausa	131.1	106.8	103.37	82.6	86.5	97.11	61.8	69.2	72.37143
	Jaipur	82.4	100	113.83	52.6	82.2	96.75	69.9	76.4	79.18571
	Sikar	122.6	107.1	104.24	91.7	83.1	92.74	70.5	73	74.07143
	Nagaur	122.6	108.3	109.82	67.2	76.7	84.7	57.3	64.1	67.01429
	Jodhpur	113.1	100.8	107.15	47.5	66.9	76.82	56.7	67.1	71.55714
	Jaisalmer	148.1	107.5	106.9	42.5	57.9	63.6	51	58	61
	Barmer	150.4	112.3	101.94	51	72.1	81.43	59	57.5	56.85714
	Jalor	135.8	108.2	100.16	62.6	72.8	85.02	46.5	55.6	59.5
	Sirohi	120.9	101.9	92.8	66.6	75	77.79	53.9	56	56.9
	Pali	122	112.1	101.7	65.3	82.6	90.56	54.4	63.2	66.97143
	Ajmer	99.8	107.8	103.67	57.1	84	90.77	64.8	70.5	72.94286
	Tonk	103.4	109.1	101.97	58.6	81.7	86.84	52	62.5	67
	Bundi	118.6	106.6	99.9	71.2	87	88.59	55.6	62.3	65.17143

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Bhilwara	101.1	106	101.05	57.7	78.3	83.77	50.7	62.7	67.84286
	Rajsamand	118.9	104.8	107.51	67.4	82.2	90.48	55.7	63.9	67.41429
	Dungarpur	132.9	104.4	102.13	68.9	81.8	89.54	48.6	60.8	66.02857
	Banswara	141.5	111.4	102.43	64.4	73.6	81.34	44.6	57.2	62.6
	Chittaurgarh	95.2	99.9	98.34	60	80	82.75	54.1	62.5	66.1
	Kota	96.3	108.2	107.25	69.9	89.7	95.2	73.5	77.5	79.21429
	Baran	127.4	115.3	110.98	74	88.4	87.4	59.5	67.4	70.78571
	Jhalawar	119.3	111.1	102.92	55.7	83.7	87.69	57.3	62.1	64.15714
	Udaipur	104.9	98.2	96.77	52.6	70	75.78	58.6	62.7	64.45714
Sikkim	North District	138	135.4	107.82	66.4	104.7	106.05	67.2	77.4	81.77143
	West District	133.6	150.7	126.91	66.9	111.7	128.48	58.8	78.7	87.22857
	South District	137.2	151.1	122.76	72.8	113.6	125.41	67.3	82.1	88.44286
	East District	142.8	149.9	130.44	84.2	119.2	131.87	74.7	84.7	88.98571
Tamil Nadu	Thiruvallur	102.6	103.7	107.9	100.2	96.5	101.5	76.9	83.8	86.75714
	Chennai	96.7	124.8	100.22	92.5	116.8	106.07	85.3	90.3	92.44286
	Kancheepuram	114.2	101	104.52	118.8	97	104.92	76.9	85.3	88.9
	Vellore	120.3	109.2	94.24	110.9	102.7	93.36	72.4	79.7	82.82857
	Tiruvannamalai	115.7	101.7	101.75	110.9	97.7	92.44	67.4	74.7	77.82857
	Viluppuram	123.4	95	93.76	109.4	87.5	86.08	63.8	72.1	75.65714
	Salem	122.1	105	107.35	106	97.5	101.06	65.1	73.2	76.67143
	Namakkal	111	107.4	110.38	98.6	102.4	102.17	67.4	74.9	78.11429
	Erode	101.7	137.3	138.99	87.6	131.2	135.33	65.6	73	76.17143
	The Nilgiris	106.6	101.3	107.43	97.1	94.3	100.75	80	85.7	88.14286
	Dindigul	124.5	118.2	114.07	104.3	103.5	111.92	69.3	76.9	80.15714
	Karur	113.5	106.8	105.48	94.6	92.9	94.04	68.1	75.9	79.24286
	Tiruchiappalli	113.1	107.1	109.58	100.5	98.9	103.01	77.9	83.6	86.04286
	Perambalur	291.6	175	276.72	268.2	227.3	244.43	66.1	74.7	78.38571

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Coddalore	125.7	108.2	110.91	113.2	97.1	100.45	71	79	82.42857
	Nagapattinam	127.1	116.2	110.42	113.3	106.6	111.85	76.3	84.1	87.44286
	Thiruvarur	121	117.3	114.49	111.9	103.8	116.48	76.6	83.3	86.17143
	Thanjavur	118.6	113.7	113.93	108.2	104.4	109.4	75.6	82.7	85.74286
	Pudukkottai	121.8	107.3	105.93	112.6	98	94.03	71.1	77.8	80.67143
	Sivaganga	122.8	103.8	107.19	115.6	102.6	99.86	72.2	80.5	84.05714
	Madurai	130	117.4	115.09	112.7	102.5	109.64	77.8	81.7	83.37143
	Theni	135.6	129.1	124.53	112.8	102.7	109.81	71.6	77.6	80.17143
	Virudhunagar	130.1	119.3	117.92	104.8	98.6	100.43	73.7	80.8	83.84286
	Ramanathapurm	135.2	122.4	117.4	120	100.4	98.86	73	81.5	85.14286
	Thoothukkudi	126.8	114	113.61	107.8	98.2	103.45	81.5	86.5	88.64286
	Tirunelveli	136.4	123.7	118.54	113.7	107.9	112.04	76.1	82.9	85.81429
	Kanniyakumari	114.2	108.9	105.88	101.1	97.7	104.42	87.6	92.1	94.02857
	Dharmapuri	60.4	107.4	103.61	53	99.8	100.74	61.4	64.7	66.11429
	Krishnagiri	102.8433	106.6	108.21	94.53	95.3	95.63	69.16154	72.4	73.78791
	Coimbatore	110.6	166.6	169.32	100.5	161.9	165.8	77	84.3	87.42857
Tripura	West Tripura	125.9	55.6	54.21	90.9	52.6	53.31	77.3	88.9	93.87143
	South Tripura	151.1	55.6	51.12	83	50.5	51.24	69.9	85.4	92.04286
	Dhalai	140.9	128.7	120.58	74.7	90.9	93.19	60.9	86.8	97.9
	North Tripura	124.6	67.7	61.66	74.9	56.5	55.32	73	88.3	94.85714
Uttar Pradesh	Saharampur	89.9	98.2	86.75	39	62.9	96.06	61.2	72	76.62857
	Muzaffarnagar	77.9	49.3	59.47	21.1	25.5	38.36	60.7	70.1	74.12857
	Bijnor	114.2	134.2	99.63	54.2	84.9	91.27	58.1	70.4	75.67143
	Moradabad	128.5	71.7	69.94	47	44	49.09	44.7	58.7	64.7
	Rampur	137.2	151.1	115.81	27.7	42.4	72.02	38.8	55.1	62.08571
	Jyotiba Phule Nagar	137.4	117.3	115.77	61.3	76.4	86.87	49.5	65.7	72.64286
	Meerut	59.6	105.1	95.83	28.9	67.2	71.04	64.8	74.8	79.08571

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Baghpat	78.1	92	101.75	42.9	75.7	88.02	64.2	73.5	77.48571
	Ghaziabad	64.9	60.1	68.23	22.5	43.5	46.94	69.7	85	91.55714
	Gautam Buddha Nagar	79.4	97.7	141.51	32.4	63.5	90.58	68.7	82.2	87.98571
	Bulandshahr	88	88.3	94.74	23.1	61.6	73.15	59.4	70.2	74.82857
	Aligarh	86.9	90.7	86.61	36.8	68.1	70.54	58.5	69.9	74.78571
	Mahamaya Nagar	134.7	168.8	183.4143	50.9	83.1	96.9	62.5	73.1	77.64286
	Mathura	98.4	142.4	131.62	34.8	64	70.35	61.5	72.7	77.5
	Agra	84.5	113	98.67	26.4	59.2	63.98	62.6	69.4	72.31429
	Firozabad	101.7	99.5	95.14	37.4	62.2	66.38	64.5	74.6	78.92857
	Mainpuri	109.8	110.4	120.53	34.1	74.4	87.32	65.1	78.3	83.95714
	Budaun	120.8	75.8	78.38	37.9	42.7	48.37	38.2	52.9	59.2
	Bareilly	104.6	105.4	113.24	31.9	53.9	54.87	47.8	60.5	65.94286
	Pilibhit	108.7	98.7	98.71	41.3	71.2	70.23	49.8	63.6	69.51429
	Shahjahanpur	121.9	114.4	118.43	33.4	78.5	80.66	49.1	61.6	66.95714
	Kheri	118.2	97.4	100.81	43.3	60.2	64.35	48.4	62.7	68.82857
	Sitapur	129.4	127.7	128.77	43.3	65.3	87.04	48.3	63.4	69.87143
	Harcloi	145.3	128.7	119.32	45.8	78.9	72.87	51.9	68.9	76.18571
	Unnao	119.2	112.3	92.86	46.5	47.7	58.82	54.6	68.3	74.17143
	Lucknow	79.1	165.4	192.97	26.9	75	110.5	68.7	79.3	83.84286
	Rae Bareli	103.9	68	95.7	43	38.3	56.72	53.8	69	75.51429
	Farrukhabad	121.6	117.1	112.22	37.5	80.6	92.54	60.9	70.6	74.75714
	Kannauj	100.8	125.2	112.2	32.5	73.9	86.65	61.9	74	79.18571
	Etawah	115.1	134.4	124.97	68.2	99	92.21	69.6	80	84.45714
	Auraiya	114	119.7	127.77	68.6	95.5	104.26	70.5	80.3	84.5
	Kanpur Dehat	113.2	81.5	77.27	51.7	61.7	66.24	66.4	77.5	82.25714
	Kanpur Nagar	68.6	118.3	135.53	38.7	82.8	87.38	74.4	81.3	84.25714
	Jalaun	114.5	109.7	102.46	59.8	86.2	88.5	64.5	75.2	79.78571
	Jhansi	101.5	118.3	108.22	52.4	98.8	95.07	65.5	76.4	81.07143

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Lalitpur	140.7	112.4	109.24	62.4	93.5	94.13	49.5	65	71.64286
	Hamirpur	115.8	115.8	111.99	58.6	86.1	84.02	57.4	70.2	75.68571
	Mahoba	129.7	115.2	108.81	56.8	78.5	87.97	53.3	66.9	72.72857
	Banda	127	103.6	111.19	51.3	77.7	81.32	54.4	68.1	73.97143
	Chitrakoot	138.8	114.3	115.99	55.6	82.3	93.02	85	66.5	58.57143
	Fatehpur	116	100.8	96.22	47.5	71.4	68.05	56.3	68.8	74.15714
	Pratapgarh	132.2	114	133.37	67.8	77.5	108.79	57.6	73.1	79.74286
	Kaushambi	113.6	89	87.18	35	57.2	54.32	46.9	63.7	70.9
	Allahabad	93.9	96.9	101.99	50.8	74.8	88.93	62.1	74.4	79.67143
	Bara Banki	127.9	86.5	90.85	45.1	60.6	60.99	47.4	63.8	70.82857
	Faizabad	89.8	113.6	117.94	53.7	83.4	88.87	56.3	70.6	76.72857
	Ambedkar Nagar	135.9	127.5	122.55	86.3	93.1	89.84	58.4	74.4	81.25714
	Sultanpur	111.3	65.6	68.01	51.5	49.6	52.53	55.8	71.1	77.65714
	Bahraich	111.3	86.3	95.64	22	46.3	55.32	35.2	51.1	57.91429
	Shrawasti	124.2	95	97.07	32.3	54.9	62.1	33.8	49.1	55.65714
	Balarampur	115.5	95.1	105.97	29.8	41.6	52.38	34.6	51.8	59.17143
	Gonda	121.2	91.1	107.17	35.3	64.8	67.78	42.6	61.2	69.17143
	Siddharthnagar	102.6	93	90.64	29.9	58.4	55.79	42.3	61.8	70.15714
	Basti	118	89.1	98.71	48	60.6	93.18	52.5	69.7	77.07143
	Sant Kabir Nagar	91.9	87	93.7	37.5	62.5	75.34	50.9	69	76.75714
	Maharajganj	122.5	103.7	114.35	34.8	44.9	70.93	46.6	64.3	71.88571
	Gorakhpur	88.4	87.1	100.17	35.1	65.9	70.89	85.5	73.3	68.07143
	Kushinagar	127.9	99.5	109.54	40.5	55	61.21	46.9	67.7	76.61429
	Deoria	100.3	95.8	101.15	35.7	67.2	78.08	58.6	73.5	79.88571
	Azamgarh	120.8	105.7	113.04	56.6	71.3	76.82	57	72.7	79.42857
	Mau	118.6	104.4	93.7	37.3	79.3	89.21	62.2	75.2	80.77143
	Ballia	110.9	94.3	106.28	46.6	63.1	73.87	57.9	73.8	80.61429
	Jaunpur	94.4	121.6	110.31	36	85.8	78.89	59.8	73.7	79.65714

			GER_P			GER_UP			LR	
States	**District**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**	**2006**	**2013**	**2016**
	Ghazipur	104.9	126.9	117.54	26.6	91.2	98.83	59.6	74.3	80.6
	Chandauli	119.4	95.4	99.07	141.3	75	78.66	59.7	73.9	79.98571
	Varanasi	73.3	81.8	83.43	41	70.6	75.37	66.1	77.1	81.81429
	Sant Ravidas Nagar	96.9	99.5	100.6143	59.2	74.9	81.62857	61.95399	71.1	75.01972
	Mirzapur	121.5	106.4	103.68	60.8	81.6	78.55	55.3	70.4	76.87143
	Sonbhadra	118.4	101	104	47.2	74	76.81	49.2	66.2	73.48571
	Etah	123.4	111.6	115.83	101.7	78.6	88.71	54.6	73.3	81.31429
West Bengal	Darjiling	44.9	49.5	36.19	40.5	36.1	31.92	71.8	79.9	83.37143
	Jalpaiguri	95.8	136.2	67.69	108.4	103.2	61.68	62.9	73.8	78.47143
	Koch Bihar	102.2	135.6	117.21	130.5	161.4	156.86	66.3	75.5	79.44286
	Uttar Dinajpur	117.8	121.4	112.8	80.6	73.7	79.38	47.9	60.1	65.32857
	Dakshin Dinajpur	100.6	138.4	114.36	110.8	98.9	96.63	63.6	73.9	78.31429
	Maldah	120.3	127.1	120.04	95.3	85	95.25	50.3	62.7	68.01429
	Murshidabad	103	126.5	110.6	108.7	87.5	98.59	54.3	67.5	73.15714
	Birbhum	96.2	118.2	103.03	106.3	88.3	96.4	61.5	70.9	74.92857
	Bardwan	74.6	115.9	99.99	95.9	87.2	96.51	70.2	77.2	80.2
	Nadia	103.6	120.2	100.68	64.6	102.2	105.43	66.1	75.6	79.67143
	North Twenty Four Parganas	60.8	100.3	83.89	88.9	84.2	87.15	78.1	85	87.95714
	Hoogly	74	105.5	88.59	94.9	93	96.88	75.1	82.6	85.81429
	Bankura	91.2	118.7	100	104.4	95.8	102.86	63.4	71	74.25714
	Puruliya	104.7	120.1	98.13	90.8	87.9	95.89	55.6	65.4	69.6
	Howrah	70.3	98.3	89.37	95.8	84.7	92.36	77	83.9	86.85714
	Kolkata	37.8	90.5	85.89	55.5	77.3	86.25	80.9	87.1	89.75714
	South Twenty Four Parganas	88.3	116.7	102.7	100	83.4	91.91	69.4	78.6	82.54286
	Paschim Mednipur	37.9	125.7	108.31	55.2	96.9	99.45	61.13797	79	86.65516
	Purba Medinipur	37.9	110.6	102.75	55.2	98.5	98.77	61.13797	87.7	99.08373

Appendix 1D: Data of Education Indicators of 539 Districts (2006, 2011 and 2016)

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
Andhra Pradesh	Sarikakulam	0.555556	0.555556	0.714286	939.75	942	944.25
	Vizianagaram	0.465116	0.555556	0.689655	940.25	927	913.75
	visakhapatnam	0.512821	0.588235	0.689655	953.3	940	926.7
	East Godavari	0.540541	0.625	0.740741	964.65	954	943.35
	West Godavari	0.555556	0.625	0.714286	965.3	956	946.7
	Krishna	0.588235	0.666667	0.769231	973.1	940	906.9
	Guntur	0.571429	0.625	0.689655	972.65	959	945.35
	Prakasam	0.47619	0.526316	0.588235	962.2	956	949.8
	Sri Potti Sriramulu	0.540541	0.588235	0.645161	956	960	964
	Y.S.R	0.47619	0.526316	0.588235	978	956	934
	Kurnool	0.384615	0.454545	0.555556	956.3	945	933.7
	Anantapur	0.465116	0.526316	0.606061	949.3	927	904.7
	Chittoor	0.5	0.555556	0.625	962.2	944	925.8
	Mahbubnagar	0.363636	0.416667	0.487805	945.3	937	928.7
	Rangareddi	0.434783	0.5	0.588235	965.3	948	930.7
	Hyderbad	0.571429	0.625	0.689655	952.5	948	943.5
	Medak	0.392157	0.454545	0.540541	964.4	952	939.6
	Nizamabad	0.465116	0.555556	0.689655	963.3	947	930.7
	Adilabad	0.408163	0.5	0.645161	958.75	945	931.25
	Karlmnagar	0.540541	0.666667	0.869565	969.9	962	954.1
	Warnagal	0.487805	0.625	0.869565	964.5	952	939.5
	Khammar	0.512821	0.625	0.8	963.85	945	926.15
	Nalgonda	0.454545	0.555556	0.714286	954.75	949	943.25
Arunachal Pradesh	Tawang	0.288462	0.357143	0.424528	911	933	955
	West kameng	0.309278	0.344828	0.373444	923.5	932	940.5

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	East Kameng	0.227273	0.227273	0.227273	864.5	889	913.5
	Papumpare	0.309278	0.37037	0.42654	937	944	951
	Upper Subansiri	0.25641	0.285714	0.309278	890.5	910	929.5
	West Siang	0.291262	0.37037	0.452261	936	947	958
	East Siang	0.30303	0.4	0.508475	951.5	958	964.5
	Upper Siang	0.27027	0.322581	0.37037	937	955	973
	Chanalang	0.241935	0.277778	0.308219	934.5	943	951.5
	Tirap	0.23622	0.25641	0.271903	915	930	945
	Lower Subansiri	0.309278	0.344828	0.373444	903.5	943	982.5
	Dibang Valley	0.277778	0.333333	0.384615	912.5	907	901.5
	Lohit	0.252101	0.285714	0.313589	923.5	940	956.5
Assam	Kokrajhar	0.315789	0.344828	0.367347	935.3	925	914.7
	Dhubri	0.23622	0.243902	0.249307	917.2	925	932.8
	Goalpara	0.265487	0.285714	0.301003	934.1	936	937.9
	Barpeta	0.294118	0.384615	0.483871	937.6	938	938.4
	Morigaon	0.263158	0.277778	0.288462	920.8	931	941.2
	Nagaon	0.285714	0.30303	0.315789	929.5	937	944.5
	Sontipur	0.344828	0.37037	0.38961	940.4	936	931.6
	Lakhimpur	0.319149	0.357143	0.387931	935.45	945	954.55
	Dhemaji	0.30303	0.344828	0.379747	943	948	953
	Tinsukia	0.361446	0.4	0.430622	957.5	951	944.5
	Dibrugarh	0.434783	0.47619	0.508475	962.3	951	939.7
	Sivasagar	0.434783	0.47619	0.508475	939.3	949	958.7
	Jorhat	0.47619	0.526316	0.566038	960.75	951	941.25
	Golaghat	0.38961	0.434783	0.471204	949.3	944	938.7
	Karbi Anglong	0.265487	0.25641	0.250696	935.6	930	924.4
	Dima Hasao	0.32967	0.344828	0.355731	940.5	947	953.5

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Cachar	0.32967	0.344828	0.355731	934.9	944	953.1
	Karimganj	0.275229	0.27027	0.267062	923.35	933	942.65
	Hailakandi	0.265487	0.27027	0.273556	934.2	929	923.8
	Bongaigaon	0.291262	0.30303	0.311419	931.7	941	950.3
	Kamrup	0.394737	0.416667	0.432692	947.7	944	940.3
	Nalbari	0.394737	0.454545	0.505618	943	952	961
	Darrang	0.294118	0.294118	0.294118	922	930	938
Bihar	Paschim Champaran	0.208333	0.217391	0.227273	950.7	936	921.3
	Purba Champaran	0.208333	0.212766	0.217391	947.6	936	924.4
	Sheohar	0.204082	0.212766	0.222222	940.1	929	917.9
	Sitamarhi	0.206186	0.217391	0.229885	931.5	933	934.5
	Madhubani	0.240964	0.25	0.25974	945.4	943	940.6
	Supaul	0.21978	0.227273	0.235294	945.2	942	938.8
	Araria	0.204082	0.204082	0.204082	938.85	929	919.15
	Kishanganj	0.190476	0.192308	0.194175	931.8	928	924.2
	Purnia	0.204082	0.208333	0.212766	942.5	930	917.5
	Katihar	0.196078	0.204082	0.212766	935.6	933	930.4
	Madhepura	0.210526	0.212766	0.215054	933.95	940	946.05
	Saharsa	0.217391	0.217391	0.217391	949.05	943	936.95
	Darbhanga	0.229885	0.238095	0.246914	942.25	936	929.75
	Muzaffarpur	0.229885	0.243902	0.25974	939.3	940	940.7
	Gopalganj	0.240964	0.25641	0.273973	956.2	938	919.8
	Siwan	0.273973	0.27027	0.266667	957.5	945	932.5
	Saran	0.229885	0.25	0.273973	955.05	946	936.95
	Vaishali	0.229885	0.243902	0.25974	952.55	944	935.45
	Samastipur	0.215054	0.227273	0.240964	950.4	946	941.6
	Begusarai	0.21978	0.232558	0.246914	948.35	944	939.65

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Khagaria	0.196078	0.196078	0.196078	951.3	946	940.7
	Bhagalpur	0.227273	0.232558	0.238095	942.85	950	957.15
	Banka	0.222222	0.238095	0.25641	946.15	944	941.85
	Munger	0.253165	0.25641	0.25974	948.85	946	943.15
	Lakhisarai	0.222222	0.232558	0.243902	944.95	946	947.05
	Sheikhpura	0.21978	0.227273	0.235294	940.2	941	941.8
	Nalanda	0.243902	0.25	0.25641	943.5	940	936.5
	Patna	0.27027	0.285714	0.30303	956.05	938	919.95
	Bhojpur	0.25	0.263158	0.277778	947.05	942	936.95
	Buxer	0.238095	0.25	0.263158	944.85	936	927.15
	Kaimur	0.215054	0.222222	0.229885	923	929	935
	Rohtas	0.240964	0.263158	0.289855	950.5	941	931.5
	Aurangabad	0.240964	0.25	0.25974	945.25	940	934.75
	Gaya	0.238095	0.25	0.263158	947.6	934	920.4
	Nawada	0.246914	0.263158	0.28169	946.5	943	939.5
	Jumai	0.232558	0.243902	0.25641	944.2	942	939.8
	Jehanabad	0.25	0.25641	0.263158	943.85	935	926.15
Delhi	North West	0.384615	0.416667	0.454545	950.5	953	955.5
	North	0.47619	0.47619	0.47619	956	958	960
	North East	0.344828	0.384615	0.434783	945	947	949
	East	0.444444	0.5	0.571429	948.5	950	951.5
	New Delhi	0.606061	0.714286	0.869565	933	914	895
	Central	0.555556	0.588235	0.625	954	957	960
	West	0.444444	0.47619	0.512821	946	944	942
	South West	0.408163	0.454545	0.512821	939.5	930	920.5
	South	0.408163	0.454545	0.512821	941.5	937	932.5
Goa	North Goa	0.625	0.666667	0.714286	958	951	944

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	South Goa	0.588235	0.625	0.666667	957	945	933
Gujrat	Kachchh	0.292184	0.322581	0.360036	950.45	949	947.55
	Banaskantha	0.277778	0.30303	0.333333	942.6	948	953.4
	Patan	0.350877	0.384615	0.425532	926.15	943	959.85
	Mehsana	0.444444	0.5	0.571429	946.85	941	935.15
	Sabarkantha	0.357143	0.37037	0.384615	937.75	942	946.25
	Gandhinagar	0.454545	0.5	0.555556	935.85	944	952.15
	Ahmadabad	0.465116	0.5	0.540541	955.2	951	946.8
	Surendranagar	0.327869	0.37037	0.425532	949.25	956	962.75
	Rajkot	0.5	0.47619	0.454545	955.8	946	936.2
	Jamnagar	0.434783	0.454545	0.47619	958.2	952	945.8
	Porabandar	0.444444	0.5	0.571429	961.2	949	936.8
	Junagadh	0.425532	0.47619	0.540541	953.85	948	942.15
	Amreli	0.425532	0.454545	0.487805	962.3	950	937.7
	Bhavnagar	0.357143	0.384615	0.416667	956.05	954	951.95
	Anand	0.434783	0.454545	0.47619	934.25	938	941.75
	Kheda	0.408163	0.434783	0.465116	930.5	936	941.5
	Pachmahal	0.30303	0.322581	0.344828	940.5	941	941.5
	Dohad	0.235294	0.238095	0.240964	924.75	934	943.25
	Vadodara	0.444444	0.47619	0.512821	940.3	942	943.7
	Narmada	0.37037	0.384615	0.4	934.05	940	945.95
	Bharuch	0.434783	0.47619	0.526316	946.05	944	941.95
	The Dangs	0.27027	0.277778	0.285714	941.45	945	948.55
	Navsari	0.526316	0.555556	0.588235	953.5	948	942.5
	Valsad	0.425532	0.454545	0.487805	964.75	955	945.25
	Surat	0.425532	0.454545	0.487805	960.4	952	943.6
Himachal Pradesh	Chamba	0.363636	0.384615	0.408163	967.9	954	940.1

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Kangra	0.5	0.555556	0.625	970.5	943	915.5
	Lahul and Spiti	0.540541	0.588235	0.645161	947.5	957	966.5
	Kullu	0.425532	0.47619	0.540541	960.85	954	947.15
	Mandi	0.465116	0.526316	0.606061	960.8	962	963.2
	Hamirpur	0.5	0.555556	0.625	966.25	954	941.75
	Una	0.444444	0.5	0.571429	973.15	941	908.85
	Bilaspur	0.47619	0.526316	0.588235	967.15	944	920.85
	Solan	0.434783	0.47619	0.526316	963.9	954	944.1
	Sirmaur	0.350877	0.384615	0.425532	961.25	942	922.75
	Shimla	0.5	0.555556	0.625	962.25	955	947.75
	Kinnaur	0.412371	0.526316	0.727273	936	953	970
Haryana	Panchkula	0.4	0.454545	0.526316	969.3	950	930.7
	Ambala	0.454545	0.5	0.555556	972.4	957	941.6
	Yamunanagar	0.392157	0.434783	0.487805	964.95	949	933.05
	Kurukshetra	0.4	0.434783	0.47619	963.45	951	938.55
	Kaithal	0.350877	0.384615	0.425532	959.55	936	912.45
	Karnal	0.357143	0.384615	0.416667	965.85	935	904.15
	Panipat	0.3125	0.344828	0.384615	962.95	951	939.05
	Sonipat	0.344828	0.37037	0.4	968.3	955	941.7
	Jind	0.338983	0.384615	0.444444	955.35	944	932.65
	Fatehabad	0.350877	0.4	0.465116	953.05	943	932.95
	Sirsa	0.384615	0.434783	0.5	964.5	948	931.5
	Hisar	0.363636	0.416667	0.487805	963.4	947	930.6
	Bhiwani	0.344828	0.4	0.47619	960.4	950	939.6
	Rohtak	0.37037	0.416667	0.47619	968.15	954	939.85
	Jhajjar	0.363636	0.416667	0.487805	962.95	953	943.05
	Mahendragarh	0.350877	0.416667	0.512821	960.25	946	931.75

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Rewari	0.357143	0.4	0.454545	964.6	919	873.4
	Gurgaon	0.25974	0.3125	0.392157	958.75	959	959.25
	Faridabad	0.307692	0.357143	0.425532	968.75	955	941.25
Jammu & Kashmir	Kupwara	0.341312	0.336509	0.335954	951.85	940	928.15
	Badgam	0.349305	0.341855	0.335393	965.45	961	956.55
	Ladakh	0.338171	0.377489	0.378285	943.1717	940.707	940.6624
	Kargil	0.351506	0.358098	0.353195	885.5	895	904.5
	Punch	0.353734	0.361458	0.362467	932	940	948
	Rajouri	0.365492	0.360076	0.362667	943	952	961
	Kathua	0.363113	0.366559	0.366961	966.35	960	953.65
	Baramula	0.344355	0.360765	0.358311	954.05	949	943.95
	Srinagar	0.335386	0.346494	0.347597	960.75	953	945.25
	Pulwama	0.353651	0.350525	0.347677	970.75	957	943.25
	Anantang	0.347613	0.334492	0.333426	961.45	950	938.55
	Doda	0.350606	0.361718	0.361458	941.5	949	956.5
	Udhampur	0.357682	0.36998	0.368739	952.25	948	943.75
	Jammu	0.359046	0.375139	0.378171	966.05	958	949.95
Karnataka	Belgaum	0.392157	0.416667	0.444444	953.75	943	932.25
	Bagalkot	0.344828	0.37037	0.4	941.5	938	934.5
	Bijapur	0.333333	0.333333	0.333333	950.7	947	943.3
	Bidar	0.327869	0.37037	0.425532	957.2	953	948.8
	Raichur	0.322581	0.344828	0.37037	949.85	937	924.15
	Koppal	0.31746	0.344828	0.377358	931.8	929	926.2
	Gadag	0.408163	0.434783	0.465116	942.4	935	927.6
	Dharwad	0.434783	0.47619	0.526316	954.15	947	939.85
	Uttar Kannada	0.512821	0.588235	0.689655	969.6	951	932.4
	Haveri	0.416667	0.454545	0.5	942.85	945	947.15

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Bellary	0.344828	0.37037	0.4	934.6	930	925.4
	Chitradurga	0.465116	0.5	0.540541	940.15	939	937.85
	Davangere	0.465116	0.526316	0.606061	944.45	941	937.55
	Shimoga	0.540541	0.588235	0.645161	967.65	941	914.35
	Udupi	0.740741	0.833333	0.952381	977.75	941	904.25
	Chikmagalur	0.606061	0.714286	0.869565	952.25	931	909.75
	Tumkur	0.512821	0.588235	0.689655	941.75	937	932.25
	Bangalore	0.555556	0.588235	0.625	970.6	946	921.4
	Mandya	0.588235	0.666667	0.769231	951.3	943	934.7
	Hassan	0.588235	0.666667	0.769231	961.25	942	922.75
	Dakshin Kannada	0.625	0.666667	0.714286	973.85	955	936.15
	Kodagu	0.571429	0.666667	0.8	970.4	952	933.6
	Mysore	0.526316	0.588235	0.666667	944.5	943	941.5
	Chamarajanagar	0.555556	0.625	0.714286	940.6	942	943.4
	Gulbarga	0.307692	0.333333	0.363636	944.85	946	947.15
	Kolar	0.454545	0.526316	0.625	950.6	945	939.4
	Bangalore Rural	0.487805	0.526316	0.571429	957.2	946	934.8
Kerala	Kasaragod	0.540541	0.555556	0.571429	987.1	976	964.9
	Kannur	0.606061	0.625	0.645161	986	978	970
	Wayanad	0.540541	0.588235	0.645161	981.2	973	964.8
	Kozhikode	0.606061	0.625	0.645161	985.75	966	946.25
	Malappuram	0.434783	0.454545	0.47619	990.6	977	963.4
	Palakkad	0.588235	0.625	0.666667	981.2	977	972.8
	Thrissur	0.645161	0.666667	0.689655	985.65	976	966.35
	Ernakulam	0.666667	0.666667	0.666667	985.75	976	966.25
	Idukki	0.666667	0.714286	0.769231	985.3	973	960.7
	Kottayam	0.666667	0.714286	0.769231	986.45	973	959.55

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Aloppuzha	0.689655	0.714286	0.740741	985.3	969	952.7
	Pathanamthitta	0.714286	0.769231	0.833333	984.75	971	957.25
	Kollam	0.666667	0.714286	0.769231	983.85	971	958.15
	Thiruvananthapuram	0.666667	0.714286	0.769231	981.75	970	958.25
Maharastra	Nandurbar	0.322581	0.344828	0.37037	936.4	945	953.6
	Dhule	0.377358	0.384615	0.392157	944.95	946	947.05
	jalgaon	0.392157	0.416667	0.444444	954.15	949	943.85
	Buldhana	0.357143	0.384615	0.416667	950.15	949	947.85
	Akola	0.408163	0.454545	0.512821	953.95	947	940.05
	Washim	0.363636	0.4	0.444444	951.4	952	952.6
	Amravati	0.444444	0.5	0.571429	940.15	956	971.85
	Wardha	0.5	0.588235	0.714286	950.15	961	971.85
	Nagpur	0.5	0.555556	0.625	955.45	952	948.55
	Bhandara	0.465116	0.526316	0.606061	942.5	948	953.5
	Gondiya	0.454545	0.526316	0.625	934.7	934	933.3
	Gadchiroli	0.408163	0.5	0.645161	921.35	938	954.65
	Chandrapur	0.47619	0.555556	0.666667	938.45	945	951.55
	Yavatmal	0.392157	0.454545	0.540541	947.65	944	940.35
	Nanded	0.327869	0.357143	0.392157	941.85	953	964.15
	Hingoli	0.31746	0.344828	0.377358	950.7	950	949.3
	Parbhani	0.31746	0.333333	0.350877	954.05	954	953.95
	Jalna	0.3125	0.3125	0.3125	942.85	951	959.15
	Aurangabad	0.338983	0.357143	0.377358	949.95	953	956.05
	Nashik	0.350877	0.384615	0.425532	952.5	952	951.5
	Thane	0.425532	0.47619	0.540541	957.35	950	942.65
	Mumbai Suburban	0.555556	0.625	0.714286	958.5	957	955.5
	Mumbai	0.666667	0.714286	0.769231	955.5	953	950.5

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Raigarh	0.465116	0.5	0.540541	961.3	953	944.7
	Pune	0.465116	0.5	0.540541	973.6	962	950.4
	Ahmednagar	0.4	0.434783	0.47619	956.85	958	959.15
	Bid	0.322581	0.333333	0.344828	958.95	959	959.05
	Latur	0.350877	0.384615	0.425532	957.95	946	934.05
	Osmanabad	0.357143	0.384615	0.416667	954.75	957	959.25
	Solapur	0.392157	0.416667	0.444444	954.65	958	961.35
	Satara	0.47619	0.526316	0.588235	968.75	960	951.25
	Ratnagiri	0.540541	0.625	0.740741	968.95	973	977.05
	Sindhudurg	0.625	0.714286	0.833333	970.3	955	939.7
	Kolhapur	0.487805	0.555556	0.645161	963.35	963	962.65
	Sangli	0.47619	0.526316	0.588235	967.75	960	952.25
Meghalaya	West Garo Hills	0.25	0.25641	0.263158	907.5	908	908.5
	East Garo Hills	0.235294	0.243902	0.253165	920.5	925	929.5
	South Garo Hills	0.384615	0.217391	0.151515	905.5	917	928.5
	West Khasi Hills	0.176991	0.172414	0.168067	926	930	934
	Ribhoi	0.196078	0.208333	0.222222	923.5	923	922.5
	East Khasi Hills	0.28169	0.285714	0.289855	934	933	932
	Jaintia Hills	0.181818	0.178571	0.175439	916.5	919	921.5
Manipur	Senapati	0.416667	0.384615	0.357143	948	957	966
	Tamenglong	0.363636	0.37037	0.377358	940	958	976
	Churachandpur	0.4	0.4	0.4	949	957	965
	Bishnupur	0.408163	0.416667	0.425532	954	960	966
	Toubal	0.3125	0.322581	0.333333	955.5	957	958.5
	Imphal West	0.47619	0.5	0.526316	959.5	958	956.5
	Imphal East	0.392157	0.4	0.408163	954.5	958	961.5
	Ukhrul	0.338983	0.357143	0.377358	942	951	960

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Chandel	0.408163	0.47619	0.571429	944	949	954
Madhya Pradesh	Sheopur	0.238095	0.263158	0.294118	921.5	912	902.5
	Morena	0.25641	0.277778	0.30303	926.1	939	951.9
	Bhind	0.273973	0.30303	0.338983	929.45	943	956.55
	Gwalior	0.338983	0.384615	0.444444	930.15	934	937.85
	Datia	0.28169	0.322581	0.377358	915.55	926	936.45
	Shivpuri	0.224719	0.263158	0.31746	910.05	920	929.95
	Tikamgarh	0.253165	0.294118	0.350877	915.9	928	940.1
	Chhatarpur	0.227273	0.263158	0.3125	914.05	923	931.95
	Panna	0.240964	0.277778	0.327869	898.9	912	925.1
	Sagar	0.266667	0.30303	0.350877	915.15	927	938.85
	Damoh	0.273973	0.30303	0.338983	903.8	927	950.2
	Satna	0.263158	0.30303	0.357143	896.95	918	939.05
	Rewa	0.263158	0.3125	0.384615	914.85	932	949.15
	Umaria	0.27027	0.294118	0.322581	920.85	912	903.15
	Neemuch	0.344828	0.4	0.47619	928.4	941	953.6
	Mandsaur	0.327869	0.384615	0.465116	925.2	942	958.8
	Ratlam	0.294118	0.322581	0.357143	923.2	935	946.8
	Ujjain	0.31746	0.357143	0.408163	926.6	945	963.4
	Shajapur	0.28169	0.333333	0.408163	931	940	949
	Dewas	0.294118	0.333333	0.384615	931.55	944	956.45
	Dhar	0.263158	0.285714	0.3125	937	946	955
	Indore	0.377358	0.416667	0.465116	948.75	949	949.25
	Khargone	0.25641	0.285714	0.322581	971	943	915
	Barwani	0.210526	0.227273	0.246914	912.55	943	973.45
	Rajgarh	0.266667	0.30303	0.350877	921.7	932	942.3
	Vidisha	0.243902	0.27027	0.30303	948	928	908

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Bhopal	0.37037	0.416667	0.47619	941	945	949
	Sehore	0.25	0.294118	0.357143	920.1	931	941.9
	Raisen	0.25	0.285714	0.333333	951.8	931	910.2
	Betul	0.294118	0.344828	0.416667	920.75	923	925.25
	Harda	0.266667	0.30303	0.350877	924.3	925	925.7
	Hoshangabad	0.30303	0.344828	0.4	920.3	933	945.7
	Katni	0.298507	0.322581	0.350877	916.5	911	905.5
	Jabalpur	0.384615	0.434783	0.5	930.55	927	923.45
	Narsimhapur	0.322581	0.37037	0.434783	918.5	929	939.5
	Dindori	0.3125	0.3125	0.3125	917.2	923	928.8
	Mandla	0.31746	0.344828	0.377358	922.25	931	939.75
	chhindwara	0.31746	0.357143	0.408163	918.55	930	941.45
	Seoni	0.327869	0.37037	0.425532	921.45	937	952.55
	Balaghat	0.357143	0.4	0.454545	920.05	930	939.95
	Guna	0.238095	0.263158	0.294118	948.65	933	917.35
	Ashoknagar	0.240964	0.27027	0.307692	965	925	885
	Shahdol	0.298507	0.322581	0.350877	911.75	912	912.25
	Anuppur	0.307692	0.344828	0.392157	959	918	877
	Sidhi	0.232558	0.25641	0.285714	918.55	916	913.45
	Jhabua	0.192308	0.2	0.208333	915.35	925	934.65
	khandwa	0.3125	0.4	0.555556	921.5	936	950.5
	Burhanpur	0.344828	0.344828	0.344828	973	946	919
Mizoram	Mamit	0.285714	0.27027	0.25641	931.5	933	934.5
	Kolasib	0.3125	0.333333	0.357143	944.5	950	955.5
	Aizawl	0.377358	0.434783	0.512821	961	966	971
	Champhai	0.289855	0.294118	0.298507	954.5	960	965.5
	Serchhip	0.327869	0.357143	0.392157	953	962	971

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Lunglei	0.3125	0.344828	0.384615	939	943	947
	Lawngtlai	0.243902	0.25	0.25641	913.5	914	914.5
	Saiha	0.273973	0.30303	0.338983	946	941	936
Nagaland	Mon	0.294118	0.294118	0.294118	923.5	920	916.5
	Mokokchung	0.540541	0.588235	0.645161	926.5	942	957.5
	Zunehboto	0.31746	0.357143	0.408163	930.5	946	961.5
	Wokha	0.363636	0.434783	0.540541	941.5	943	944.5
	Dimapur	0.338983	0.384615	0.444444	944	945	946
	Phek	0.246914	0.232558	0.21978	938.5	939	939.5
	Tuensang	0.28169	0.27027	0.25974	923	934	945
	Kohima	0.350877	0.37037	0.392157	948.5	955	961.5
Orissa	Bargarh	0.434783	0.47619	0.526316	935.35	947	958.65
	Jharsugudha	0.425532	0.47619	0.540541	945.05	944	942.95
	Sambalpur	0.425532	0.47619	0.540541	928.7	940	951.3
	Debagarh	0.357143	0.4	0.454545	925.35	930	934.65
	Sundargarh	0.4	0.434783	0.47619	936.9	935	933.1
	Kendujhar	0.434783	0.5	0.588235	929.4	940	950.6
	Mayurbhanj	0.350877	0.37037	0.392157	941.6	945	948.4
	Baleshwar	0.384615	0.434783	0.5	946.25	945	943.75
	Bhadrak	0.384615	0.434783	0.5	936.9	944	951.1
	Kendrapara	0.434783	0.5	0.588235	932.4	939	945.6
	Jagatsinghapur	0.5	0.588235	0.714286	939.5	947	954.5
	Cuttack	0.47619	0.555556	0.666667	931.15	941	950.85
	Jaipur	0.416667	0.454545	0.5	940.25	943	945.75
	Dhenkanal	0.416667	0.47619	0.555556	919.05	938	956.95
	Anugul	0.392157	0.454545	0.540541	937.4	932	926.6
	Nayagarh	0.434783	0.47619	0.526316	923.65	932	940.35

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Khordha	0.465116	0.526316	0.606061	932.85	941	949.15
	Puri	0.47619	0.555556	0.666667	917.95	940	962.05
	Ganjam	0.392157	0.454545	0.540541	927.75	932	936.25
	Gajapati	0.322581	0.344828	0.37037	912.05	909	905.95
	Kandhamal	0.30303	0.333333	0.37037	893.5	899	904.5
	Baudh	0.333333	0.357143	0.384615	919.8	925	930.2
	Subarnapur	0.377358	0.4	0.425532	939.25	943	946.75
	Balangir	0.363636	0.37037	0.377358	920.55	931	941.45
	Nuapada	0.338983	0.344828	0.350877	928.25	927	925.75
	Kalahandi	0.333333	0.357143	0.384615	923.6	917	910.4
	Rayagada	0.322581	0.344828	0.37037	916.15	910	903.85
	Nabarangapur	0.289855	0.285714	0.28169	917.4	916	914.6
	Koraput	0.327869	0.333333	0.338983	925.1	912	898.9
	Malkangiri	0.294118	0.285714	0.277778	915.75	909	902.25
Punjab	Gurdaspur	0.454545	0.5	0.555556	967.4	957	946.6
	Kapurthala	0.487805	0.526316	0.571429	967.4	950	932.6
	Jalandhar	0.512821	0.555556	0.606061	970.05	955	939.95
	Hoshiarpur	0.47619	0.526316	0.588235	960.6	957	953.4
	Sahid Bhagat Singh Nagar	0.487805	0.526316	0.571429	974	948	922
	Fatehgarh Sahib	0.487805	0.526316	0.571429	960.55	956	951.45
	Ludhiana	0.465116	0.5	0.540541	962.2	957	951.8
	Moga	0.454545	0.5	0.555556	962.55	937	911.45
	Firozpur	0.384615	0.416667	0.454545	957.85	952	946.15
	Muktsar	0.416667	0.454545	0.5	955.95	939	922.05
	Faridkot	0.444444	0.47619	0.512821	958.55	949	939.45
	Bathinda	0.444444	0.47619	0.512821	950.85	951	951.15
	Mansa	0.416667	0.47619	0.555556	946.05	941	935.95

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Patiala	0.454545	0.47619	0.5	964.15	947	929.85
	Amritsar	0.416667	0.47619	0.555556	962.95	958	953.05
	Rup Nagar	0.465116	0.526316	0.606061	974.6	953	931.4
	Sangrur	0.434783	0.47619	0.526316	945.95	944	942.05
Rajasthan	Ganganagar	0.338983	0.4	0.487805	945.35	944	942.65
	Hanumangarh	0.327869	0.37037	0.425532	942.85	906	869.15
	Bikaner	0.25	0.277778	0.3125	945.1	948	950.9
	Churu	0.266667	0.30303	0.350877	941.4	946	950.6
	Jhunjhunun	0.30303	0.357143	0.434783	946.1	950	953.9
	Alwar	0.246914	0.277778	0.31746	934.25	943	951.75
	Bharatpur	0.222222	0.243902	0.27027	935.55	940	944.45
	Dhaulpur	0.196078	0.222222	0.25641	927.1	934	940.9
	Karauli	0.222222	0.243902	0.27027	925.45	934	942.55
	Sawai Maghopur	0.253165	0.285714	0.327869	928.45	937	945.55
	Dausa	0.240964	0.27027	0.307692	931.3	932	932.7
	Jaipur	0.298507	0.344828	0.408163	939.15	954	968.85
	Sikar	0.289855	0.333333	0.392157	943.1	952	960.9
	Nagaur	0.266667	0.30303	0.350877	935.15	937	938.85
	Jodhpur	0.246914	0.27027	0.298507	938.8	944	949.2
	Jaisalmer	0.188679	0.208333	0.232558	936.6	944	951.4
	Barmer	0.188679	0.204082	0.222222	928.05	942	955.95
	Jalor	0.215054	0.243902	0.28169	916.95	939	961.05
	Sirohi	0.235294	0.263158	0.298507	926.75	930	933.25
	Pali	0.25641	0.294118	0.344828	923.85	929	934.15
	Ajmer	0.289855	0.3125	0.338983	932.2	928	923.8
	Tonk	0.27027	0.3125	0.37037	929.65	932	934.35
	Bundi	0.28169	0.322581	0.377358	927.8	938	948.2

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Bhilwara	0.273973	0.30303	0.338983	919.85	922	924.15
	Rajsamand	0.277778	0.30303	0.333333	918.8	925	931.2
	Dungarpur	0.238095	0.25641	0.277778	922.25	933	943.75
	Banswara	0.222222	0.238095	0.25641	921.3	910	898.7
	Chittaurgarh	0.30303	0.357143	0.434783	921.35	928	934.65
	Kota	0.327869	0.384615	0.465116	948.25	949	949.75
	Baran	0.273973	0.30303	0.338983	926.3	932	937.7
	Jhalawar	0.277778	0.3125	0.357143	927.8	938	948.2
	Udaipur	0.263158	0.285714	0.3125	926	924	922
Sikkim	North District	0.357143	0.454545	0.625	945	954	963
	West District	0.357143	0.47619	0.714286	937.5	948	958.5
	South District	0.377358	0.526316	0.869565	948.5	954	959.5
	East District	0.47619	0.588235	0.769231	946.5	953	959.5
Tamil Nadu	Thiruvallur	0.555556	0.588235	0.625	964.2	961	957.8
	Chennai	0.740741	0.714286	0.689655	953	963	973
	Kancheepuram	0.555556	0.588235	0.625	966.2	957	947.8
	Vellore	0.540541	0.555556	0.571429	956.95	954	951.05
	Tiruvannamalai	0.5	0.526316	0.555556	957.75	953	948.25
	Viluppuram	0.487805	0.5	0.512821	956.65	955	953.35
	Salem	0.571429	0.625	0.689655	952.3	952	951.7
	Namakkal	0.625	0.666667	0.714286	946.65	954	961.35
	Erode	0.666667	0.714286	0.769231	961.05	955	948.95
	The Nilgiris	0.689655	0.769231	0.869565	961.85	960	958.15
	Dindigul	0.588235	0.625	0.666667	954.6	937	919.4
	Karur	0.588235	0.625	0.666667	962.4	957	951.6
	Tiruchiappalli	0.588235	0.625	0.666667	963.85	957	950.15
	Perambalur	0.526316	0.555556	0.588235	955.65	924	892.35

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Coddalore	0.526316	0.588235	0.666667	964.2	961	957.8
	Nagapattinam	0.571429	0.625	0.689655	963.05	960	956.95
	Thiruvarur	0.606061	0.666667	0.740741	969.65	951	932.35
	Thanjavur	0.606061	0.666667	0.740741	972.4	959	945.6
	Pudukkottai	0.540541	0.588235	0.645161	973.5	963	952.5
	Sivaganga	0.571429	0.625	0.689655	959.65	958	956.35
	Madurai	0.588235	0.625	0.666667	952.35	956	959.65
	Theni	0.588235	0.625	0.666667	954.3	939	923.7
	Virudhunagar	0.571429	0.625	0.689655	954.3	948	941.7
	Ramanathapurm	0.540541	0.625	0.740741	972.25	961	949.75
	Thoothukkudi	0.588235	0.625	0.666667	948	960	972
	Tirunelveli	0.555556	0.588235	0.625	969.3	957	944.7
	Kanniyakumari	0.666667	0.714286	0.769231	980.3	969	957.7
	Dharmapuri	0.444444	0.526316	0.645161	954.4	933	911.6
	Krishnagiri	0.434783	0.5	0.588235	968	939	910
	Coimbatore	0.645161	0.714286	0.8	955.45	964	972.55
Tripura	West Tripura	0.47619	0.526316	0.588235	946	951	956
	South Tripura	0.408163	0.434783	0.465116	936	942	948
	Dhalai	0.357143	0.357143	0.357143	931	930	929
	North Tripura	0.37037	0.384615	0.4	928.5	932	935.5
Uttar Pradesh	Saharampur	0.266667	0.285714	0.307692	927.65	929	930.35
	Muzaffarnagar	0.246914	0.27027	0.298507	936.55	930	923.45
	Bijnor	0.243902	0.277778	0.322581	933.5	924	914.5
	Moradabad	0.222222	0.25	0.285714	931.4	923	914.6
	Rampur	0.217391	0.243902	0.277778	922.05	928	933.95
	Jyotiba Phule Nagar	0.227273	0.25641	0.294118	929.05	926	922.95
	Meerut	0.277778	0.30303	0.333333	940.4	938	935.6

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Baghpat	0.27027	0.285714	0.30303	943.3	939	934.7
	Ghaziabad	0.277778	0.30303	0.333333	946.65	935	923.35
	Gautam Buddha Nagar	0.25	0.277778	0.3125	964.05	939	913.95
	Bulandshahr	0.243902	0.263158	0.285714	933.2	927	920.8
	Aligarh	0.238095	0.25641	0.277778	923.45	927	930.55
	Mahamaya Nagar	0.240964	0.25641	0.273973	924	937	950
	Mathura	0.235294	0.25641	0.28169	943.2	927	910.8
	Agra	0.273973	0.285714	0.298507	942.7	936	929.3
	Firozabad	0.235294	0.27027	0.31746	926.75	930	933.25
	Mainpuri	0.246914	0.27027	0.298507	937.45	922	906.55
	Budaun	0.196078	0.212766	0.232558	900.45	915	929.55
	Bareilly	0.232558	0.27027	0.322581	923.95	921	918.05
	Pilibhit	0.235294	0.277778	0.338983	917	921	925
	Shahjahanpur	0.224719	0.243902	0.266667	907.15	921	934.85
	Kheri	0.232558	0.25641	0.285714	927.85	918	908.15
	Sitapur	0.227273	0.243902	0.263158	911.25	913	914.75
	Harcloi	0.222222	0.238095	0.25641	908.3	916	923.7
	Unnao	0.27027	0.30303	0.344828	926.6	924	921.4
	Lucknow	0.357143	0.4	0.454545	945.55	941	936.45
	Rae Bareli	0.266667	0.3125	0.377358	928.8	926	923.2
	Farrukhabad	0.243902	0.25641	0.27027	917.85	928	938.15
	Kannauj	0.243902	0.263158	0.285714	923.5	930	936.5
	Etawah	0.27027	0.294118	0.322581	933.75	939	944.25
	Auraiya	0.263158	0.285714	0.3125	932.55	935	937.45
	Kanpur Dehat	0.263158	0.294118	0.333333	928.25	932	935.75
	Kanpur Nagar	0.416667	0.454545	0.5	964.2	938	911.8
	Jalaun	0.294118	0.322581	0.357143	925.55	944	962.45
	Jhansi	0.327869	0.37037	0.425532	939.5	939	938.5

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Lalitpur	0.222222	0.243902	0.27027	915.3	923	930.7
	Hamirpur	0.266667	0.30303	0.350877	938.05	935	931.95
	Mahoba	0.253165	0.294118	0.350877	934	932	930
	Banda	0.232558	0.25	0.27027	928.3	928	927.7
	Chitrakoot	0.208333	0.227273	0.25	919.75	927	934.25
	Fatehpur	0.246914	0.277778	0.31746	929.15	924	918.85
	Pratapgarh	0.273973	0.322581	0.392157	935.2	932	928.8
	Kaushambi	0.246914	0.232558	0.21978	912.05	915	917.95
	Allahabad	0.263158	0.294118	0.333333	906.6	920	933.4
	Bara Banki	0.235294	0.263158	0.298507	921.8	915	908.2
	Faizabad	0.273973	0.30303	0.338983	932.75	928	923.25
	Ambedkar Nagar	0.273973	0.322581	0.392157	930.4	931	931.6
	Sultanpur	0.25974	0.30303	0.363636	932.2	934	935.8
	Bahraich	0.204082	0.217391	0.232558	919.15	920	920.85
	Shrawasti	0.215054	0.222222	0.229885	912.7	918	923.3
	Balarampur	0.208333	0.212766	0.217391	900.7	922	943.3
	Gonda	0.232558	0.25641	0.285714	919	932	945
	Siddharthnagar	0.206186	0.217391	0.229885	912.4	927	941.6
	Basti	0.240964	0.277778	0.327869	927.95	933	938.05
	Sant Kabir Nagar	0.227273	0.25641	0.294118	926.9	936	945.1
	Maharajganj	0.229885	0.27027	0.327869	907.6	923	938.4
	Gorakhpur	0.273973	0.333333	0.425532	943.75	941	938.25
	Kushinagar	0.240964	0.277778	0.327869	933.75	925	916.25
	Deoria	0.25974	0.30303	0.363636	931.05	944	956.95
	Azamgarh	0.253165	0.294118	0.350877	923.4	943	962.6
	Mau	0.25	0.294118	0.357143	943.1	933	922.9
	Ballia	0.289855	0.322581	0.363636	960.6	940	919.4
	Jaunpur	0.263158	0.30303	0.357143	922.65	934	945.35

			LTFR			ISR	
States	**District**	**2006**	**2011**	**2016**	**2006**	**2011**	**2016**
	Ghazipur	0.25641	0.285714	0.322581	943.75	930	916.25
	Chandauli	0.246914	0.277778	0.31746	927.1	943	958.9
	Varanasi	0.28169	0.333333	0.408163	927.1	936	944.9
	Sant Ravidas Nagar	0.25	0.277778	0.3125	912.8	923	933.2
	Mirzapur	0.235294	0.263158	0.298507	921.3	922	922.7
	Sonbhadra	0.229885	0.25641	0.289855	929	931	933
	Etah	0.222222	0.243902	0.27027	913.05	925	936.95
West Bengal	Darjiling	0.540541	0.625	0.740741	947.2	957	966.8
	Jalpaiguri	0.408163	0.47619	0.571429	934.05	951	967.95
	Koch Bihar	0.377358	0.434783	0.512821	931.05	953	974.95
	Uttar Dinajpur	0.266667	0.3125	0.377358	942.6	944	945.4
	Dakshin Dinajpur	0.37037	0.47619	0.666667	927.95	948	968.05
	Maldah	0.289855	0.344828	0.425532	927.95	942	956.05
	Murshidabad	0.322581	0.37037	0.434783	936.05	947	957.95
	Birbhum	0.377358	0.434783	0.512821	945.6	951	956.4
	Bardwan	0.487805	0.555556	0.645161	952.95	956	959.05
	Nadia	0.487805	0.588235	0.740741	944.05	958	971.95
	North Twenty Four Parganas	0.540541	0.625	0.740741	944.95	956	967.05
	Hoogly	0.555556	0.625	0.714286	966.1	962	957.9
	Bankura	0.425532	0.47619	0.540541	953.3	962	970.7
	Puruliya	0.344828	0.37037	0.4	953.4	960	966.6
	Howrah	0.512821	0.555556	0.606061	960.65	959	957.35
	Kolkata	0.769231	0.833333	0.909091	940.5	946	951.5
	South Twenty Four Parganas	0.384615	0.454545	0.555556	941.6	952	962.4
	Paschim Mednipur	0.434783	0.5	0.588235	955.15	960	964.85
	Purba Medinipur	0.434783	0.5	0.588235	956.8	957	957.2

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Is India experiencing health convergence? An empirical analysis

Sulekha Hembram[1] · Sushil Kr. Haldar[2]

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Abstract
A comprehensive study on health convergence based on beta (β), sigma (σ) and club convergence is attempted here across 26 Indian states over time using NFHS (1–4) data. We formulate an overall health index (OHI) from three sub-health dimensions like child, reproductive and general health based on selected health indicators. The results show that the states are improving in respect of OHI; there exist absolute $\boldsymbol{\beta}$ convergence in respect of OHI and its sub-dimensions; however, we find $\boldsymbol{\sigma}$ divergent in respect of OHI and its sub-health dimension indices except child heath index. The club convergence based on kernel density provides a clear picture about stratification, polarization and uni-modal distributions of states in respect of OHI; over time states are converging to a steady state at higher value of OHI, but in the long-run there exists 'low level health trap' among five major states like UP, MP, Rajasthan, Bihar and Assam. Except Rajasthan, all the four major states remain at the lower level in respect of sub-health dimensions too. These five major states roughly account for 50% of India's population, and more than 50% of India's future demographic dividend will emerge from these major states. Therefore, in order to reap the benefits of demographic return, a major investment in human capital is urgently needed. Such 'low level health trap' justifies the 'big push' theory to health. This analysis can be applied at the sub-state level for policy intervention.

Keywords Health inequality · Convergence · Kernel density · Markov process of probability transition · Panel data regression · India

JEL Classification C10 · C18 · C46 · 110 · I14

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RESEARCH PAPER

Regional convergence of social and economic development in the districts of West Bengal, India: Do clubs exist? Does space matter? An empirical analysis using DLHS I–IV and NFHS IV data

Sulekha Hembram[1] · **Sohini Mukherjee**[1] · **Sushil Kr. Haldar**[2]

Abstract

The present study attempts to explore the progress of social development [captured by Social Development Index (SDI)] across 17 districts of West Bengal over five time points (during 1998–1999 to 2015–2016) using District-Level Household Survey (DLHS I–IV) and National Family Health Survey (NFHS IV) data. The inequality of SDI and its components are found to be declining but the income [measured by per capita district domestic product (PCDDP)] inequality is found to be fluctuating over time. Thus, the inequality of social and economic development does not move in the same direction. The distribution dynamics of SDI is captured by kernel density function over five time points that clearly gives twin peaks distribution of SDI and ensures the possibility of 'club convergence.' Using the components of SDI, we employ K-means cluster; both kernel distribution and K-mean cluster confirm the existence of low-level trap found in four districts of West Bengal. We estimate Moran's Index and results suggest that SDI is more spatially dependent than PCDDP. This analysis may be helpful to understand the dynamics of social changes observed among the districts of West Bengal over time.

Keywords Social development · Cluster analysis · Kernel density · Low-level trap · Spatial dependence · Moran's Index

JEL Classification D63 · I0 · R13

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Article

Multidimensional Human Deprivation in India: Does Club Convergence Exist?

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Sushil Kr. Haldar[1], **Sulekha Hembram**[2] **and Suraj Das**[2]

Abstract

A new measure of multidimensional human deprivation index (MHDI) across 24 states (over 4 time points corresponding to NFHS 1, 2, 3 and 4) is suggested here using principal component analysis (PCA). We observe that our weighted MHDI is found to be consistent with the Human Poverty Index (HPI) and the Multidimensional Poverty Index (MPI) introduced by UNDP in 1997 and 2010, respectively. Though most of the states in India have been experiencing a decline of the incidence of MHDI, but club convergence clearly proves that five major states such as Rajasthan, Madhya Pradesh, Bihar, Uttar Pradesh and Odisha are found consistently to be stable in the higher group of MHDI. Lagged MHDI, human capital investments along with availability of infrastructure are the underlying factors of differential MHDI across states. Therefore, allocation of grants should consider these issues of chronic MHDI found in five major states in order to ensure regional balance, equity and social justice in our federal structure.

Keywords

Multidimensional human deprivation, club convergence, Markov chain, Kernel density, panel data regression

I. Introduction

India has been sharing about 17.5 per cent and 28 per cent of total world's population and multidimensionally poor respectively; 8 Indian states that have a similar number of poor as in 25 African countries are Bihar, Jharkhand, Madhya

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