INTER-DISTRICT INEQUALITIES IN PER CAPITA REAL INCOME: A STUDY OF ODISHA

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Abstract: There have been concerns about the spatial distribution of income as it forms enabling components of overall welfare. Income inequality is a source of concern not just from a social, but also from an economic point of view. Divergence in real incomes could result in socio-political and economic unrest. In view of this, whether the regions diverge or converge in terms of real per capita income over time is a question explored by many growth theorists. Disaggregated study using districts as the unit is limited due to lack of time series data on income and other socio economic indicators. In line with the neo-classical growth theory, this paper empirically examines whether the real per capita incomes have converged or diverged over 1999-00 to 2010-11 across 30 districts of Odisha. Our empirical findings reveal that though the inter-district regional income inequality in Odisha has widened but there is absence of any significant divergence in per capita income over the studied period. The conditional convergence results convey that availability of banking and education (schooling) facilities are crucial to the economic development of the State and reducing inequality. Decomposing Gini coefficient shows that Primary sector income has a slight equalizing effect on the distribution of total income whereas both the secondary and tertiary sector contributes to widening income inequality with tertiary sector income contributes most. The convergence rate at 1.68 per cent per annum will lead to 41years for the poorest districts to fill half the gap with the richest ones. The study has used spatial regression, Unit root test etc.

Keywords: About Convergence, District Level, Economic Growth, Regional Disparities.

Introduction: Inequality is a major concern among policy makers in India. The concerns of rise in regional income inequality in India post economic reform 1991 has been widely studied using state as the basic unit. There is a significant econometric advantage with district level data as districts are much more homogeneous in size than are the states themselves. Hence, a cross-sectional analysis with district level data avoids the problem of unevenness in the underlying size of the units represented by different observations within states.

The Raghuram Rajan Committee Report on Composite Development Index of States in 2013 has identified Odisha as the most backward state of the country. Though the state has been consistently progressing in achieving economic growth, it lags in many other aspects of social and human development indicators compare to other states. As the study aims at measuring the extent of income inequality and also targets to find the conditional variables/factors through which appropriate policy can be implemented to bridge the income inequality gap, the neo-classical growth approach scores over other inequality measuring indices in identifying conditional variables driving inequality among the economies and hence is useful in policy implementation purpose.

The structure of the rest of the paper is as follows. Section 2 provides compact state profile of Odisha. It also presents a comparison of basic socio-economic indicators of the state with India. Section 3 describes the theoretical background on which the study is based upon. It also provides reviews of literature relevant to the study. Research methodology and the description of data used are mentioned in Section 4. Methodology to test the convergence hypothesis, the nature and quality of the data, and the statistical techniques used are also discussed in this section. Section 5 presents the empirical findings of the study as well as its interpretations. Finally, the paper concludes with a brief discussion of the results in section 6. The last section has tried to provide a note on the limitations of the present study as well as the further scope.

State Profile:

Odisha: The recent transformation of the State's economy from agriculture base to an industry and service-oriented economy has put it on a high growth trajectory. In real terms at 2004-05 prices, the economy expanded at an average annual rate of 8.8

per cent during the 10th Five Year Plan and moderated to 7.1 per cent during the 11th plan and as per the advanced estimates, it expanded by 8.1 per cent during 2014-15 after a sluggish growth of 2.2 per cent in 2013-14 due to the adverse impact of the natural shocks and industrial recession during the year. The standard of living of people in Odisha has improved over the years with the rise in real per capita income. But the continuing gap in real per capita income between India and Odisha is a matter of concern. As per 2014-15 advance estimates, service sector[1] accounts for 51.2 per cent of the Gross State Domestic Product (GSDP), followed by industry (33.4 per cent) and agriculture (15.4 per cent). Among the districts, the share of Gross District Domestic Product (GDDP) to GSDP was highest for Sundargarh district (8.54 per cent), followed by Khurda (7.52 per cent) and Deogarh contributes least at 0.53 per cent. In 2010-11, the real per capita Net District Domestic Product (NDDP) at 2004-05 prices was highest in Jharsuguda (Rs 49,021) and lowest in Nabarangpur (Rs 14,700) district.

Disparity in social and economic factors is a common phenomenon in Odisha. The southern districts of Odisha including Malkanagiri, Nawarangpur, Nuapada, Gajapati, Kalahandi and Kandhamal etc. are considered to be the most underdeveloped districts in the country. The incidence of poverty remains high in Odisha. As per the Tendulkar Committee report, poverty in Odisha declined from 57.2 per cent in 2004-05 to 32.6 per cent in 2011-12 (21.9 pan India). The overall literacy rate in Odisha (73.5 per cent) was at par with the national average (74 per cent). The school dropout rates have come down sharply from 41.8 per cent in 2000-01 to 1.97 per cent in 2013-14 at primary level and from about 57 per cent in 2000-01 to 2.40 per cent in 2013-14 at upper primary level. There are several factors responsible for driving regional disparities and imbalances in Odisha. Some of the common causes believed to contribute to regional disparities in income and living standards are education, health, unemployment and caste, etc.

Theoretical Framework and Review of Literature: Convergence as implied by neo-classical growth model, (Solow, 1956 and Swan, 1956), advocates that countries with same population growth, savings rate and technology but with low capital-labour ratio grow faster than the countries with high capita labour ratio. In simple language, ceteris paribus, countries with low capital-labour ratio will 'catch up' with those with high capital-labour ratio in the long run. The whole idea of catch up is based on diminishing returns to capital. A rich economy will grow slower as diminishing marginal returns to capital set-in. Thus the economies with lower initial values of capital-labour ratios will have high marginal productivity of capital and therefore tend to grow at higher rates (Evans and Karras, 1996).

A large and burgeoning literature has already focused on the concept of existence and the factors supporting the convergence hypothesis in inter and intra country level. Barro (1991), Barro and Sala-i-Martin (1992, 1995) and Sala-i-Martin (1996) have tested the well-defined convergence hypothesis empirically. The two standard methods of examining the unconditional convergence are σ-convergence, where dispersion is measured through standard deviation of logarithm of per capita income across a group of regions and the second measure is β-convergence, where proportionate growth in income is regressed on initial income. There is β-convergence if the coefficient of initial income, denoted by β, is negative and statistically significant. A value of β in the range of $-1< \beta <0$ would be an evidence of β-convergence. Nearer the value of β to -1, higher the speed of convergence and nearer to 0, lower the speed of convergence. Also, zero β implies no convergence and a positive β indicates a divergence.

Studies among developed economies have supported the neo-classical convergence hypothesis. Barro and Sala-i-Martin (1992) got the evidence of β-convergence at 2 per cent rate across 48 states of USA. Armstrong (1995) too found the existence of convergence in per capita income across 85 regions in the European Union (EU), but at a low rate of 1 per cent per year. Similarly, Barro and Sala-i-Martin (1995) in their study of Japanese prefectures using data for 60 years have got the evidence of unconditional convergence. De la Fuente (2002) on Spanish regions over three decades from 1965 to 1995 got the evidence of convergence. Barro (2012) in an 80-country panel study since 1960 got the evidence of conditional convergence and the rate of convergence is around 1.7% per year. However, the convergence study on developing economies throws mixed result. Juan-Ramon and Rivera-Batiz (1996) got the evidence of convergence between 1970 and 1985, among Mexican states and divergence for the rest of the studied period (1986-1993). Similarly, the study based on provinces of China by Jian, Sachs, and Warner (1996) between 1952 and 1993 got the evidence of convergence from 1978 to 1990 and divergence in real per capita income thereafter.

Empirical evidence of the studies on Indian economy throws more interesting findings. However, the studies on the domestic economy can be broadly classified under three categories, unconditional convergence, conditional convergence and divergence. Chikte (2011) among Indian states has seen unconditional convergence in income during both pre (1970-90) and post liberalization period (1991-2005). Ghosh (2008) got the evidence of conditional convergence among Indian states using inter-state variation in human capital, production structures, and physical, social and economic infrastructure. Kar and Sakthivel (2007) study found that during post reform period, industrial sector contribution showed a rising trend along with a sharp rise in service sector contribution to overall inequality. Bandyopadhyay (2004) in studying convergence club using distribution dynamic approach found the evidence of 'twin peaks' and 'polarisation' in the early 90's among 17 major Indian states. Capital expenditures, education expenditures and fiscal deficits were seen to be robust conditional factors explaining formation of the upper convergence club and infrastructure strongly explained the formation of the lower convergence club. But comprehensive empirical analysis by Nayyar (2008) on a of 16 Indian states for the period 1978-79 to 2002-03 using dynamic panel with fixed effect framework got the evidence of unconditional divergence at the rate of 1.4 per cent per annum. After controlling for physical capital formation that includes both private and public investment and human capital, the study got the evidence of conditional convergence. Other studies including Bhattacharya and Sakthivel (2004), Trivedi (2003), Dholakia (2003), Sachs et al. (2002), Ahluwalia (2002), Nagraj et al. (2000), Rao, Shand and Kalirajan (1999), Rao and Sen (1997), Cashin and Sahay (1996) etc. have also got the evidence of conditional convergence though not absolute convergence.

The inter district literature on inequality are limited in India. Das, Ghate and Robertson (2015) using district-level income and socio-economic data for two years (2001 and 2008) explored the determinants of transitional growth at the district level. The evidence of absolute divergence across districts was observed at the first place. However, after controlling for district characteristics, particularly urbanization and the distance from a major urban agglomeration, evidence of conditional convergence was seen. Singh et al. (2014) has examined the role of physical infrastructure, financial development, and human capital in influencing regional patterns of growth among Indian states. The study didn't find any statistically significant indication of absolute convergence or divergence. On district level, credit-deposit ratio and literacy rate are seen to be the most important and robust conditioning factors across the states and not within the individual states driving convergence in income. Hatekar and Raju (2013) on Maharashtra got significant spatial spillover effects for both unconditional and conditional beta convergence.

Data and Methodology: Empirical literatures on studies on income inequality have used both income and expenditure data for India. But, there are significant differences between the two and studying inequality through income approach (Per capita income: PCI) is superior to the expenditure approach (monthly per capita expenditure: MPCE). Expenditure method (MPCE) always under-measures the difference between relatively wealthy and poor areas as compared to the PCI. The economic identity is said as, $Y = C + I + G$, and dividing both sides by population we get, $Y/N = C/N + (I+G)/N$. The question is whether to use Y/N or C/N? The difference is clear as by using C/N, we would miss out the term $(I + G)/N$, in other words, per capita savings (= per capita investment) and the Government expenditure. Additionally, MPCE in India are estimated in nominal terms (current prices) and the state level the inter-state price differentials are very high, sometimes ranges above 20 to 30 per cent and proper adjustment of price data among regions is difficult as the exact consumption basket information is not available.

Current study measures inter-district disparities in income for Odisha. Data of Per Capita Gross District Domestic Product (GDDPPC) at constant prices is taken for the period 1999-00 to 2010-11. As the district income over the studied period is mainly available under two different base periods, 1999-00 to 2004-05 is available at 1999-00 base and the rest is at 2004-05 base. For comparability purpose, the 2004-05 data series is rebased to 1999-00. The data used is annual in frequency and is collected from Directorate of

Economics and Statistics of the GoO. Financial, Physical and Human development related conditional variables are sourced from Census of India data base. Percentage of households having access to banking facility is used as proxy for financial sector development indicator. Availability of credit from the formal financial sources promotes economic growth and raises financial depth. The related information on percentage of households availing banking facility is taken from census database. We have used percentage of population attending schools as well as and female literacy rate as physical and human development indicators in the study as these variables explains many of the major trends and developments of our society. Population attending schools is one of the important indicator explains the utilization of formal schooling facility among people. This variable explains different story as compare to literacy rate. For 2001, percentage of population attending schools was recorded at 18.07% for Odisha as against a literacy rate of 63.1%. Female literacy as a variable explains the extent of gender gap in education in the state. As per the census 2011, an effective literacy rate for men was 81.59% whereas for women it was 64.01%. The effective literacy gap in the rural area stands at 18.91% (Male: 79.65% & Female: 60.74%) is much higher than urban area effective literacy gap of 10.30% (Male: 90.72% & Female: 80.42%). Females constitutes nearly 50% of state's human resource but females in total workforce stands at 31%, lower than male ratio of 69%. The data is sourced from Census of India data base.

The study has used both the neo-classical approach and standard index methodology in measuring inequality in income over the years. Moreover, neo-classical growth approach of convergence hypothesis is widely used to find out the conditional variables explaining growth and inequality. Some of the measures used in the study are as follows;

Following neo-classical approach, σ-convergence occurs if the dispersion which is measured through the standard deviation of the log of per capita income across a group of districts declines over time.

$$\sigma Log(PCY_{t1}) - \sigma Log(PCY_{t0}) < 0 \quad (1)$$

Where, PCYt1 stands for district per capita income at time t1; t1 >to

Kendall's Co-efficient of Concordance is used to measure the relative ranking of the districts over the years. To ascertain the stability or concordance between the rankings of the districts in different years the co-efficient of concordance has been computed. The co-efficient of concordance signifies the agreement of ranks over the entire period and for the sub-periods.

$$\emptyset_k(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{x - x_i}{h}\right) \quad (2)$$

With K columns and n items each and rank each column with 1 to n. Sum of ranks is computed as SRi for each row. Then $S = \Sigma(SR)^2 - n(\overline{SR})^2$. Where, $\overline{SR} = \frac{(n+1)k}{2}$ is the mean of all SR elements,

$$\chi^{2(n-1)} = k(n-1)W = \frac{S}{1/12kn(n+1)} \quad (3)$$

Where, $W = \frac{S}{1/12k^2(n^3-n)}$

The Kendall Coefficient of Concordance must lie between 0 and 1

While testing β-convergence in real per capita income among districts following neo classical growth approach, it becomes necessary to account for spatial spillover effects of economic activity. As it is well known that all places are related but nearby places are more related than distant places and moreover, social and physical phenomena are often highly clustered in space. Often OLS regression ignores these spatial relationships. Spatial regression models include relationships between variables and their neighboring values. The standard OLS assumptions may not always satisfy in reality in the presence of spatial effect as uncorrelated residuals and constant variance assumptions get violated. For the correct specification, the spatial structure of autocorrelation of residuals needs to be taken into account. In the spatial analysis process it is required to create a spatial weights matrix which provides a unified approach to incorporate the spatial configuration information and reflects the intensity of the geographic relationship between observations in a neighborhood. The simplest form tell that the element (i,j) of the spatial weight matrix, Wij=1, if the region i and j share a common border, and zero otherwise. Significant positive spatial autocorrelation indicates the clustering of similar values across geographic space while significant negative spatial autocorrelation indicates that neighbouring values are more dissimilar. We have used Moran's I statistic. The spatial weights matrix using Moran's I is computed as follows:

$$I = (p/s_0)\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij} X_i X_j / \sum_{i=1}^{p} X_i^2 \quad (4)$$

Where, ρ is the number of observations, Wij is the element in spatial weight matrix W corresponding to the region i and j, Xi and Xj are deviations from mean values for the region i and j, respectively. 'so' is the normalizing factor equal to the sum of the elements of the weight matrix, i.e., so= $\sum_i \sum_j W_{ij}$.

With, Ho : There is no spatial clustering. If the computed 'I' is larger than its expected value, the overall distribution of variable 'X' can be seen as being characterised by positive spatial autocorrelation and if the computed 'I' is smaller than the expected value, the overall distribution of 'X' is characterised by negative spatial autocorrelation. 'Moran's I' lies between -1 and +1.

In spatial regression, we assume that either the outcome in one region is affected by the outcome in neighbouring regions (a spatial lag model) or the outcome in one region is affected by unknown characteristics of the neighboring regions (a spatial error model).

Spatial Lag Model is a mixed spatial autoregressive process and written as;

$$y = \alpha + \beta X + pWy + \Omega \quad (5)$$

Where, 'X' being the vector of independent variables and y is the dependant variable, ρ is the spatial autoregressive parameter i.e., the coefficient estimated for the spatial lag. Wy is the spatially lagged dependent variable and W, the spatial weights matrix.

Spatial Error Model takes the form of a spatial autoregressive process in the error term.

$$Y = \alpha + \beta X + \varepsilon \quad (6)$$

Where ε= λWε+μ and λ denotes the spatial auto regressive parameter and μ represents a vector of homoscedastic and uncorrelated errors.

It is however, very important to know whether studied districts are converging to or diverging from the state average steady state path in terms of per capita income. The results obtained through cross sectional convergence regression has limited scope as it does not tell whether economies are following or not following a common steady state path of per capita income. To find out convergence clubs among economies, unit-root test under the time series framework is widely used. Under this framework, convergence requires per capita income differentials across economies to be stationary (Bernard and Durlauf, 1995; and Li and Papell, 1999).

Shorrocks (1982), Lerman and Yitzhaki (1985) and Stark, Taylor and Yitzhaki (1986) have suggested methods to decompose the Gini coefficient by income source. The decomposition method allows the calculation of the impact that a marginal change in a particular income source will have on inequality. Following the Shorrocks (1982), Lerman and Yitzhaki (1985), the Gini coefficient for total income inequality, G, can be represented as;

$$G = \sum_{k=1}^{K} S_k G_k R_k \quad (7)$$

Where;

- Sk represents the share of source k in total income
- Gk is the source Gini corresponding to the distribution of income from source k
- Rk is the Gini correlation of income from source k with the distribution of total income

A large income source may potentially have a larger impact on inequality. But, if income is equally distributed (G_k=0), it cannot influence inequality, even if its magnitude is large. In a simple way, if this income source is large and unequally distributed (S_k and G_k are large), it may either increase or decrease inequality, depending on which individuals, at which points in the income distribution, earns it. An unequally distributed income source leads to disproportionately flow of income towards those at the top of the income distribution showing positive and large R_k, its contribution to inequality will be positive. However, unequally distributed income source but targeting poor individuals may have an equalizing effect on the income distribution.

Empirical Results and Interpretation: Income inequality, measured by both indices as well as neoclassical approach has shown the evidence of rising disparity among the districts over the years but with different degrees. Following neoclassical approach, the σ-convergence has measured inequality at two different time points, 1999-00 and 2010-11. For all the thirty districts together, though the co-efficient widened but didn't give any evidence of divergence as the F-test for the null hypothesis that the variance of per capita income of 2000 is equal to the variance of capita income of 2011 is not rejected showing the differences in variance are not significant in both the years. Similar result was witnessed for the districts in the North and Central Odisha (Appendix 1).

However, the Southern part of the state has shown divergence of districts in per capita real income.

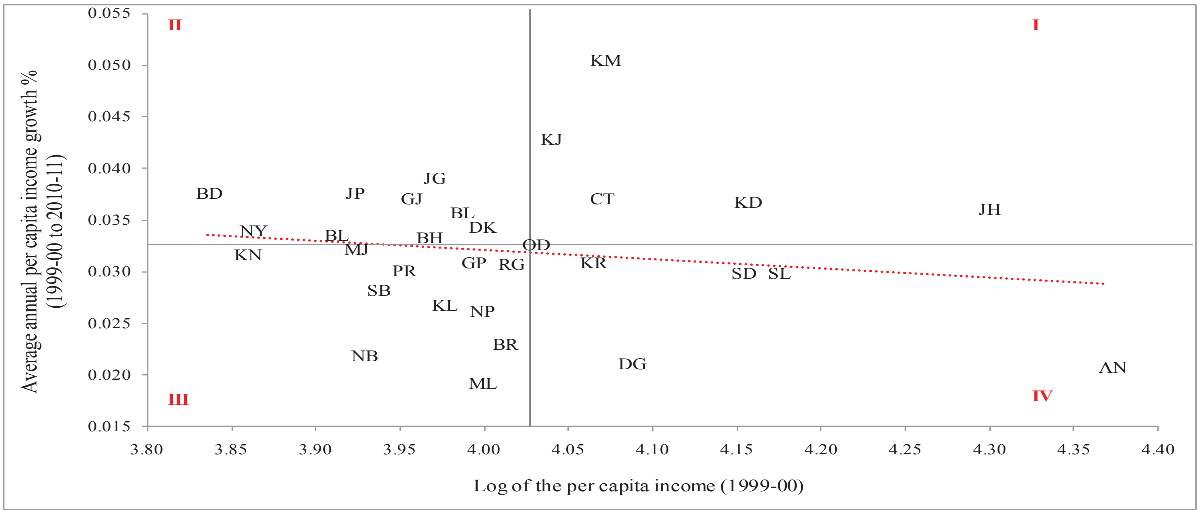
Economic and infrastructure developmental activities have lost momentum in the southern districts due to Maoist activities. Moreover, these areas are prone to natural disasters and many of these districts are dominated by tribal population. This clearly shows that economically weak districts including Boudh, Kalahandi, Malkangiri and Nabarangpur etc. have experienced twin shocks of rising population growth and lower economic performance compare to the other districts.

Table 1: σ-convergence for District Real Income of Odisha

Region	1999-00	2010-11	F-Stat	P-value
North (10)	0.143	0.141	1.034	0.961
South (10)	0.045	0.121	7.389	0.007
Central (10)	0.099	0.107	1.183	0.806
All (30)	0.120	0.128	1.125	0.753

Following the neo-classical growth hypothesis, average annual per capita income of districts from 1999-00 to 2010-11 is plotted graphically against the log of per capita income of 1999-00 to find any evidence of convergence in income across districts. To support convergence hypothesis, the graph should show negative relation between two variables, i.e., those districts which were poorer in 1999-00 grew significantly faster in per capita terms to catch up with their rich counterparts.

The total area of the graph is divided into four quadrants based on positioning of the state average. First quadrant (North-East-I) have the districts with high initial income and high economic growth whereas second quadrant (North-West-II) have those districts with low initial income and high economic growth. Third quadrant(South-West-III) have the districts with low initial income and low economic growth, and finally fourth quadrant (South-East-IV) have districts with high initial income and low economic growth. The four quadrant diagram plotted above provides a case of highly scattered districts. Most of the districts are clustered in the III-quadrant with low initial income and low economic growth and is mainly dominated by southern Odisha districts. The North-West quadrant shares the second position with having nine districts.



ig.1: Four Quadrant Diagram for Odisha

Note: Alpha codes for districts have been given in Appendix 1

This result goes along with neoclassical convergence hypothesis showing poor districts have grown faster. The North-East quadrant holds most economically prosperous districts of the state with high initial income and high economic growth. Central and North Odisha districts have dominated the space with exception of Kandhamal district. Kandhamal district that is mainly dominated by tribal population (52 per cent) and schedule caste population (17 per cent) in the top most quadrants seem to be questionable. But, it is mainly due to low density of population in the district which increased from 81 per sq. km in 2001 to 91 per sq. km in 2011, compare to state average population density of 269 per sq. km in 2011. Total population of the district to the state is only 1.7% and higher per capita income growth along with development of health and educational infrastructure has contributed to its significant positioning in the top most quadrant. The trend line is with a negative but statistically insignificant slope coefficient doesn't support the evidence of neither convergence nor divergence in real income. But, economically weak districts of 1999-00 including Bhadrak, Jagatsinghpur, Jajpur, Balangir, Ganjam and Dhenkanal have grown faster compared to rich ones in the studied period.

The kernel density function that is used to measure non-parametric estimate of the distribution of per capita incomes across districts show that over the whole period, income distribution has changed significantly for three years, 1999-00, 2005-06 and 2009-10. The plotted diagram below shows that there has been an increase in mean income in 2009-10 as compared to 1999-00 and 2005-06. The peak of the distribution has come down and the right-hand tail also has become flat. A rise in the per capita income is evident.

Fig. 2 . Kernel Density Function for Odisha (1999-00 to 2010-11)

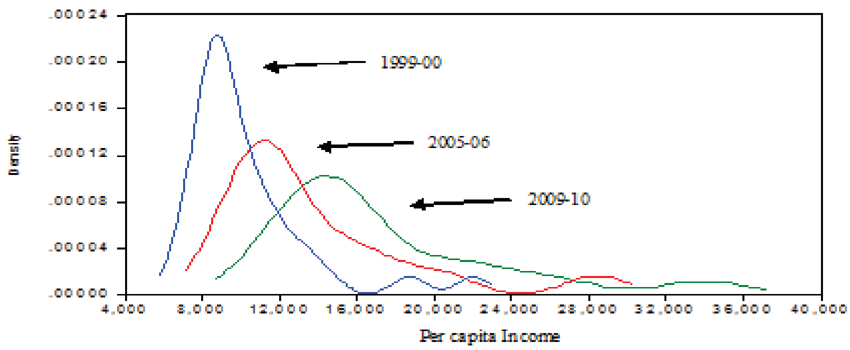


Fig. 2 . Kernel Density Function for Odisha (1999-00 to 2010-11)Per capita Income

Kendall's rank correlation is used to capture possible change in rankings of the districts during the two studied periods. The null hypothesis of independence in ranking between two time periods is rejected at 1% level. Kendall's tau statistic is recoded at 0.60, suggesting a high correlation of rankings among districts between both the periods. Districts have more or less maintained their rank over the studied period. Though the poor districts have performed better but at the same time the rich ones have maintained their growth.

Income inequality measured through indices has all shown the same widening inequality during the studied period. These measures are selected to measure variety of attributes of the income distribution. The Gini Coefficient is sensitive to changes across the distribution. It meets the criteria of mean independence, symmetry, independence from sample size, and Pigou-Dalton transfer sensitivity.

Gini and Theil indices are measures that rank the distribution of income with equal weights above and below the average. The Entropy index is most sensitive to changes at the lower end of the distribution. The Theil index is more balanced in giving weight across the distribution and is closer to the Gini in this regard. The Mehran Index gives higher weights to low incomes. The Kakwani Index is similar to the Gini, which is one minus the area under the Lorenz curve measuring the inequality in the distribution of income, except that the Kakwani Index squares the area under the Lorenz Curve so that larger values are given weights. The Gini coefficient is most widely used measure of inequality.

Table 2: Inequality Measures over the Years		
Measures	2000	2011
Entropy Index (GE (a), a=-1)	0.0389	0.0436
Entropy Index (GE (a), a=0)	0.0414	0.0451
Theil Index (GE (a), a=1)	0.0461	0.0483
Kakwani Index	0.0252	0.0272
Mehran Index	0.2071	0.2264
Atkinson Index	0.0406	0.0441
Gini Coefficient	0.1565	0.1687
Piesch Index	0.1312	0.1398

The index values brings out that all the inequality measures reported indicate a worsening of inequality over the years. Having found that inequality of income has worsened over the years, it would be relevant from a policy perspective to enquire whether inequality is pervasive in all sectors of the economy or whether it is confined to a few specific sectors. In other words, deciphering the sectoral pattern of inequality can help in identifying the sources of inequality.

Table 3: Gini Decomposition by Income Source

Source	S_k	G_k	R_k	Share	% Change
Primary	0.323	0.304	0.875	0.245	-0.078
Secondary	0.216	0.509	0.888	0.277	0.062
Tertiary	0.461	0.396	0.918	0.478	0.017
Total Income		0.351			

Decomposing Gini coefficient from income sources shows that 1 per cent increase in tertiary sector income, all else being equal, increases the Gini coefficient of total income by 0.017 per cent. Tertiary sector income is the largest share in total income (0.461) and is unequally distributed (0.396) and the Gini correlation between tertiary income and total income is the highest (0.918), compare to the other two sectors, indicating that tertiary sector income favours the rich more than any other income source. Similarly, 1 per cent increase in secondary sector income all else being equal, increases the Gini coefficient of total income by 0.062 per cent. Secondary sector income has the lowest share in total income (0.216) and is unequally distributed (0.509) and the Gini correlation between secondary income and total income is the second highest (0.888), indicating that secondary sector income favours the rich after tertiary sector. Whereas, the primary sector results are fairly different. One per cent increase in primary sector income (all else being equal), reduces the Gini coefficient of total income by 0.078 per cent. Primary sector income has a slight equalizing effect on the distribution of total income given that the primary sector income is second largest share in total income (0.323) and is unequally distributed (0.304).

Following Tobler (1970) first law of geography, "All places are related, nearby places are more related than distant places". To start with, Moran's I Statistic is used to find any spatial correlation among neighboring districts. The null hypothesis of a no spatial autocorrelation is rejected for per capita income growth and initial income level at 1% and 5% level of significance, respectively suggesting significant spatial effect among districts both in per capita income growth rate and initial income level. After identifying the presence of spatial dependence, we estimate the model with maximum likelihood approach while controlling for spatial dependence. The unconditional growth regression coefficient has come up with a negative but statistically insignificant 'β'.

Table 4: *Moran's I* Test

Variable	Moran's I Statistic
Log PCGDDP (2000)	0.070** (2.185)
PCGDDP growth	0.328*** (7.438)

*The numbers in parentheses are z-statistics; ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.*

This shows the absence of unconditional convergence in per capita real income across districts of Odisha. Both the lambda and the rho parameters are statistically significant at 1% level, showing the justification for using spatial model. The Lambda co-efficient for unconditional spatial error model and lag model recorded at 0.910 and 0.909 with z-statistics of 10.09 and 10.08, respectively and are statistically significant at 1% level in both the cases.

The conditional convergence hypothesis is tested using financial, physical and human development related indicators in our study. Spatial model is used to deal with both types of spatial dependence, namely spatial lag dependence and spatial error dependence. The conditional convergence test using lag model gives negative and statistically significant (1% level) co-efficient of the initial per capita income in the presence of conditional variables whereas, the coefficient of initial income for error model stands negative and significant at 5% level. However, though the LM test result of the lag model is higher than the error model but, both the models are statistically significant at 1% level. Given high squared correlation (0.725 against 0.412)) and log likely hood ratio (-13.933 against -17.175), spatial lag model best fits the model and is appropriate for our analysis.

Table 5: Spatial Regression Result of Unconditional β Convergence

Dependent Variable: *PCGDDP growth*	Constant	Log Initial PCGDDP	Variance Ratio	Squared Correlation	LM Test of Spatial Effects	Lambda/Rho
Spatial Error Model	4.22 (1.22)	-0.357 (-0.46)	0.004	0.042	18.753***	0.910*** (10.09)
Spatial Lag Model	2.82 (0.94)	-0.641 (-0.87)	0.149	0.695	21.221***	0.909*** (10.08)

*Note: The numbers in parentheses are z-statistics. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.*

It can be seen that, the sign of the convergence coefficient, 'β' is negative and statistically significant at 1% level and this has only become possible after allowing for various observable characteristics across districts. The Rho parameter shows the spatial dependence inherent in the data measuring the average influence on observations by their neighbouring observations is significant at 1% level. The financial development conditional variable i.e., percentage of households having access to banking facility that explains the financial depth or access to formal financial source of funding is seen positive and significant at 1% level, showing better access to banking facility promotes growth. The physical infrastructure indicator i.e., percentage of population attending schools is seen positively contributes to economic growth and is statistically significant at 5% level. To note, this indicator not only throws light on literacy, but the availability and utilization of school infrastructure facility in the district. Importantly, there is significant difference between the literacy rate and the percentage of population attending schools. For instance, the percentage of population attending school was 18.07 against a literacy rate of 63.08 per cent in Odisha in the year 2001. Population growth, low death rate and high birth rate some of the important factors explain the differences.

Table 6: Spatial Regression Result of Conditional β Convergence

Dependent Variable: PCGDDP growth	Spatial Lag Model	Spatial Error Model	OLS Regression
Constant	4.335* *(1.82)*	6.710** *(2.23)*	0.0967*** *(2.82)*
Initial PCGDDP	-0.0168*** *(-2.75)*	-0.0152** *(-2.02)*	-0.0248** (-2.76)
Percentage of Population attending School	0.0386** (2.45)	0.0360** (2.08)	0.0004* (1.83)
Percentage of Households having Banking Facility	0.035*** (3.93)	*0.031**** *(3.08)*	0.0005*** *(3.42)*
Female Literacy Rate	-0.028** (-2.37)	-0.027** (-2.13)	-0.0003 (-1.53)
Variance Ratio	0.511	0.169	F Stat: 5.12***
Squared Correlation	0.725	0.412	R-Squared: 0.45
LM Test of Spatial Effects	16.764***	5.120***	Root MSE: 0.005
Log Likelihood	-13.933	-17.175	Breusch-Pagan Chi^2: 1.61
Lambda/Rho	0.907*** *(9.81)*	0.887*** *(7.67)*	Prob Chi^2: 0.20

*Note: The numbers in parentheses are z-statistics. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.*

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The human development indicator i.e., female literacy rate is seen to be statistically significant at 5% level with negative slope coefficient. Though from a broader prospective, the negative coefficient of female literacy with growth raises a lot of questions, but micro analysis of the numbers at district level supports the negative coefficient. First, the ratio of female to total population for the state is 50% and the percentage of female workforce of total was limited at 32%. With women literacy rate at 64% (male: 81.6%), only 27.2% of females are a part of the work force (Male: 56.1%).

The negative coefficient of female literacy variable with the growth highlights that most of the benefits of female education is not realized for the growth of the native district. The outward migration rate [2] at district level is considerably high at 8.6%, with male and female migration rate [3] at 6.2% and 11.1%, respectively. Moreover, female migration population constitutes 63.5%[4] of the outward district migration. Digging down further shows that marriage is the main reason for female outward migration from the native district as 64% (12.9 lakh) of total female outward migrants out of (20.1 lakh) leave their own district after marriage, and only 3% move out for better employment, 1% for both education and business purpose. The benefit of female education is not getting materialised to the origin districts due to lack of employment opportunity and urbanization process. The individual districts get deprived from enjoying the benefits of female education as the post education employment of this segment of labour force is outside the native district. The conditional convergence test highlights the importance of education infrastructure (schooling) and availability of banking facility to households as vital indicators of growth. Facilitating and promoting these services is crucial to the economic development of the state. The speed of convergence at 1.68 per cent per annum shows that, the poorest district would take nearly 41 years to reach half of the income level of the rich one.

The cross-sectional convergence regressions do not provide any scope for identifying the districts that can be described as following or not following a common steady-state path of per capita income. It is, however, important to identify the districts, which are converging to or diverging from the state average steady-state path of per capita income. The primary objective of such an exercise is to examine convergence clubs. We have performed this, utilising unit-root test for convergence under the time-series framework. Club convergence is measured through per capita income differentials of each district to the average state per capita income by evaluating the particular univariate time series property. Convergence of a district's per capita income to the state average level requires its income differential to be stationary. Convergence club result obtained from PP test for null hypothesis of a unit root against the alternative hypothesis of stationarity is rejected for five districts only. The result suggest that while five districts (Balangir, Boudh, Dhenkanal, Jagatsinghpur and Nayagarh) share a common steady-state path with the state average, the remaining twenty five districts have been following steady-state paths which are different from the state average path.

Conclusions: Evaluating the trends in the convergence in per capita real income among districts of Odisha using newly available district income data from 1999-00 to 2010-11, the study has come with many interesting findings.

Disparity measured through σ-coefficient widened for all the districts, but didn't give any evidence of divergence. Similar set of results were observed for the districts in the north and central Odisha except the southern part that showed divergence. The four-quadrant diagrams revealed that lower income districts are mainly those where agriculture is the main occupation and moreover business centres, mining and industrial areas have maintained their high income growth status over the years. The districts having industry and services as main sectors have grown well over the years.

Convergence club result suggest that while five districts share a common steady-state path with the state average, the remaining twenty five districts have been following steady-state paths which are different from the state average path. Non-parametric estimates of the distribution of per capita incomes across districts using kernel density function have showed that for three years, 1999-00, 2005-06 and 2009-10, income distribution has changed significantly. With the expansion in per capita income, it is also observed that income distribution has improved to some extent. Rankings of the districts measured through the Kendall's rank correlation has shown that though the poor districts have performed better but at the same time the rich ones have maintained their growth pace.

The inequality indices including Entropy Index (GE (a), a=-1,0,1), Theil Index, Kakwani Index, Mehran Index, Atkinson Index, Gini Coefficient, Piesch Index have all shown a worsening of inequality over the years. Decomposing Gini coefficient from income sources shows that primary sector income has a slight equalizing effect on the distribution of total income whereas both the secondary and tertiary sector contributes to widening income inequality with tertiary sector income contributes most.

Evidence of neither convergence nor divergence is seen when we measured disparity through unconditional β-convergence. The Moran's I statistics gave the evidence of existence of spatial autocorrelation. The conditional convergence test using spatial lag model shows negative and statistically significant (1% level) co-efficient of the initial per capita income in the presence of conditional variables including availability of banking and schooling facility and female literacy rate. Among the conditional variables, the co-efficient for availability of banking facility that explains the financial depth or access to financial services is seen positive and significant

at 1% level indicating better access to financial services promotes growth and reduces income inequality. The importance of physical infrastructure, measured through percentage of population attending schools is reflected with a positive significant slope coefficient and contributing to growth significantly. The female literacy, though seems to be very important indicator for growth, but didn't give favourable result in support of convergence hypothesis. Rather the negative coefficient of female literacy variable with the growth highlights that most of the benefits of female education is not realized for the growth of the native district. The benefit of female education is not materialized to the origin districts due to lack of employment opportunity and gradual urbanization process. The individual districts get deprived from enjoying the benefits of female education as the post education employment of this segment of labour force is outside the native district. The half life theory suggested that with the convergence rate at 1.68 per cent per annum, poorest district would take 41years to fill half the income gap with the richest ones.

Present study has its importance as it looks into the income inequality patterns at district level, contributing to the empirical economic literature which looks into the validation of convergence hypothesis. Still the study in its present form has limited scope in advising appropriate policy at disaggregated level. Detailed analysis with inclusion of more conditional variables and addressing data insufficiency issue is the next challenge and further scope of the current study.

Appendix: Appendix 1:

Alpha Codes for Districts/State

North Districts	Code	Central Districts	Code	Southern Districts	Code
Angul	AN	Balasore	BL	Boudh	BH
Balangir	BL	Bhadrak	BD	Gajapati	GP
Bargarh	BR	Cuttack	CT	Ganjam	GJ
Deogarh	DG	Jagatsinghpur	JG	Kalahandi	KL
Dhenkanal	DK	Jajpur	JP	Kandhamal	KM
Jharsuguda	JH	Kendrapara	KN	Koraput	KR
Kendujhar	KJ	Khordha	KD	Malkangiri	ML
Sambalpur	SL	Mayurbhanj	MJ	Nabarangpur	NB
Subarnapur	SB	Nayagarh	NY	Nuapada	NP
Sundargarh	SD	Puri	PR	Rayagada	RG
Odisha			OD		

Appendix 2: List of Abbreviations

CSO	Central Statistical Office
CV	Co-efficient of Variation
EU	European Union
GDDP	Gross District Domestic Product
GDP	Gross Domestic Product
HDI	Human Development Index
IHDI	Inequality-Adjusted Human Development Index
NDP	Net Domestic Product
PCNDDP	Per Capita Net District Domestic Product
NDDP	Net District Domestic Product
NSDP	Net State Domestic Product
RBI	Reserve Bank of India
SDP	State Domestic Product
PCGDDP	Per Capita Gross District Domestic Product
PCY	Per Capita Income
GoO	Government of Odisha

Note:

1. CSO Classification
2. Outside district migration to total Population
3. Outside district female migration to total outside district migration
4. Female outside district migration to total outside district migration

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