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# EXAMINING CHANGES IN THE LEVEL AND SHAPE OF INCOME DISTRIBUTIONS IN INDIA, 2005-2012

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**Abstract:** Though Indian economy since 1980s has expanded very rapidly, yet the benefits of growth remain very unevenly distributed. This is corroborated while examining the panel data from the India Human Development Survey for 2005 and 2012. We find that Gini as a measure of income inequality has increased from 0.52 to 0.53 between 2005 and 2012. While, income inequality in rural area has increased from 0.49 to 0.52, in urban area, the same has increased from 0.47 to 0.49 during the same period. Adding to this, based on a recent distribution analysis tool, "ABG" the paper focuses on local inequality, which summarizes the shape of inequality in terms of three inequality parameters ($\alpha$, $\beta$ and $\gamma$) to examine how the income distributions have changed over time. Here, the central coefficient ($\alpha$) measures inequality at the median level, with correction parameters at the top ($\beta$) and bottom ($\gamma$). The results reveal that at the middle of distribution ($\alpha$), there is almost the same inequality in both the period, but the coefficients on the curvature parameters $\beta$ and $\gamma$ show that there is less inequality in 2005 at the extremes than in 2012 ($\alpha+\beta$ and $\alpha+\gamma$ are both smaller in 2005). Surprisingly, there is more inequality in rural India than its counterpart at both the extremes. Thus, this paper stresses the importance of inequality reduction in ending poverty and boosting shared prosperity in two core areas namely; progressive taxation and substantial social spending in education and health sectors compared to its present level.

**Keywords:** Income inequality, Isograph, Gini-coefficient, India

## I. Introduction:

Over the last decades, the world has witnessed impressive average gains against multiple indicators of material prosperity. For instance, gross domestic product (GDP) per capita in low- and middle-income countries has more than doubled in real terms since 1990. Today's globalization, like earlier globalizations, has seen growing prosperity alongside growing inequality. Countries that were poor not long ago, like China, India, Korea, and Taiwan, have taken advantage of globalization and grown rapidly, much faster than have today's rich countries (Deaton 2013).

But this progress is under threat from the scourge of rapidly rising inequality. A recent study reveals that the richest 1 percent now have more wealth than the rest of the world combined and it is more alarming that 'power and privilege is being used to skew the economic system to increase the gap between the richest and the rest'(OXFAM 2016). The poor and the middle class matter the most for growth via a number of interrelated economic, social, and political channels. Moreover, high and sustained levels of inequality, especially inequality of opportunity can entail large social costs. Entrenched inequality of outcomes can significantly undermine individuals' educational and occupational choices. Further, inequality of outcomes does not generate the "right" incentives if it rests on rents (Stiglitz 2012). Thus, reductions in inequality are important intrinsically and because they are associated with reductions in absolute poverty and greater sharing of prosperity.

Turning onto the trends in economic inequality globally (as measured through the global Gini index), there has been a long-term secular rise in interpersonal inequality. The industrial revolution led to a worldwide divergence in incomes across countries, as today's advanced economies began pulling away from others. However, in the late 1980s and

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early 1990s, the global Gini index began to fall. This coincided with a period of rapid globalization and substantial growth in populous poor countries, such as China and India. Nevertheless, the national inequality measured by the Gini index also increased steeply in a number of developing countries (World Bank 2016).

Against this backdrop, the objective of this paper, based on longitudinal household surveys, is to examine recent trends and dimensions of income inequality in India- the third largest economy in the world, after that of China and the United States. Needless to mention, at present, the seven largest emerging market economies - China, Brazil, Mexico, India, Indonesia, Turkey and Russia - are the key engine for the world economy. The IMF (2017), in its World Economic Outlook, projected that while the world growth is expected to rise from 3.1 percent in 2016 to 3.5 percent in 2017 and 3.6 percent in 2018, India country is expected to accelerate from 6.8 per cent to 7.2 per cent and further to 7.7 per cent during the same period. It further projected that 8 per cent growth in the medium-term is within reach and, thus would experience the highest economic growth resulting from the implementation of important structural reforms.

Needless to mention, it is indisputable that standards of living have improved for a significant share of India's poor during the period of rapid economic growth since the early 1990s. Even though a trend decline in poverty emerged around the early 1970s, the year 1991-92 – the benchmark year for economic reforms in India – stands out as the year of the great divide. There was a significant spurt in economic growth, driven by growth in the tertiary sector and to a lesser extent, secondary sector. The pace of poverty reduction also accelerated, with a 3-4 fold increase in the proportionate rate of decline in the post-1991 period (Dutt, Ravallion & Murgai, 2016). Nonetheless, India is the second (next to Russia) most unequal country in the world with the top one per cent of the population owning nearly 60% of the total wealth, according to Global Wealth Report 2016 compiled by Credit Suisse Research Institute.

In India, however, the inequality data collected most frequently and most systematically – by the National Sample Survey (NSS) – involve the distribution of expenditure on consumption rather than income. Even by this measure, studies show a significant increase in inequality both within and between urban and rural areas in the post-1991 period (Dutt & Ravallion, 2009). Furthermore, the NSS has a practice of oversampling the poor and under sampling the rich (often missing the super-rich altogether), so its survey results tend to understate the degree of inequality even of consumption.

Nonetheless, measures of inequality calculated, based on consumption in India is significantly lower than the actual degree of inequality in income. Because the rich tend to save a significant fraction of their income, while the poor tend to use all of their income – and often some borrowed money as well – for consumption, the distribution of consumption is considerably less unequal than that of income. An example of the degree to which measures of consumption inequality understate income inequality in India may be gauged by comparing estimates of the Gini coefficient for all-India consumption in 2004-05 (which was roughly 35%), as compared to an estimated Gini coefficient of 54% for all-India income calculated by the Indian National Council for Applied Economic Research (NCAER) from a household survey carried out in the same year (Weisskopf, 2016). A study by Banerjee and Piketty (2003) suggest that the gradual liberalization of the Indian economy did make it possible for the rich (the top 1 percent) to substantially increase their share of total income.

Adding to this, there are little evidences based on large-scale longitudinal household survey, especially in the context of India, in examining these three specific issues: (a) trends in the standard of living (in terms of distribution of income) and movements in inequality in recent years in rural and urban India, (b) how this growth has been shared among these households and, finally (c) the intensity and shape of inequality in these two geographic regions in the country.

The objective of our paper is to address the above mentioned three questions based on recent data. The remainder of this paper is structured in four parts. Section II provides details relating to data, definitions being used in the study and methodology. Here, we report a number of different inequality measures including recent ones. Section III focuses major findings. Section IV presents conclusions.

**II. Data, Definition and Methodology:**

**II.1. Data:**

This study uses the first nationally representative detailed income data for India from the 2004-05 and 2011-12 India Human Development Survey (IHDS). This survey was conducted by researchers from the National Council of Applied Economic Research (NCAER) and the University of Maryland.

In 2004-05, IHDS began as a multi-topic panel study of 41,554 house-holds from 33 states and union territories(excluding only the small populations living in the island states of the Andaman and Nicobar Islands and Lakshadweep) across 1,503 villages and 971 urban neighborhoods. The survey was designed to be nationally representative at its inception. In 2011–12, all of the 2004–05 households as well as any households separating from the root household but residing in the same area were selected for re-interviews. Comparison of IHDS data with other reputable data sources such as the Census, National Sample Surveys (NSS) and National Family Health Survey (NFHS) shows that the IHDS compares well with these sources on common items (Desai et al. 2010). For example, the NSS estimates poverty rate to be 37 per cent in 2004–05 and 22 per cent in 2011–12; IHDS estimates are similar at 38 per cent in 2004–05 and 21 per cent in 2011–12(Thorat et al. 2017).

IHDS2 reinterviewed 83 per cent of the original IHDS1 households that held 85 per cent of the Indian population—92 per cent of households in rural areas and 76 per cent in urban areas (*ibid*). Attrition was lower among larger, rural households, especially those who owned agricultural land. With an additional replacement sample of 2,134 households, IHDS –II has a sample size of 42,152 households. This has created a unique longitudinal or panel dataset, which provides a rich description of changes in the Indian society.

While looking at unweighted data at household level, it is observed that about 1 per cent of the total households in each of these two rounds is said to have reported negative incomes mostly owing to agricultural and business losses (461 and 452 HHs in 2004-05 and 2011-12 respectively). However, their consumption expenditures and household possessions resemble average households more than they do to other low-income households. Because of this incongruity, for income calculations in the remainder of the study, we exclude all households who have reported negative incomes.

**II.3. Methodology:**

**II.3.1. Overall Intensity & Population Class-wise Measures of Inequality:** The Gini coefficient is widely used to measure inequality in the distribution of income, consumption, and other welfare proxies. While the relative Gini coefficient is usually explained with the use of the Lorenz curve, there is an alternative way to understand it. Consider an economy composed of N individuals, with $\mathbf{y_i}$ referring to income (or expenditure) of the $i^{th}$ individual, with i = 1,2,..., N. Let $\boldsymbol{\mu = (1/N)\ \Sigma\ y_i}$ refer to the mean income in this economy. In the N individual economy under consideration, by arranging individuals in an increasing order of their income and then comparing two randomly picked incomes. Since there are $N^2$ possible pairs of incomes (including pairing of an income with itself), the expected value of the absolute difference between a random pair of incomes is given by

$$\overline{\mathbf{D}} = \frac{\mathbf{1}}{\mathbf{N^2}} \sum_{\mathbf{i=1}}^{\mathbf{N}} \sum_{\mathbf{j=1}}^{\mathbf{N}} \left| \mathbf{y_i} - \mathbf{y_j} \right| \text{------------------------------------} (1)$$

The relative Gini coefficient let's denote as $G^R$ - is defined as half of $\overline{\mathrm{D}}$ normalized by the mean of the distribution, μ:

$$G = \frac{\mathbf{1}}{\mathbf{2}\mu} \overline{\mathbf{D}} \text{------------------------------------} (2)$$

Further, a Gini coefficient can be decomposed in two different ways. First, if the total population is divided into a few classes(by sex, occupation, region, etc.), the Gini coefficient for the entire population can be decomposed into three components: (a) an intra-class component arising from income variations within each class; (b) an inter-class component arising from the differentials of mean incomes between classes; and (c) an overlapped component arising from the fact that poor people in a high-income class may be worse off than rich people in a low-income class. Second, for the total population, if per capita income can be divided into several sources (e.g. agricultural wage, non-agricultural wage, etc.), the Gini coefficient can be decomposed by income source.
Turning on to the first case,
.As this paper uses data from a longitudinal household survey in India, the classification of population is first made by a rural/urban division. The rural and urban sub-populations are then classified by region. As a result, the Gini coefficient is decomposed twice (two-tier decomposition). The decomposition is, however, based on exactly the same formula and principle. If one understands the first tier decomposition, one should be able to do the second tier decomposition. Let G denotes the Gini coefficient for the entire population under consideration. It can be decomposed into three components – intra-class, inter-class and overlapped as shown in Equation 3:

$$\mathbf{G = G_W + G_B + G_O} \text{ -----------------------------------------------(3)}$$

$G_W$ is the intra-class component of G. If there is no income inequality within each of the classes, $G_W = 0$. $G_B$ is the inter-class component of G. If the mean incomes of all classes are identical, $G_B = 0$. $G_O$ is the overlapped component of G. If the richest person in any low income class "I" is not better off than the poorest person in any high income class "J", $G_O = 0$. The relative contribution of $G_B$ to G has important implications for inter-class income inequality. If $G_B$ is small, inter-class inequality is small, and vice versa. Equation 3 is due to Pyatt (1976) who uses matrix algebra based on game theory to derive the Gini coefficient and its class components (for more detailed discussion, see Yao and Liu, 1996).

**II.3.2. Shape of Income Inequality:**

Through Gini coefficient, we can understand the intensity of inequality, but it does not help us in distinguishing the inequality at the top, middle and bottom level of income distribution. Assuming that we are dealing with income dynamics, like in our case, and it may turn out that this coefficient of both the periods is similar. Does it mean that there is no change in inequality at all? To answer this question, we need to examine the shape of inequalities at the local level. A pioneering work in this context has recently been made by Chauvel (2016). The author used the well-known Champernowne I – Fisk (CF) distribution (Champernowne, 1937, 1952; Fisk, 1961) as a baseline for local inequality analysis and accordingly, has proposed an ABG (α, β, γ) method of estimating three inequality parameters, compatible with the Pareto properties of the tails. In this method, the level-specific measures of inequality can be deducted from the CF hypothesis at the median but with additional curvature at the top and bottom of the distribution.

Here, the central coefficient (α) measures inequality at the median level with correction parameters at the top (β) and bottom (γ). In this approach, the magnitudes of ranks and incomes, defined by logit (quantile) and log (income), are (almost) linearly-related as given in the following equation:

$$\mathbf{M_i = \alpha X_i + \beta B(X_i)X_i + \gamma G(X_i)X_i} \text{ ---------------------------------(5)}$$

Where, $X_i$=logit ($p_i$)=ln[$p_i$/(1-$p_i$)] is the logit-rank, and $M_i$=ln($m_i$)=ln($y_i$/median) is the log of medianized incomes. On the other hand, B and G are two simple linear combinations hyperbolic tangent functions: $\theta_1 = \tanh(X/2)$ & $\theta_2 = \tanh^2(X/2)$ such that $B(X) = \frac{\theta_1(X) + \theta_2(X)}{2}$ & $G(X) = \frac{-\theta_1(X) + \theta_2(X)}{2}$.

Thus, individuals are defined by their logit (quantile) of income and their related B and G functions. The OLS linear regression proposed by Chauvel is easy to carry out and produces the estimates of the ABG parameters. For the detail derivation of the above equation pls. refer Chauvel's seminal work.

In the above decomposition, α, α + β and α + γ are the inequality measures at the median, top and bottom of the distribution, respectively. Besides this, Chauvel (2016) proposed the introduction of an ISO function that generalizes the quantile CF income distribution ($CF_\alpha$) given by:

$$M_i = \alpha \mathbf{X_i}, \quad where \quad M_i = \ln(\frac{y_i}{Median}) \quad \& \quad \mathbf{X_i} = \ln(\frac{p_i}{1-p_i}) ------------------- (6)$$

(where α measures the degree of inequality understood as the stretching out of the distribution curve) in to the form:

$$M_i = ISO(\mathbf{X_i})\mathbf{X_i}, \quad where \quad M_i = \ln(\frac{y_i}{Median}) -------------------------- (7)$$

$$Thus, \quad ISO(\mathbf{X_i}) = \frac{M_i}{\mathbf{X_i}}, \quad where \quad M_i = \ln(\frac{y_i}{Median}) ------------------------ (8)$$

However, the isograph representing ISO ($X_i$) is not a constant (due to the presence of B and G functions as shown in equation (5)) and expresses the intensity and the shape of local inequality. The higher is ISO ($X_i$), the greater the stretching out of incomes at the logit rank level $X_i$. The change in ISO ($X_i$) along the distribution measures "local inequality", which can be thought of as the local stretching of the distribution. The empirical isographs are horizontal lines that are often bent at the two extremes in different ways.

Most importantly, in equation (5)

(a) The coefficient α measures inequality close to the median;

(b) The coefficient β characterizes the additional inequality at the top of the distribution, β being positive when the rich are richer than in the $CF_\alpha$, so that the upper tail is stretched; and

(c) The coefficient γ characterizes the additional inequality at the bottom of the distribution, γ being positive when the poor are poorer than in the $CF_\alpha$.

(d) The signs of β and γ can be positive or negative and can move in opposite directions as well. Thus, there can be four possibilities:

(i) Type 1(When β +ve and γ –ve**)**: Rich are richer and the poor richer than under the CF. The isograph has a positive slope;

(ii) Type 2(When β +ve and γ +ve**)**: Rich are richer and the poor poorer, but the middle class is relatively homogeneous. The isograph has a U shape;

(iii) Type 3(When β -ve and γ -ve**)**: Rich are poorer and the poor are richer than under the CF. The isograph has an inverted-U shape; and

(iv) Type 4(When β -ve and γ +ve**)**: Rich are poorer and the poor are poorer. The isograph has a negative slope.

Thus, the above methodology will help us in examining contours of inequality in terms of both measurement and graphical representation in terms of isograph.

**III. Empirical Results:**

**III.1. Levels, Growth and Facets in Inequality of Income Distribution:**

The typical mean household income per capita has increased from Rs. 8,746 in 2004-05 to Rs. 23,831 in 2011-12 (henceforth the year 2005 and 2012 respectively). On the other hand, the median household income per capita has increased from Rs. 8,746 in 2004-05 to Rs. 23,831 in 2011-12. Further, a perusal mean and median per capita income reveal that whereas, the former got increased from Rs. 5,141 to Rs. 13,860 during the sample period. In terms of spatial income distribution by rural and urban areas, it is observed that whereas, the average mean and median growth of household income per capita in the former case was 24.4 per cent and 22.9 per cent respectively, the average mean and median growth of household income per capita in the latter case was 20.2 per cent and 18.0 per cent respectively (**Table 1**).

Table 1: The level and Growth of Household Income Per Capita (in Rs.)

| **Rural India** | **2004-05** | **2011-12** | **Urban India** | **2004-05** | **2011-12** | **All India** | **2004-05** | **2011-12** |
|---|---|---|---|---|---|---|---|---|
| Mean | 6711 | 18158 | Mean | 14953 | 36101 | Mean | 8746 | 23831 |
| Avg. Mean Growth Rate (%) | | 24.37 | Avg. Mean Growth Rate (%) | | 20.21 | Avg. Mean Growth Rate (%) | | 24.64 |
| Median | 4260 | 11085 | Median | 10000 | 22595 | Median | 5141 | 13860 |
| Avg. Median Growth Rate (%) | | 22.89 | Avg. Median Growth Rate (%) | | 17.99 | Avg. Median Growth Rate (%) | | 24.23 |
| S.D. | 12142 | 35777 | S.D. | 20176 | 50372 | S.D. | 14973 | 41799 |

Source: Author's calculation based on IHDS-I & IHDS-II data.

The distribution of household income per capita by quintile groups reveal that for the top quintile (i.e., for the 20 percent highest) group, it has increased from Rs. 25, 266 in 2005 to Rs. 70,197 in 2012 with an average growth of 25.4 per cent, whereas for the bottom quintile (i.e., for the 20 percent lowest) group, the mean household income per capita has increased from a mere amount of Rs. 1,675 in 2005 to Rs. 4,196 in 2012 with an average growth of 21.5 per cent (Table 2).

Table 2: Household Income Per Capita by Quintile Groups

| **Quintile Groups** | **Rural** | | | **Urban** | | | **Combined** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **2004-05** | **2011-12** | **Avg. Growth Rate** | **2004-05** | **2011-12** | **Avg. Growth Rate** | **2004-05** | **2011-12** | **Avg. Growth Rate** |
| Q1 | 1464 | 3501 | 19.87% | 3350 | 7771 | 18.85% | 1675 | 4196 | 21.51% |
| Q2 | 2905 | 7410 | 22.16% | 6396 | 14881 | 18.95% | 3350 | 8928 | 23.79% |
| Q3 | 4372 | 11376 | 22.89% | 10085 | 23054 | 18.37% | 5317 | 14212 | 23.90% |
| Q4 | 6917 | 18156 | 23.21% | 16103 | 37680 | 19.14% | 8914 | 23760 | 23.79% |
| Q5 | 18638 | 52482 | 25.94% | 39460 | 98579 | 21.40% | 25266 | 70197 | 25.40% |

Source: Same as Table 1

As mentioned above, percentile shares have become increasingly popular for the analysis of distributional inequality. Percentile shares quantify the proportions of total outcome (e.g. of average or total income) that go to different groups defined in terms of their relative ranks in the distribution. Since, they have an intuitive and appealing interpretation, before we interpret Gini coefficient for the analysis of income inequality over time, it is quite relevant to analyse of distributional changes in income through this measure.

Table 3: Share of Household Income Per Capita by Quintile Groups

| **Quintile Groups** | **Rural** | | **Urban** | | **Combined** | |
|---|---|---|---|---|---|---|
| | **Relative Share in 2004-05 (%)** | **Relative Share in 2011-12 (%)** | **Relative Share in 2004-05 (%)** | **Relative Share in 2011-12 (%)** | **Relative Share in 2004-05 (%)** | **Relative Share in 2011-12 (%)** |
| 0-20 | 4.27 | 3.77 | 4.44 | 4.27 | 3.76 | 3.46 |
| 20-40 | 8.47 | 7.97 | 8.48 | 8.18 | 7.52 | 7.36 |
| 40-60 | 12.75 | 12.24 | 13.38 | 12.67 | 11.94 | 11.72 |
| 60-80 | 20.17 | 19.54 | 21.36 | 20.71 | 20.02 | 19.59 |
| 80-100 | 54.34 | 56.48 | 52.34 | 54.17 | 56.75 | 57.87 |

Source: Same as Table 1

The table above confirms the high inequality in India. We can see, for example, that the top quintile (i.e., for the 20 percent highest) group receive 57.9 per cent of the total of income, whereas the bottom quintile (i.e., for the 20 percent lowest) group only receive 3.5 per cent. Further, an examination of distribution of household income per capita reveals that inequality is more in rural India as compared to urban India irrespective of quintile groups. Taking our analysis, a step forward, percentile share densities have an intuitive interpretation. They indicate how much each member in a group gets (on average) in relation to the overall average (Jann, 2016).

As we see from Table 4 that average household income per capita of the lowest 10 percent in 2005 was only about 12.6 per cent of the overall average, whereas in 2012 it plummeted further to 11.3 per cent of the overall average. On the other hand, average household income per capita in the highest 10 percent group in 2005 was about 401 per cent of the overall average, whereas in 2012 was about 414 per cent of the overall average. We also see that about 70 per cent of people are below the equal distribution line (that is, receive below average per capita income).

Table 4: Percentile Share Densities: Average Household Income Per Capita as compared to the Overall Average by Decile Groups

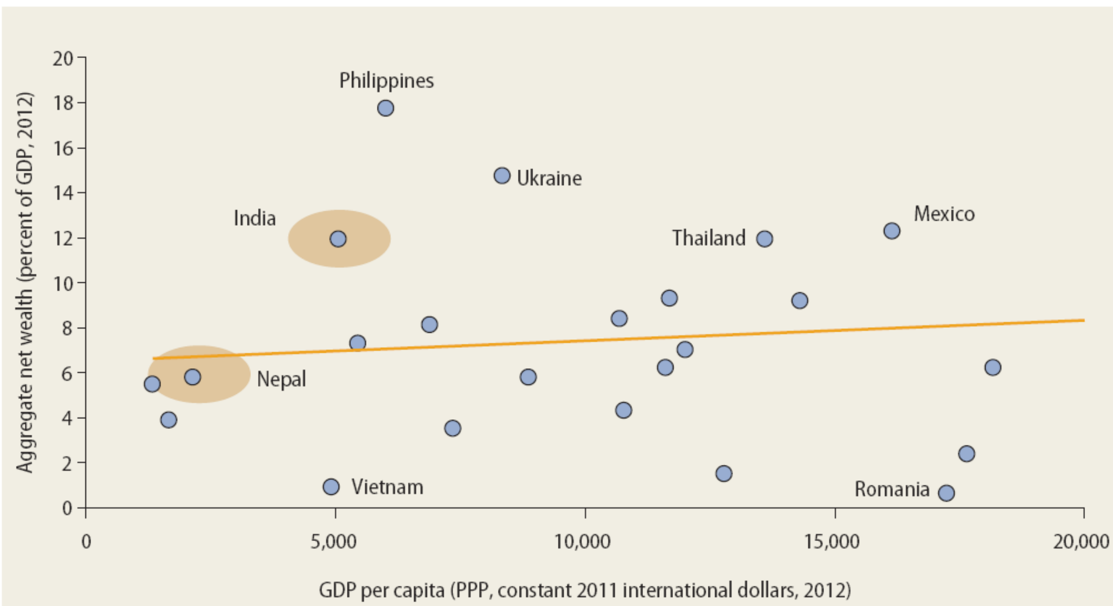
| **Decile Groups** | **Rural** | | **Urban** | | **Combined** | |
|---|---|---|---|---|---|---|
| | **2004-05** | **2011-12** | **2004-05** | **2011-12** | **2004-05** | **2011-12** |
| 0-10 | 14.17% | 12.24% | 16.27% | 15.41% | 12.61% | 11.31% |
| 10-20 | 28.53% | 25.44% | 28.17% | 27.30% | 25.01% | 23.29% |
| 20-30 | 38.16% | 35.07% | 37.17% | 36.20% | 33.25% | 32.30% |
| 30-40 | 46.54% | 44.67% | 47.67% | 45.58% | 42.00% | 41.32% |
| 40-50 | 57.08% | 54.76% | 59.53% | 56.41% | 52.88% | 52.01% |

| | | | | | | |
|---|---|---|---|---|---|---|
| 50-60 | 70.39% | 67.66% | 74.23% | 70.29% | 66.54% | 65.16% |
| 60-70 | 87.96% | 84.29% | 93.46% | 89.70% | 85.39% | 83.89% |
| 70-80 | 113.73% | 111.10% | 120.12% | 117.37% | 114.83% | 112.00% |
| 80-90 | 161.69% | 158.17% | 166.69% | 166.08% | 166.24% | 164.86% |
| 90-100 | 381.76% | 406.61% | 356.70% | 375.67% | 401.26% | 413.87% |

Source: Same as Table 1

A recent study reveals that the concentration of billionaire wealth appears to be exceptionally large in India. According to Forbes magazine (2014), total billionaire wealth represented about 10 percent of gross domestic product (GDP) in 2012. As such, India is an outlier in the ratio of billionaire wealth to GDP among economies at a similar development level (Figure 1).

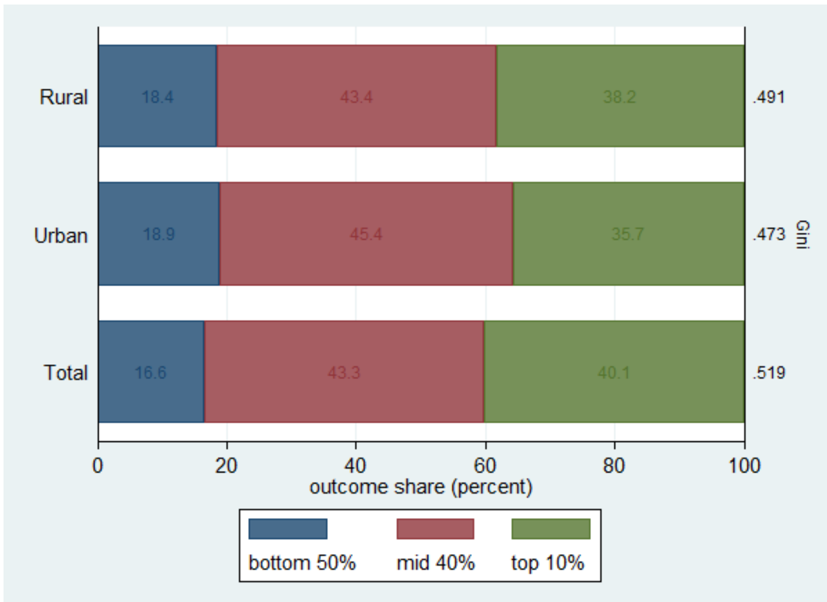
Figure 1: Billionaire wealth in India




Source: Based on Forbes magazine's billionaires database, http://www.forbes.com/billionaires/, and World Bank's WDI database, http://data.worldbank.org / data-catalog / world-development-indicators *cited in* Rama, Martín, Tara Béteille, Yue Li, Pradeep K. Mitra, and John Lincoln Newman. 2015. Addressing Inequality in South Asia. South Asia Development Matters. Washington, DC: World Bank.
Note: PPP = purchasing power parity.

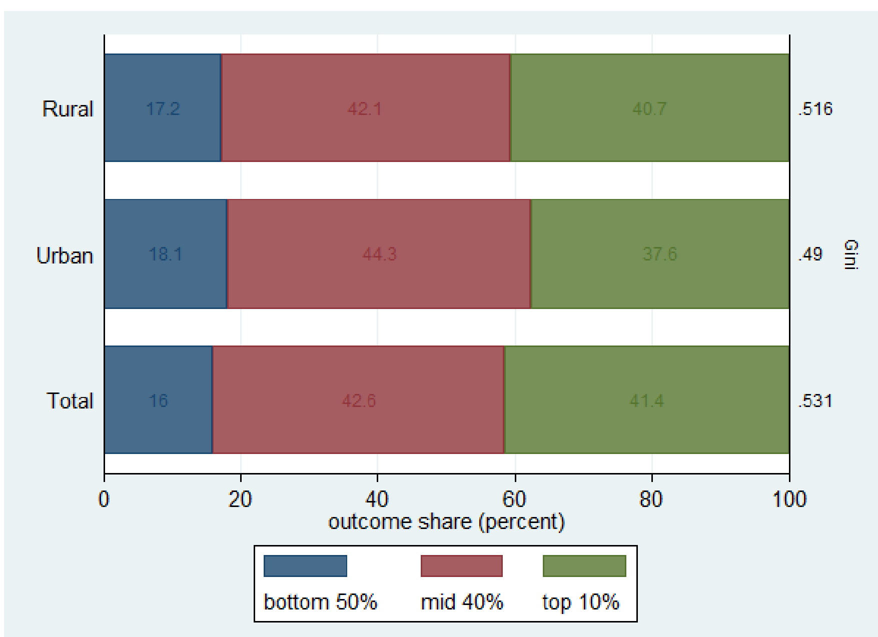
The final thing that we analysed here is the magnitude and trends in the per capita income Gini at the all-India level (and in rural and urban areas as well) during the sample study period. Figure 2 and Figure 3 show that the Gini coefficient has increased from 0.519 in 2005 to 0.531 in 2012. Moreover, it has increased steeper in rural areas (from 0.491 in 2005 to 0.516 in 2012 as compared to urban areas (from approximately, 0.473 in 2005 to 0.490 in 2012). The pattern of rising inequality at the aggregate and/or rural and urban level, is not only revealed by the Gini coefficient but also in terms of income share of select percentile groups, such as "bottom 50%" "mid 40%" "top 10%". For example, the Palma ratio of per capita income (top 10% share divided by bottom 40% share; see, e.g., Cobham et al., 2015) has increased from 3.56 to 3.82 at all-India level. Similar interpretations can be made for other select percentile groups.

Figure 2: Gini Coefficients with "bottom 50%" "mid 40%" "top 10%" Income Share in 2005




Source: Same as Table 1

Figure 3: Gini Coefficients with "bottom 50%" "mid 40%" "top 10%" Income Share in 2012




Source: Same as Table 1

### III.2. Shape of Inequality of Income Distribution:

It is often worthwhile in understanding the population's mobility across different income levels in different regions. The following table is helpful in this regard.

Table 5: Distribution of Population across Quintiles

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| **2004-05** | | | | | |
| Urban | 5.5 | 9.0 | 17.2 | 25.7 | 42.5 |
| Rural | 24.7 | 23.6 | 20.9 | 18.1 | 12.6 |
| Total(A) | 20.0 | 20.0 | 20.0 | 20.0 | 20.0 |
| **2011-12** | | | | | |
| Urban | 6.6 | 12.2 | 19.2 | 26.0 | 36.0 |
| Rural | 26.2 | 23.6 | 20.4 | 17.2 | 12.6 |
| Total(B) | 20.0 | 20.0 | 20.0 | 20.0 | 20.0 |
| **% Point Change** | | | | | |
| Urban | 1.1 | 3.2 | 2.0 | 0.3 | -6.6 |
| Rural | 1.4 | 0.0 | -0.5 | -0.9 | 0.0 |
| Total(C) | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

Table 3 analyzes the population distribution in India and its rural and urban areas across five quintiles of per capita income during the period under study. Each of the five columns denotes a quintile. Column 1 denotes the lowest, or first quintile, column *2* denotes the second quintile, and so forth.

All cells in row A or B have a value of 20, obtained by dividing India's entire population into five equal groups in terms of per capita income. Each group contains 20 percent of the population. The fifth quintile contains the richest 20 percent of the population, the fourth quintile consists of the second-richest 20 percent of the population, and so on, and the first quintile consists of the poorest 20 percent of the population.

Rows *2* and *3* report the population distribution in urban and rural areas for 2005 using the national quintiles. Consider the value 5.5 in the urban row. This value implies that 5.5 per cent of the total urban population falls in the first quintile. Similarly, 42.5 percent of the total urban population falls in the fifth quintile.

The picture is considerably different for the rural area, where only 12.6 per cent of the total rural population falls in the fifth quintile and 24.7 per cent falls in the lowest quintile. In 2012, the urban population share in the first two quintiles increased to 6.6 percent and 12.2 per cent respectively, but for the rural areas, while in the first quintile, the population share increased to 26.2 per cent, for the second quintile it remained the same at 23.6 per cent. In contrast, the rural population share in the two highest quintiles taken together has decreased in 2012 as compared to 2005, and likewise the urban population share in the two highest quintiles taken together, has decreased in 2012 as compared to 2005.

Another way of examining income distribution in India and its rural and urban areas is to compare average household income per capita as compared to the overall average by select percentile groups. As we see from Table 6 that average household income per capita of the lowest 10 per cent in 2005 was only about 12.6 per cent of the overall average, whereas in 2012 it plummeted further to 11.3 per cent of the overall average. On the other hand, average household income per capita in the highest 10 percent group in 2005 was about 401 per cent of the overall average, whereas in 2012 was about 414 per cent of the overall average. We also see that about 70 per cent of people are below the equal distribution line (i.e., percentage of population that, receive below average per capita income).

Table 6: Percentile Share Densities: Average Household Income Per Capita as compared to the Overall Average by Decile Groups

| **Decile Groups** | **Rural** | | **Urban** | | **Combined** | |
|---|---|---|---|---|---|---|
| | **2004-05** | **2011-12** | **2004-05** | **2011-12** | **2004-05** | **2011-12** |
| 0-10 | 14.17% | 12.24% | 16.27% | 15.41% | 12.61% | 11.31% |
| 10-20 | 28.53% | 25.44% | 28.17% | 27.30% | 25.01% | 23.29% |
| 20-30 | 38.16% | 35.07% | 37.17% | 36.20% | 33.25% | 32.30% |
| 30-40 | 46.54% | 44.67% | 47.67% | 45.58% | 42.00% | 41.32% |
| 40-50 | 57.08% | 54.76% | 59.53% | 56.41% | 52.88% | 52.01% |
| 50-60 | 70.39% | 67.66% | 74.23% | 70.29% | 66.54% | 65.16% |
| 60-70 | 87.96% | 84.29% | 93.46% | 89.70% | 85.39% | 83.89% |
| 70-80 | 113.73% | 111.10% | 120.12% | 117.37% | 114.83% | 112.00% |
| 80-90 | 161.69% | 158.17% | 166.69% | 166.08% | 166.24% | 164.86% |
| 90-100 | 381.76% | 406.61% | 356.70% | 375.67% | 401.26% | 413.87% |

Source: Same as Table 1

It may be noted that the mean and the median, two different measures of standard of living, are differently sensitive to the distribution of per capita income. Mean is more sensitive to extreme values, whereas median is more robust to extreme values. For example, if the only change in the distribution of per capita income is at the highest quintile or the lowest quintile, the change would be reflected by the mean, but the median would not change. In contrast, in certain situations, when changes occur in the middle of the distribution, mean per capita income may remain unaltered, but the median may reflect the change.

However, ABG (α, β, γ) method as mentioned above, addresses these issues with α, α + β and α + γ are the inequality measures at the median, top and bottom of the distribution, respectively. The results shown on the following table based on earlier discussed ABG (α, β, γ) method reveal that at the middle of income distribution, there is more inequality in 2005 as compared to 2012 and which is more prominently observed in urban area. On the other hand, the negative coefficients of β and γ values in both the years(2005 and 2012)  in urban India show that there is less inequality at the extremes than in the rural counterpart (α+β and α+γ are both smaller in Urban India). But, in urban area, there is an increase in inequality at the top end of income distribution during the study period and, in contrast, there is suggestive evidence of a decrease in inequality at the bottom of income distribution. On the other hand, in rural area, there is an increase in inequality at the top and bottom of social ladder than near the median during the reference period. Overall, a net increase in both α+β and α+γ values suggest increasing inequality in extreme ends meaning thereby a polarization in the society where rich are getting richer and poor are getting poorer.  In contrast, the net (small) negative coefficients on the parameter α shows there is a marginal decline in inequality at median income distribution at all-India level.

The above analysis can be corroborated with the help of Isograph-a tool which represents the diversity of local inequality over the income distribution- as represented in Figure 4. The higher the curve at a given level of X (logit rank), the greater are the income inequalities at this level (For more details, pls. refer Chauvel(2016)). As can be seen from the figure, there is more inequality in 2012 at the extremes than in 2005. In other words, the inequality measures at the top and at the bottom of income distribution is found to be more unequal in 2012 as compared to 2005.

Figure 4: The Isograph for India in 2004-05 vs. 2011-12

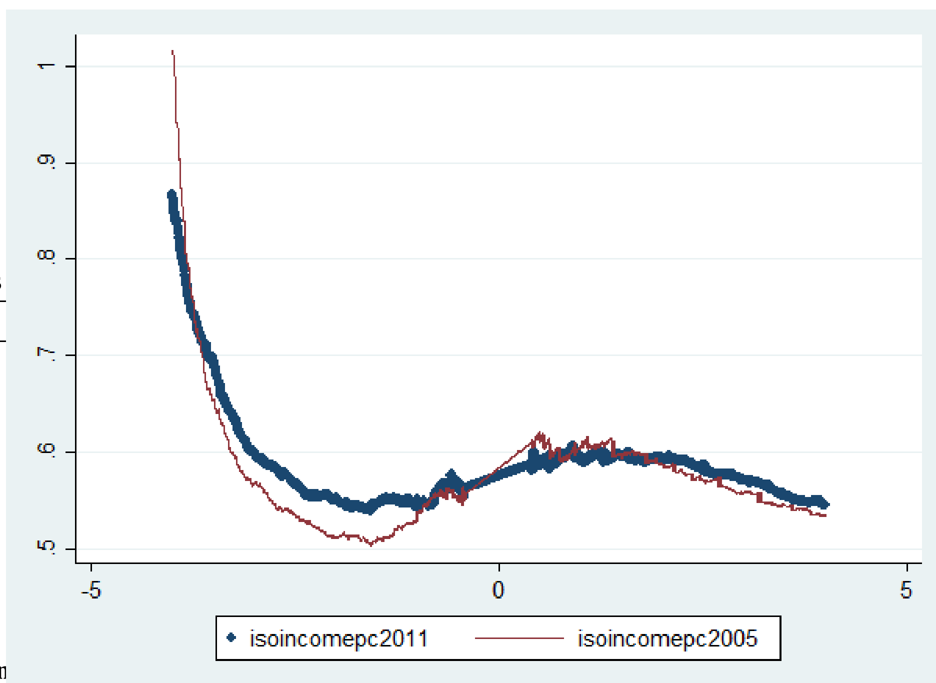



Table 7: Estimates

| Parameters | | | | α+β | α+γ |
|---|---|---|---|---|---|
| **2004-05** | | | | | |
| Urban | | | | 0.475 | 0.474 |
| Rural | | | | 0.554 | 0.558 |
| Total | | | | 0.590 | 0.526 |
| **2011-12** | | | | | |
| Urban | | | | 0.532 | 0.437 |
| Rural | | | | 0.585 | 0.611 |
| Total | | | | 0.602 | 0.577 |
| **Change in Paran** | | | | | |
| Urban | 0.003 | 0.055 | -0.039 | 0.058 | -0.036 |
| Rural | 0.001 | 0.030 | 0.053 | 0.030 | 0.053 |
| Total | -0.006 | 0.018 | 0.057 | 0.012 | 0.051 |

Note: Changes shown between years 2004-05 and 2011-12. All these parameters are statistically significant at 1% level.

**Note:** isoincomepc2011 and isoincomepc2005 represent Isograph based on per capita income in the year 2011-12 and 204-05 respectively.

## IV. Concluding Remarks:

The paper examines the trends, levels and shapes of income inequality in India between 2005 and 2012. The paper also uses Gini as a measure of inequality and finds that income inequality in rural India has increased from 0.49 to 0.52 between 2005 and 2012. On the other hand, income inequality in urban India has increased from 0.47 to 0.49 during the same period. However, this measure of inequality does not provide information on where the stroke is: at the bottom, middle, or top of the distribution.

To answer this, apart from examining incomes at certain points(in terms of percentile shares) in the distribution, we have used the ABG (α, β, γ) method which reveals that at the middle of income distribution, there is more inequality in 2005 as compared to 2012 and which is more prominently observed in urban area. On the other hand, the negative coefficients of β and γ values in both the years(2005 and 2012) in urban India show that there is less inequality at the extremes than in the rural counterpart (α+β and α+γ are both smaller in Urban India). But, in urban area, there is an increase in inequality at the top end of income distribution during the study period and, in contrast, there is suggestive evidence of a decrease in inequality at the bottom of income distribution. On the other hand, in rural area, there is an increase in inequality at the top and bottom of social ladder than near the median during the reference period. Overall, a net increase in both α+β and α+γ values suggest increasing inequality in extreme ends meaning thereby a polarization in the society where rich are getting richer and poor are getting poorer. In contrast, the net (small) negative coefficients on the parameter α shows there is a marginal decline in inequality at median income distribution at all-India level.

Thus, our research suggests that not only is income inequality very high in India, but also the shape of inequality matters a lot. The Government of India, in the last a few decades, is engaged in several concerted actions to address poverty: an ambitious economic reform agenda; announcement and allocation of resources for a range of social protection measures; and a strong commitment to good governance. Concomitantly, there is need to tackle growing inequality. From policy perspective, one way to mitigate inequality is for the state to step in social spending in education, healthcare, and generating a pool of skilled labour force so as to ensure employment and income security both in rural and urban areas and above all, progressive taxation in order to redistribute resources across society. Policymakers seeking to combat inequality overall also need to focus on ways to lift the incomes of the very poorest, to get them closer to the middle class, so as to contain the pace of social polarization.

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