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Inequality of Opportunity and Growth in India: A Dynamic Panel Estimation by Using New Measurement Methodology

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Inequality of Opportunity and Growth in India: A Dynamic Panel Estimation by Using New Measurement Methodology

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This study analyses the lack of robust conclusions about the association between inequality and economic growth. On the basis of ex-ante concept of inequality of opportunity, the parametric measure of unequal opportunity is used by partitioning the total sample in to 16 mutually exclusive circumstance groups. Theil's T index of monthly per capita consumption expenditure in household survey conducted by the NSSO in different rounds since the early 1980s is used to measure overall inequality and unequal opportunity. The relative index of inequality of opportunity is used as explanatory variable in the growth regression equation. To find out the direction of causality, we also estimate inequality equation by taking growth as an explanatory variable in presence of some control variables. Empirical findings of this study suggest that overall inequality and inequality of opportunity have negative effects on subsequent growth, while initial growth has no significant effect overall inequality and has a significant positive effect on inequality of opportunity.

JEL classification: D63, E24, O15, O40

Keywords: Income inequality, Inequality of opportunity, Growth

1.1 Introduction

The rise in inequality has been treated in the literature as one of the major contributors to rising economic insecurity (Alesina and Rodrik, 1994) and is intrinsically undesirable, particularly if it is originated from the differences in circumstances[1]. Inequality of opportunity is unfair in a sense that it is originated from circumstances that are beyond individuals' control and it has negative effect on growth (Mejia and St-Pierre 2008, Marrero and Rodríguez 2013). While an increase in inequality due to efforts like higher skill or risky entrepreneurship could boost economic growth, higher inequality because of circumstances has negative effect on growth. Inequality of opportunity has a decisive role in determining the shape of relationship between inequality and growth (Barro 2000, Berg et al. 2018). The

[1] Inequality is decomposed approximately into two parts: inequality due to efforts and inequality due to circumstances or inequality of opportunity.

objective of this study is to test this hypothesis empirically with micro level data from India.

The measurement of unfair inequality has been appealing recently in analysing growth-inequality relationship. But, measuring the sources of inequality is constrained by insufficient information in the household survey data. Inequality of opportunity has received relatively less attention in the growth literature mainly because of the difficulty in measuring it in an operational manner. This paper uses a simple alternative method to overcome this limitation in measuring inequality of opportunity and apply it to study the growth-effects of the components of inequality. Our approach is parametric and closely related to the methodology used in Ferreira and Gignoux (2011) and is motivated by the work of Marrero and Rodríguez (2013) who analysed the PSID database for the U.S. economy in 1970, 1980 and 1990 to find out the relationship between components of income inequality and growth. No attempt, however, has been made so far in finding out the role of unequal opportunities in analysing the relationship between inequality and growth in a transitional developing economy with household survey data. This study is an attempt in this direction by using household survey data from India.

We hypothesise that in a society where unequal opportunities act as binding constraints in getting quality education or quality job, income inequality dampens economic growth. Higher unequal opportunity creates misallocation of human capital on the basis of social stratification and has negative effect on growth. If there exists unequal access to education because of circumstances, for example, then human capital accumulation will be less that results in slower productivity growth. Similarly, unequal access to finance affects badly the investment opportunities among the lower strata resulting in lower economic growth. The adverse effect of unequal opportunity may even be greater in a transitional developing economy where majority of the population do not able to acquire sufficient skill through proper education and training needed for technological innovation.

Inequality of opportunity prevents utilisation of potential workers or entrepreneurs in full capacity in the production process and hence reduces potential output of an economy. It may be detrimental to the functioning of a market economy. This study attempts to quantify the effect of inequality of opportunity on economic growth. We measure the potential loss of output generated by the lack of opportunity because of people's backwardness in the society with survey data since the early 1980s by taking regional economies within India as macroeconomic units. Marrero and Rodriguez (2013) estimated the effect of inequality of

opportunity on growth by using the concept of inequality of opportunity developed in Roemer (1993) with the US data. In Roemer (1993), inequality of opportunity is the part of overall inequality which is determined by the circumstances, the factors beyond the individuals' control.

In this study, we use parent's education and social status as the circumstances to compute inequality of opportunity in household's consumption per capita at the regional level and then estimate the relationship between inequality of opportunity and economic growth. Estimated results indicate a negative relationship between inequality of opportunity and growth. The effect of unequal opportunity is observed to be so strong that relationship between overall inequality and growth becomes negative. Growth is positively correlated with human capital as expected, but is negatively correlated with the rise in proportion of urban population. The empirical results of this study fail to reject the hypothesis that higher the inequality of opportunity, more detrimental would be the impact of income inequality on growth.

The rest of the study is organised as follows: section 2 describes selected literature on unequal opportunity and growth. Section 3 deals with econometric methods used in this study. The measurement issues of inequality of opportunity have been highlighted, then it discusses why system GMM may be the appropriate method in estimating the relationship between growth and inequality. Section 4 is the description of survey data used in this study. Sampling distribution of households and consumption per capita are shown in section 5. Variation of unequal opportunity based on non-parametric measure across the state economies is discussed in section 6. Empirical relationship between growth and inequality is examined in section 7. Section 8 provides summary findings and major conclusions of this study.

2. Unequal opportunity and growth: selected literature

The barriers to access to quality education and employment because of the differences in social status, gender and parental background are associated with inequality of opportunity (Lucas, 1995) which requires compensations (Rawls 1971[2], Sen 1980[3]). Roemer (1993)

[2] The concept of primary goods as postulated in the second principle of justice put forward by John Rawls is related to the concept of basic opportunities. The *Difference Principle* in *A Theory of Justice* by Rawls highlighted that the optimal allocation of basic opportunities is beneficial for the least privileged.

[3] In Sen's (1980) terminology, more focus should be given on the distribution of those capabilities, not on the distribution of functionings.

popularised the concept by emphasising that individual's income or any other outcome variable depends on effort like investment in human capital or number of hours worked which are within the individual's control, and on circumstances like socioeconomic conditions which are beyond the individual's control. Bowles et al. (2005) pointed out that the likelihood to achieve higher education or access to employment of individuals with high inborn talent is affected badly by the circumstances. Easterly and Levine (1997) developed a theoretical model showing a negative impact of ethnic heterogeneity on growth. The theoretical framework by Gradstein and Justman (2002) shows how the racial and ethnic heterogeneity lower the effectiveness of education on growth. In the framework of Galor et al. (2009) distribution of land is highly determined by inequality of opportunity which has adverse effects on promotion of human capital through public schooling.

Unequal opportunity favours more the socially well-off people than the poor individuals with more talent for higher and quality education (Mejia and St-Pierre 2008). People with unfavourable initial circumstances have to face considerable barriers for accessing human and physical capital, regardless of their efforts. As productivity and wages are determined by the quality schooling of a person (Ferreira 2001), children of wealthy parents can earn more than those of the poor parents. The increase in return to education provides an incentive for people to invest in more years of schooling. But it is observed in many countries that young age people from relatively disadvantaged backgrounds are not able to take advantage of this incentive because their family background is playing an important role in educational attainment. Cingano (2014) argued that higher income inequality lowers skills among individuals with poorer parental education. Unequal opportunity reduces the opportunity of access to credit for human or physical capital formation causing misallocation of skill and other resources which have negative effect on growth.

Unequal access to investment opportunities and credit market imperfections can lead to persistent credit cycles and macroeconomic volatility that have effect on long term growth (Aghion et al. 1999). Inequality may also have effect on aggregate demand and ultimately on income growth (Voitchovsky 2009, Stiglitz 2012). Lower inequality enhances aggregate demand for output which is necessary for growth. Voitchovsky (2005) found that inequality at the top of the distribution is positively associated with growth, while inequality at the lower end is negatively associated with growth. This is because inequality at the top provides

incentives for investment and risk-taking, but inequality at the bottom results in lack of opportunities for educational investment by the poor. Inequality at the bottom of the income distribution is often associated with inequality of opportunity.

3. Econometric methods

3.1 Measuring inequality of opportunity

Suppose that we have a sample of agents indexed by $i \in S=\{1,\cdots, n\}$.

In our study an agent is a household and let y_i denotes monthly per capita household consumption expenditure, a proxy for income of household *i*. As there is no income information other than wage income in the survey data used in this study, per capita household expenditure is taken as a proxy for income. The *n*-dimensional vector *y* denotes the distribution of income in the sample.

Household income depends on circumstances (C_i) and efforts (E_i):

$$y_i = f(C_i, E_i) \qquad (1)$$

Circumstances include income generating inputs that are out of control of the individual, like gender, age, ethnicity, region of residence or parental background. By following Roemer (1993, 1998), let C_i be a vector of *k* elements, all of which are discrete with a finite number of categories:

$$C_i = \{C_i^1, \dots, C_i^k\} \qquad (2)$$

We consider parental education, and social status as circumstance variables (k=2). Parental education is categorised as no education, education level up to primary, secondary and higher secondary, and graduate and above. Social status includes four categories, namely, Scheduled Tribe (ST), Scheduled Caste (SC), Other Backward Castes (OBC) and Upper Castes (UC).

$$C_i^1 = (illiterate, primary, secondary, graduate)$$

$$C_i^2 = (ST, SC, OBC, UC)$$

Each circumstance is characterised by a realisation vector denoted as C_i^k. Based on the

realisation vector we can partition the sample into a set of *m* non-overlapping types (Roemer 1998),

$T = \{T_1,\ldots,T_m\}$.

In our sample,

$T_1 = (illiterat, ST)$

$T_1 = (primary, ST)$, and so on.

Here, $T_1 \cup T_2 \cup \ldots\ldots\ldots \cup T_m = S$,$T_l \cap T_h = \emptyset, \forall l, h,$

and $C_i = C_j, \forall i, j | i \in T_m, j \in T_m, \forall m$

Every person in a particular type has the same set of circumstances.

The maximum number of types will be,

$m = \prod_{k=1}^{K} n(C_i^k)$

In this study, $n(C_i^1)$ = 4, $n(C_i^2)$=4, therefore, m = 16

We have a sample of households characterised by the triplet (*y*, *C*, *E*) that can be partitioned into 16 mutually exclusive types.

The type specific income distribution represents the set of income which can be achieved by exerting different degrees of effort with the same circumstance. The type distribution is a representation of the opportunity set expressed in terms of income for any household endowed with given circumstances. Households in the same type have different outcomes but the same opportunity set.

If income distribution of type *m* is $y_i^m = f_m(y)$ and p_m is its population share in that type, the overall income distribution will be

$g(y) = \sum_{m=1}^{16} p_m f_m(y)$ (3)

The income set is partitioned by type as $y_i = (y_i^1, y_i^2, \ldots\ldots, y_i^{16})$

Inequality of opportunity is measured by the degree of inequality between types.

One approach to measure inequality of opportunity is to compute inequality index based on the counterfactual distribution of income obtained after the following transformation: $g(C, E) \rightarrow g(C, \bar{E})$

Van de gaer and Ramos (1993) and Checchi and Peragine (2010) proposed a measure of inequality in terms of a counterfactual distribution obtained by removing inequality within types from the original distribution.

The mean income of type *m*, $\bar{y}_m$, is used as a measure of the value of the opportunity set faced by the people in that type (Ferreira and Gignoux 2011). Inequality of opportunity presents if $\bar{y}_l \neq \bar{y}_h$, $\forall l, h \,|T_l \in T, T_h \in T$

Therefore, the inequality index, $I = I\big(g(C, \bar{E})\big)$ provides inequality of opportunity.

By following Ferreira and Gignoux (2011), in this study, inequality of opportunity is measured by "between group" component of the Generalised Entropy class of inequality index where groups are defined by the circumstances. As the Generalized Entropy (GE) class are additively decomposable into a between-group and a within-group component, we measure inequality by using Theil index. The Theil 0 index is decomposed as:

$$T(y) = T(\bar{y}) + \sum_{m=1}^{16} p_m T(y_m) \qquad (4)$$

The first component is the between-group inequality measuring inequality of opportunity while the second part is the within group inequality measuring inequality of effort.

Inequality of opportunity captures inequality among individuals with same degree of efforts. Therefore, inequality of opportunity can also be measured by calculating inequality index to the earning distribution at each quantile of the effort distribution and then aggregating the index across quantiles. This measure satisfies the symmetry, transfer, scale invariance, population replication, additive decomposability and path-independent decomposability axioms.

Efforts includes those factors on which individuals have control, and is represented by a vector,

$$E_i = \{E_i^1, \dots, E_i^l\}$$

Efforts not only depend on a person's exerts, but on circumstances and other background traits of the individual like ability, talent, luck, and so on.

Individuals sharing the same expression of effort form a tranche. The sample can be partitioned into *p* tranches: $\tilde{T} = \{\tilde{t}_1, \dots \dots . \tilde{t}_p\}$

Distribution of income in a particular tranche is obtained because of the differences in circumstances at a particular effort level, and thus provides a measure of inequality of opportunity. Equality of opportunity would be satisfied if individual outcomes are equal within each tranche, i.e. individuals with equal levels of effort exertion realise the same income. Roemer (1998) suggested to rank the individual in the type specific income distributions to measure the degree of individual effort. Two individuals of different types with the same rank of their relevant distributions have exerted the same effort, despite having different outcomes.

Let the level of effort exerted by the individual in type *m* at the q^{th} quantile of the distribution of effort is $E^m(q)$

We define the level of income of an individual in type *m* at q^{th} quantile as

$$y_m^q = f_m^q(y) = y_m\big(E^m(q)\big)$$

This is known in the literature as the Roemer identification assumption.

To eliminate all the inequality between tranches, Checchi and Peragine (2010) suggested the following rescaling of the outcome of a generic individual of type *m* and tranche *p*

$$y_{m,p}^{\tilde{t}} \to \hat{y}_{m,p}^{\tilde{t}} = \frac{y_{m,p}^{t}}{\mu_p}\mu$$

Here μ_p is the mean income of tranche *p*.

The standardized income distribution: $y^{\tilde{T}} = \left(\hat{y}_1^{\tilde{T}}, \dots . . \hat{y}_i^{\tilde{T}}, \dots . . \hat{y}_n^{\tilde{T}}\right)$

Inequality in terms of the mean logarithmic deviation is

$$MLD\left(y^{\tilde{T}}\right) = \frac{1}{n}\sum_{i=1}^{n} ln\left(\frac{\mu}{\hat{y}_i^{\tilde{T}}}\right) \qquad (5)$$

While circumstances are exogenous, efforts can be influenced by circumstances. Therefore,

equation (1) can be written as

$$y_i = f\left(C_i, E_i(C_i)\right) \qquad (6)$$

In practice we do not observe the full set of circumstances *C*. Rather we observe the subset. To address this problem, the literature commonly resorts to parametric estimation approaches. Here, the researcher obtains the counterfactual distribution by estimating a Mincerian regression with circumstances as the sole right-hand side variables (Bourguignon et al., 2007; Ferreira and Gignoux, 2011):

$$y_i = \acute{C}_i\beta + \varepsilon_i \qquad (7)$$

The estimated variance of predicted income from this OLS regression will be the measure of inequality of opportunity (Ferreira et al. 2011). The standard version of the parametric approach assumes a linear impact of all circumstances and therefore neglects the existence of interdependencies and non-linearities in the impact of circumstances

In our proposed methodology we, first, regress household consumption on a set of effort variables like education (x_1) and work experience (x_2):

$$lnc_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + u_i \qquad (8)$$

Results from this regression suggest that household consumption is positively related to education and experience. The predicted household consumption (used as proxy for household income) based on equation (8) provides the part which is explained by the efforts. Therefore, the residual, $\hat{u}_i$,which measures the component of consumption unexplained by the efforts, is used to calculate Theil's index of inequality. This residual based approach incorporates the effects of all observed and unobserved circumstances on inequality.

We test its reliability and compare with the conventional nonparametric measure based on the baseline set of circumstances with household level survey data in India. Among the conventional measures we have chosen Theil index of inequality which is additively decomposable into a 'between group' and 'within group' components. In this approach, inequality 'between group' is treated as a proxy for inequality of opportunity, and inequality 'within group' as inequality of effort. The inequality between groups is unfair and is measured by using these methods in each region to display the spatial heterogeneity in inequality in India.

3.2 Estimating relation between growth and inequality

To find out the effects of overall inequality and inequality of opportunity on growth we have estimated separately the growth equation in reduced form with the balanced panel data by taking growth of per capita consumption expenditure (*c*) as dependent variable and lagged values of inequality index (y_1) and inequality of opportunity (y_2), and the lag dependent variable as explanatory variables along with a set of control variables (Z):

$$\Delta lnc_{it} = \delta_0 + \delta_1 y_{1it-s} + \delta_3 \Delta lnc_{i,t-s} + \delta_4 Z_{it-s} + u_{it} \qquad (9)$$

$$\Delta lnc_{it} = \delta_0 + \delta_2 y_{2it-s} + \delta_3 \Delta lnc_{i,t-s} + \delta_4 Z_{it-s} + u_{it} \qquad (10)$$

The control variables account for the share of population living in urban location (z_1) as a measure of urbanisation and the share of population having education level secondary and above (z_2) as a measure of human capital.

Similarly, to find out the possible effects of growth on inequality we have estimated the following equations:

$$y_{1it} = \delta_0 + \delta_1 y_{1it-s} + \delta_3 \Delta lnc_{i,t-s} + \delta_4 Z_{it-s} + u_{it} \qquad (11)$$

$$y_{2it} = \delta_0 + \delta_2 y_{2it-s} + \delta_3 \Delta lnc_{i,t-s} + \delta_4 Z_{it-s} + u_{it} \qquad (12)$$

$$u_{it} = \mu_i + \varepsilon_{it}$$

where μ_i denotes cross section specific fixed effect, and ε_{it} is random disturbance term following identical and independent distribution.

The OLS estimates of equations (9) to (12) would be biased due to the fact that the lagged dependent is correlated with the fixed effect in the error term. Fixed effects estimation also will not be appropriate because of inherent endogeneity problem. The use of within-region variability fails to solve the endogeneity problem. Whereas the OLS is biased, the fixed effects estimation will be inconsistent. One possible way to resolve the endogeneity problem is to use instrumental variables. The difference GMM could be used to eliminate the fixed effects by using longer lags of the regressors as instruments. The difference GMM transforms all regressors by differencing them and uses as instruments to improve efficiency. It is assumed that the first differences of instrument variables are uncorrelated with the fixed

effects. In this method we have 2 sets of equations—the original equation and the transformed one—and is called the system GMM. As the time dimension in our dataset is not so long we have used the system-GMM method where an additional set of moment restrictions are used to combine the usual equation in first-differences using lagged levels as instruments, with an additional equation in levels, using lagged first-differences as instruments. This approach can reduce the problem of finite-sample bias (Blundell and Bond 1998, Blundell et al. 2000 and Bond 2002). The difference and system GMM estimators make fewer assumptions about the underlying data-generating process and use more complex techniques to isolate useful information.

The problem of heteroscedasticity and serial correlation is corrected by considering panel robust standard errors. We carry out the Sargan and Hansen test for joint validity of the instruments after GMM estimation. In addition, we test for autocorrelation in the idiosyncratic disturbance term to find out whether some lags are invalid as instruments. To test for autocorrelation, the Arellano–Bond test is applied to the residuals in differences. Although system GMM estimation is more preferred, it is not problem-free. Bontempi and Mammi (2012) suggested two approaches to limit the number of instruments in GMM estimation: i) collapse the instrument set, which makes the instrument count linear in time periods T, ii) apply principal component analysis to the instruments and limit the number of instruments by retaining components of the instruments with eigenvalues above a certain threshold. It is possible to apply these approaches by using the Stata command *xtabond2*. As the first-difference transform is affected by gaps in the panel data, orthogonal deviations transformation is used for robustness checks in the NSS data set.

4. Data

We use household level survey on employment and unemployment, and periodic labour force for 1983, 1993, 2004, 2011 and 2017 data collected by the National Sample Survey Office (NSSO). The cross-sectional survey of these rounds is roughly representative of the national, state, and the region level. It gathers information about demographic characteristics of household members, household consumption expenditure and many characteristics relating to labour market. Each survey round is segregated into four sub-rounds[4] covering the whole

[4] The sub-rounds are from July-September, October to December, January to March, and April to June. The number of sample villages and blocks are allotted for these surveys in each of these four sub-rounds are equal.

country excepting few regions[5]. A stratified multi-stage sampling has been adopted for the survey both in rural and urban areas[6].

As there is no income information in this database, per capita consumption expenditure is taken as a proxy for household income. There are 89 regional units in each survey round and by using these units as cross section over 5 time points we form a panel. In this dataset information on social status and parent's education are available and we use them as the observed set of circumstances. Parent's education is categorised into 4 groups: no education, education level up to primary, secondary and higher secondary, and graduate and above. Social status is a categorical variable with 4 groups: Scheduled Tribe, Scheduled Caste, Other Backward Castes and Upper Castes. On the basis of these observed circumstances, the sample is partitioned into 16 mutually exclusive and exhaustive groups of households.

Unequal opportunity appears when people living in the same society do not have access to the same opportunities in getting education, and job. Parents' education and social status are important in forming circumstance groups to calculate inequality of opportunity across the region. In estimating the relationship between inequality of opportunity and growth we have constructed region specific variables: inequality index, relative measures of inequality of effort and inequality of opportunity, share urban population as a measure of urbanisation, and share of population with education level secondary and above as a measure of human capital.

5. Distribution of population and consumption per capita by circumstances

In calculating inequality of opportunity we have considered parent's education and social status as circumstance variable. Table 1 shows population share and income share in the sample by each circumstance group over different periods since the early 1980s. The circumstance group with parent's education level secondary among other backward class has been dominating followed by the group with similar education level of the parents in higher castes. A mismatch is observed between population share and income share in the sample across the circumstance groups in every survey round indicating the persistence of inequality.

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[5] i) Leh(Ladakh) and Kargil districts of Jammu & Kashmir ii)interior villages of Nagaland situated beyond five kilometres of the bus route and iii) villages in Andaman and Nicobar Islands which remain inaccessible throughout the year

[6] The first stage units (FSUs) are villages for rural areas and NSS urban frame survey (UFS) blocks for urban areas. The ultimate stage units (USU) are households.

The mismatch is higher among the people with parent's education at higher level and is the highest among higher caste people. The higher caste people whose parent's education level graduate and above shared only 5.2 percent of the total population capturing 11.2 percent of total income in 2017. The distribution of population and income as shown in Table 1 clearly suggests that the incidence of overall inequality has been higher among the circumstance groups with higher parent's education.

Table 1 Population share and income share by circumstance group

Circumstance group	Population share					Income share				
	1983	1993	2004	2011	2017	1983	1993	2004	2011	2017
ST with no education	5.9	4.8	4.5	3.4	3.8	4.5	3.0	2.9	2.3	2.3
ST with primary education	3.0	3.0	3.9	3.5	3.1	5.3	2.6	3.3	2.6	2.3
ST with secondary education	1.1	2.1	3.7	5.0	5.7	1.6	2.5	3.9	4.7	5.7
ST with graduate and above	0.2	0.3	0.9	1.6	1.2	0.2	0.6	1.6	2.4	1.9
SC with no education	9.4	8.2	7.2	5.5	5.6	6.3	5.3	4.4	3.8	3.8
SC with primary education	3.7	3.8	4.4	4.1	3.6	3.5	2.9	2.9	3.0	2.8
SC with secondary education	1.4	2.3	3.7	4.6	6.2	2.0	2.2	3.1	4.0	5.5
SC with graduate and above	0.1	0.3	0.7	1.0	1.2	0.1	0.5	0.9	1.4	1.7
OBC with no education			12.6	10.4	10.0			9.1	8.3	7.0
OBC with primary education			11.4	10.2	8.2			9.4	8.8	6.8
OBC with secondary education			11.2	14.9	16.8			17.9	14.7	16.2
OBC with graduate and above			2.6	4.1	3.7			3.4	5.5	6.2
General caste with no education	31.0	24.0	7.5	5.8	5.5	27.3	18.4	6.6	5.6	4.4
General caste with primary education	23.5	21.8	8.4	6.4	5.4	21.0	19.9	7.9	6.3	5.1
General caste with secondary education	17.2	22.8	12.3	13.4	14.7	22.3	28.4	14.6	16.1	17.3
General caste with graduate and above	3.4	6.5	4.8	6.2	5.2	5.9	13.8	8.1	10.5	11.2

Source: Author's estimation with survey data

Table 2 displays Theil's inequality index based on per capita monthly consumption expenditure for all circumstance groups over different time points. The distributional pattern of inequality among the circumstance groups in different survey round is not similar. In 2017, inequality was the highest among schedule caste people with parental education graduate and above followed by other backward castes and higher castes people with similar parental background. Inequality in consumption per capita is low among the households with lower parental income.

Table 2 Theil index of inequality by circumstance group

Circumstance group	1983	1993	2004	2011	2017
ST with no education	1.27	0.14	0.18	0.21	0.14
ST with primary education	2.86	0.14	0.33	0.18	0.15
ST with secondary education	1.59	0.13	0.23	0.15	0.20
ST with graduate and above	0.22	0.15	0.54	0.16	0.19
SC with no education	0.49	0.14	0.14	0.17	0.13
SC with primary education	1.33	0.12	0.12	0.18	0.13
SC with secondary education	1.61	0.18	0.20	0.17	0.17
SC with graduate and above	0.19	0.23	0.15	0.26	0.25
OBC with no education			0.17	0.20	0.13
OBC with primary education			0.18	0.19	0.14
OBC with secondary education			3.75	0.20	0.17
OBC with graduate and above			0.16	0.20	0.23
General caste with no education	0.94	0.19	0.21	0.23	0.14
General caste with primary education	0.33	0.16	0.20	0.21	0.15
General caste with secondary education	0.67	0.20	0.22	0.20	0.19
General caste with graduate and above	0.21	0.26	0.23	0.22	0.23
Total inequality	0.87	0.25	0.89	0.23	0.23

Source: As for Table 1

6. Inequality of opportunity by states: non-parametric estimates

We decompose Theil's inequality index into within group and between group components by states in India over different survey periods between 1983 and 2017 which are displayed in Table 3. We have ignored smaller states with a very thin sample size and retain only the major states for meaningful comparison. The within group component is a measure of inequality of effort, while the between group component measures inequality of opportunity. The first component has been the dominating part for all states over the years. What is concerning is the significant increase in inequality of opportunity particularly during 2011 to 2017 in every region in India. The contribution of inequality of opportunity to total inequality increased at a significant rate in every states during this period. In some states like Jharkhand, Delhi, Assam and Bihar, inequality of effort also increased along with inequality of opportunity. The incidence of unequal opportunity varies widely across the Indian states. In 2017, the incidence of inequality of opportunity was the highest in Delhi followed by Jharkhand, Chhattisgarh and Orissa. In Delhi, more than 40 percent of total inequality was contributed by the difference in circumstances. The contribution of unequal opportunity to total inequality was high in West Bengal (34.8 percent), Orissa (34.6 percent), Chhattisgarh (33.3 percent) and Jharkhand (32.3 percent) during this period. These findings could be

explained partly by the differences in ethnic history and job distribution by social status across states in India. Wealth inequality, mainly in the form of land concentration between different social groups as inherited by the permanent settlement in the eastern part particularly in West Bengal and Orissa may be responsible for high contribution of unequal opportunity. While the contribution of unequal circumstances to overall inequality declined in many states during 1993 to 2004, the temporal progression of it was highly alarming everywhere during 2011 to 2017. In addition to economic growth, institutions and government policies might be responsible for the regional variation in temporal movement of inequality of opportunity and this issue deserves much more attention which is beyond the scope of this study.

Table 3 Inequality of effort and opportunity based on Theil index

Region	Inequality of effort					Inequality of opportunity				
	1983	1993	2004	2011	2017	1983	1993	2004	2011	2017
Andhra Pradesh	0.19	0.17	0.17	0.16	0.13	0.03	0.07	0.04	0.03	0.05
Assam	1.27	0.10	0.15	0.13	0.14	0.04	0.04	0.02	0.03	0.05
Bihar	2.04	0.13	0.13	0.12	0.13	0.05	0.05	0.03	0.02	0.03
Chhattisgarh			0.18	0.18	0.18			0.04	0.05	0.09
Delhi	0.18	0.15	0.12	0.14	0.16	0.03	0.06	0.06	0.06	0.11
Goa	0.28	0.13	0.11	0.10	0.11	0.11	0.04	0.04	0.01	0.04
Gujarat	0.27	0.13	0.14	0.18	0.12	0.02	0.06	0.04	0.02	0.05
Haryana	0.32	0.17	0.15	0.16	0.15	0.04	0.03	0.04	0.05	0.06
Himachal Pradesh	0.13	0.26	0.14	0.15	0.14	0.03	0.10	0.02	0.02	0.04
Jammu & Kashmir	0.54	0.10	0.11	0.17	0.15	0.00	0.04	0.01	0.01	0.03
Jharkhand			0.14	0.15	0.21			0.04	0.03	0.10
Karnataka	0.74	0.15	0.17	0.20	0.16	0.04	0.07	0.03	0.03	0.06
Kerala	1.25	0.20	0.17	0.26	0.13	0.19	0.07	0.03	0.03	0.03
Madhya Pradesh	0.21	0.18	0.17	0.20	0.16	0.04	0.07	0.04	0.04	0.07
Maharashtra	0.31	0.22	0.20	0.21	0.19	0.05	0.09	0.05	0.04	0.08
Orissa	0.13	0.14	0.21	0.18	0.17	0.05	0.07	0.05	0.05	0.09
Punjab	0.17	0.29	0.18	0.16	0.12	0.02	0.03	0.05	0.03	0.05
Rajasthan	0.22	0.13	0.14	0.17	0.14	0.02	0.03	0.02	0.03	0.05
Tamil Nadu	0.55	0.20	0.17	0.20	0.13	0.09	0.07	0.06	0.03	0.04
Telengana					0.13					0.06
Uttar Pradesh	0.45	0.16	0.17	0.19	0.17	0.02	0.04	0.03	0.03	0.06
Uttarakhand			0.15	0.20	0.15			0.03	0.03	0.06
West Bengal	0.58	0.14	0.17	0.19	0.15	0.05	0.08	0.04	0.06	0.08
All India	0.83	0.19	0.84	0.20	0.18	0.04	0.06	0.05	0.03	0.06

Source: As for Table 1

7. Inequality of opportunity and growth

7.1 Causation from inequality to growth

The theoretical study as well as empirical findings provides the causality from inequality to growth. Inequality may influence growth through growth promoting incentives on the top of the income distribution and growth dampening effect of inefficient investment on the bottom. This is because the marginal propensity to save for profit income is higher than the propensity to save for wage income (Kaldor 1957, Pasinetti 1962). Inequality increases growth if it creates incentives for effort and risk-taking. If more returns are provided for more efforts or taking more risk inequality will rise, and the induced extra effort or risk-taking propels the economy forward. But inefficient allocation of investment, particularly in schooling, health, and entrepreneurship, because of inequality at the bottom reduces productivity and growth. The presence of capital market imperfections produces this growth reducing effect of inequality more serious by reducing the opportunity for borrowing and lending that causes lower marginal return on investment from both physical and human capital (Aghion et al. 1999, Belley and Lochner 2007). Credit market constraints prevent the poorer agents from investing as much in forming human capital. In a society like India with greater numbers of poor people, supply of unskilled workers would be higher possibly causing lower subsequent growth with the rise in inequality.

Empirical studies to capture the overall effect of inequality on growth are inconclusive (Voitchovsky 2009). Forbes (2000) and Li and Zou (1998) found positive effects of lagged inequality on growth. Table 4 presents the estimated results of the system GMM in a dynamic panel framework of the reduced form equations. Columns (1) and (2) depict the effects of overall inequality and inequality of opportunity on growth, while columns (3) and (4) show the effects of growth on overall inequality and inequality of opportunity with full set of available instruments. The lower panel of Table 4 shows the number of instruments used and associated Sargan and Hansen χ^2 statistics of instrument validity, and Arellano-Bond (1991) autocorrelation tests for each GMM specification. We also report the number of regions used as cross section unit and number of observations in the sample. Regression diagnostics, both the Sargan and Hansen tests suggest that the instrument set used in system GMM is valid for all equations. However, the Arellano-Bond autocorrelation tests suggest the presence serial correlation in each of the GMM specifications.

In growth equations (equations 9 and 10), the coefficient of lag dependent variable is negative (columns 1 and 2) implying the conditional convergence in economic growth as observed in the growth inequality literature. The conditional correlation between overall inequality in the past and growth is negative. The estimated coefficient suggests a 5 per cent decrease in growth for a 100 point increase in total inequality. This result may support the facts that inequality has increased at higher proportional rate at the bottom of the income distribution than at the top. This type of change in income distribution particularly because of skill-biased technological change distorts optimal investment in human and physical capital creating growth reducing effect of inequality in India. This kind of situation may appear if the growth reducing effect of inequality of opportunity outweighs the growth enhancing effect of inequality of effort.

Our primary interest, in this study, is examining the association between inequality and growth when we decompose overall inequality into the opportunity and effort. Column 2 of Table 4 reports the estimated results of a regression equation where the relative measure of inequality of opportunity is used as an explanatory variable. Our findings are robust enough to allow us to conclude that the conditional correlation between lagged inequality of opportunity and growth is highly significantly negative supporting the findings of the past studies with different dataset. The negative coefficient of unequal opportunity suggests that the inequality because of circumstances is bad for growth in India. This finding is consistent with the theoretical views as available in the literature (Galor and Zeira, 1993). In our study, human capital has a positive role in economic growth, but the poor have to face a lot of constraints in choosing optimal investment because of the persistence of unequal opportunities. The suboptimal levels of investment by the poor agents are associated with reduced returns to entrepreneurial effort (Aghion and Bolton, 1997). The coefficient estimates for urbanisation are negative, although very small, when it is used as controlling factor in estimating the effects of overall inequality and inequality of opportunity on economic growth across the regions in India.

Table 4 System GMM estimation of growth and inequality effects

	(1) Growth of consumption per capita	(2) Growth of consumption per capita	(3) Total inequality	(4) Inequality of opportunity
Growth of consumption per capita (lagged)	-0.834***	-0.827***	0.001	0.020***

	(-120.18)	(-113.53)	(0.33)	(10.2)
Total inequality (lagged)	-0.052***		-0.146***	
	(-8.91)		(-12.27)	
Inequality of opportunity (lagged)		-1.066***		-0.251***
		(-4.67)		(-2.39)
Urban population share (lagged)	-0.010***	-0.009***	0.003	-0.0005
	(-3.34)	(-2.99)	(1.1)	(-0.74)
Population share with education secondary and above (lagged)	0.035***	0.031***	-0.005	0.003***
	(14.33)	(13.64)	(-1.08)	(4.79)
Number of observation	178	178	178	178
Number of regions	89	89	89	89
Number of instruments	6	6	8	8
Sargan χ^2	37.06	31.03	55.28	26.36
Hansen χ^2	26.18	20.37	4.23	10.37
AR(1)	0.93	0.82	0.94	0.03

t statistics in parentheses
*** p<0.001, the rest are insignificant

7.2 Causation from growth to inequality

To understand the relationship between growth and inequality of opportunity we need to conceptualise the relation between growth and inequality of outcome. The analysis of inequality and growth has been started with the work of Kuznets (1955). The cumulative effects of savings by the rich and structural transformation from agriculture to industry are used to explain the inverted U shaped relationship. In Kuznets' theory, the association between growth and inequality is explained primarily by technological change, factor accumulation including human capital and investment.

In Kuznets analysis the causation runs from growth to inequality. In the post-Kuznets period also it is argued that the causation from growth to inequality can be explained at least partly by the revolution in information technology that increases premium for education and technical skill. The technological change of this type has benefited entrepreneurs as well as workers involved in the development of software and the hardware sectors raising earnings inequality even at the advanced stage of development. During the initial phase of this technological change the demand for worker with adequate software skill was more than the supply of them, leading to increase in skill wage premium and a consequent increase in

earnings inequality. Economic growth because of this type of technological change increases inequality only if the rate of attainment of higher education with technical skill is not sufficient to keep up with the increase in demand for workers in the skill biased sector.

Columns 3 and 4 of Table 4 presents the estimated results of the system GMM in dynamic panel set up where overall inequality and inequality of opportunity are used as explained variable respectively. In both equations, the coefficient for lagged dependent variable is negative implying that the dynamic process is converging. Growth has no significant causal effect on overall inequality, but it has a significant positive effect on inequality of opportunity. These findings are clearly not supportive of the Kuznets hypothesis that there might be an association between inequality and growth through the growth process. However, inequality of opportunity is creased by 2 per cent due to 100 point increase in economic growth. Thus the findings in this study suggest that faster growth as experienced in India after reforms in the early 1990s aggravate the problem of unequal opportunity to quality education among the people in lower strata of te income distribution.

8. Conclusions

In this study, our basic motivation is to analyse the lack of robust conclusions about the association between inequality and economic growth as observed in the previous literature by decomposing overall inequality into inequality of opportunity and inequality due to effort. We have followed the recent literature on the measurement of ex-ante inequality of opportunity, and use parametric measure of unequal opportunity by partitioning the total sample in to 16 mutually exclusive circumstance groups. Theil's T index of monthly per capita consumption expenditure in household survey conducted by the NSSO in different rounds since the early 1980s is used to measure overall inequality and unequal opportunity. The relative index of inequality of opportunity is used as explanatory variable in the growth regression equation. To find out the direction of causality, we also estimate inequality equation by taking growth as an explanatory variable in presence of some control variables. Similar regression models are considered for overall inequality. Regressions equations are estimated by applying system GMM in dynamic panel set up where 89 regions are taken as cross section units over 5 time points. Empirical findings of this study suggest that overall inequality and inequality of opportunity have negative effects on subsequent growth, while initial growth has no significant effect overall inequality and has a significant positive effect on inequality of opportunity.

In this context, institutions can play an important role. The growth process itself may bring about institutional changes that can alter the distribution of income (Alesina and Rodrik 1994, Persson and Tabellini 1994, Levy and Temin 2007). Changes in political power in a growing economy, for example, can introduce tax and transfer policy that can bring about redistribution of income and wealth in favour of low income groups reducing inequality. If taxes distort private investment decisions, the redistributive policy might lead to lower growth rates through higher taxation. Higher spending through redistributive policy may also be growth enhancing. Increasing spending on education through subsidies for low-income families, for example, may reduce inefficiencies arising from inequality of opportunity. Ostry et al (2014) found that redistribution through tax and transfer is positively related to growth suggesting that the effect of redistribution on enhanced opportunities for low-income families outweighs any negative effects on growth by damping incentives. Redistribution of wealth from rich to poor can reduce inequality of opportunity (Chiu 1998) that could enhance the overall level of human capital and hence growth.

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