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ARTICLE

Social Identity, Gender and Unequal Opportunity of Earning in Urban India: 2017–2018 to 2019–2020

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Abstract
This study measures inequality of opportunity in earnings of different types of workers living in urban locations by using methodology similar to those developed in Ferreira and Gignoux (Review of Income and Wealth 57: 622–657, 2011) with household-level data taken from Periodic the Labour Force Surveys. In calculating the index of unequal opportunity, we use ex ante concept of equal opportunity, and gender, social status and parent's education as circumstance variables. Shapley decomposition is performed to find out the relative roles of the circumstance variables in unequal opportunity in earnings. This empirical exercise reveals that a substantial part (nearly one-fourth) of total earning inequality is accounted for by inequality of opportunity in urban India. Parental education plays a significant role in contributing to unequal opportunity for regular salaried and self-employed workers, and gender difference is very much important in explaining unequal earning opportunity for casual wage workers.

Keywords Inequality of opportunity · Earning inequality · India

JEL Classification D31 · D63 · J62

1 Introduction

Unequal opportunity creates barriers to access to quality education, jobs and other positions. Although the ultimate objective of any society is to reduce inequality of income, focus should be on reducing inequalities that arise from unequal opportunity (World Bank 2006). Unequal opportunity is a consequence of the differences in circumstances that are beyond the control of a person, and it is significant from the standpoint of social justice. Unequal access to quality education across social groups by their caste identity and also between gender classes transmits into unequal

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access to quality jobs and pay differences between them. People from less advantaged social groups are still at high risk of dropping out of school early (Shavit and Blossfeld 1993) and of having worse labour market outcomes (Hannan et al. 1995; Müller, and Shavit 1998; McCoy 2000). Parents' social status, education, occupation and income affect directly and indirectly children's education and ultimately their occupation and earnings. Gender is a critical determinant for the choice of profession. Women with equal endowment of human capital as of men have to face more constraints in selecting jobs. In many societies women have to perform additional efforts within the family and ultimately have to face many obstacles in entering into the labour market.

Historically, the Indian society is segregated by different social groups in terms of castes, religions and ethnic identities with heterogeneous characters, and substantial economic disparities have been observed on the basis of caste, religion and ethnicity (Deshpande 2001; Government of India 2006; Kijima 2006; Gaiha et al. 2007; Gang et al. 2007; Desai and Kulkarni 2008). Thus, it is important to examine the role of these social variables in explaining earning discrimination among the working age people in India. Inequality persists in a society primarily because of the presence of unequal opportunity in access to education and employment (Arrow et al. 2000). The influence of circumstances violates the meritocratic criterion in determining individual's employment and earnings. The success of policy interventions in alleviating inequalities and improving welfare depends upon their efficacy in compensating for the circumstance-based disadvantages and in expanding opportunities for the vulnerable part in the society (Peragine, 2004; Ferreira and Gignoux, 2011). Thus, correcting measures of unequal opportunity is necessary not only for egalitarian society, but also for improving economic efficiency and growth.

This study analyses how earnings are affected by social identity, gender and parents' background of the working age people in urban India controlled by their educational attainment. First, we analyse earning inequality among self-employed, regular salaried and casual wage workers in terms of circumstances and efforts (the terminologies used in the literature of inequality of opportunity) by using household- and personal-level information from periodic labour force survey (PFLS) in India for 2017–2018, 2018–2019 and 2019–2020. In measuring inequality of opportunity, we use ex ante approach in which there is equality of opportunity if all individuals face the same set of opportunities regardless of their circumstances. This paper is restricted to earning distribution among working age people (15–65 years) in urban locations in India.

The rest of the study is structured in the following way. Section 2 describes the relevant literature on methodological issues and their application in empirical research in a very short manner. Section 3 deals with the methodological issues in measuring inequality of opportunity used in this study. A short description of data used in this study is provided in Section 4. Empirical findings are discussed in Section 5. Section 6 summarises and concludes.

2 Literature Review

The concept of inequality of opportunity was popularised after the work by Roemer (1998), and a vast range of research has been growing through the development of the concept and measurement issues in the literature (Ramos and Van de gaer 2012, Ferreira and Peragine 2015; Roemer and Trannoy 2016). Checchi and Peragine (2010) used a nonparametric approach to decompose total income inequality in Italy into inequality of opportunity and inequality of efforts. They did not use any functional form and developed two alternative non-parametric approaches to measure inequality of opportunity which reports the usage of both *ex ante* and *ex post* measures. Bourguignon et al. (2007), on the other hand, used a parametric approach to measure inequality of opportunity in earnings in urban Brazil by comparing the inequality in actual distribution of earnings in the sample with the inequality in distribution of counterfactual earnings for the same sample. For generating the counterfactual distribution, earnings were assumed to be a linear function of circumstances, effort and other factors (or luck), and the estimates thus obtained were used to generate the counterfactual earnings for the whole sample simply by replacing individual circumstance values with the sample average of each circumstance variable. The difference in inequality in actual earnings distribution and the inequality in counterfactual earnings distribution is then taken as inequality of opportunity. Ferreira and Gignoux (2008) used both parametric and nonparametric approaches to estimate inequality of opportunity in earnings as well as consumption expenditure in six Latin American countries. Checchi et al. (2010) also used both approaches to estimate inequality of opportunity in earnings in 25 European countries.

The study by Lefranc et al. (2008) used stochastic dominance rankings to compare the distribution of opportunities in nine OECD countries. The use of this approach is rather limited as it fails to provide a quantification of how far the different groups based on circumstances are from one another. In this approach, the ranking of inequality of opportunity across countries is limited to a binary classification. It also fails to capture the contribution of individual circumstance variables to the overall inequality of opportunity, which is important as far as India with its complex social divide is concerned.

Fleurbaey and Schokkaert (2009) have analysed inequality of opportunity in health and health care services by using the concepts of direct unfairness and fairness gap. Direct unfairness gap is calculated by using the hypothetical distribution of medical expenditure by eliminating legitimate sources of variation. The fairness gap is associated with the differences between actual and the hypothetical distribution obtained by removing all illegitimate sources of variation. The concept of fairness gap in this study is similar to inequality of opportunity in parametric approach as proposed by Bourguignon et al. (2007) and Fleurbaey and Schokkaert (2009). Barros et al. (2009) focused on inequality of opportunity in access to basic services like education among children of different Latin American and Caribbean countries. This study used the concept of human opportunity index to analyse inequality of opportunity in access to basic services.

Some attempts have been made to enquire into income inequality in India, by applying different methodologies. Mukherjee and Majumdar (2011), for example, explored occupational distribution, wage rates and total earnings in the Indian labour market over the last decade across social classes, regions, gender and job types. The study examined the extent of discrimination in entry into the labour market and associated wage disparities by applying decomposition technique. Singh (2012) estimated inequality of opportunity in earnings and consumption expenditure for different age-based cohorts in India by using IHDS data 2004–2005. The estimation is carried out separately for urban and rural areas using nonparametric as well as parametric approaches. In this study, the sample is divided into four different age cohorts and inequality of opportunity is estimated by using both nonparametric and parametric approaches. Using the nonparametric approach, the study observed that inequality of opportunity in earnings varied across the cohorts in the range of 11–19 per cent in urban areas and 5–8 per cent in rural areas. For the parametric approach, he considered caste, religion, geographical region, father's education and father's occupation as circumstance variables and estimated the inequality of opportunity across the various age cohorts. In terms of individual circumstance variables, father's education, followed by caste, is important in urban areas. In rural areas, geographical region, father's education and caste were identified as the important circumstance variables. Choudhary et al. (2018) have used IHDS 2011–2012 to analyse inequality of opportunity among women of age group 15 years and above. In this study, the sample is divided into four cohorts by considering circumstance variables like parental education, caste, religion and geographical region and two outcome variables, income and consumption. They find that inequality of opportunity for earnings varies across age cohorts in the range 18–20 per cent in urban and 22–24 per cent in rural areas. In this study parental education and caste are important in both rural and urban areas.

There are some studies on unequal opportunities based on National Sample Survey (NSS) data. For example, Asadullah and Yalonetzky (2012) estimated inequality of opportunity in education in India during the period from 1983 to 2004 at state and regional levels. Using 61st and 66th rounds of employment and unemployment survey data, Sharma (2018) carried out a state-level analysis to find out the effects of inequality of opportunity on economic growth. Using 68th round NSS data, Lefranc and Kundu (2020) estimated inequality of opportunity in consumption expenditure and wage earning at the national level by taking caste, sex, region and parental backgrounds as circumstances. By applying both nonparametric and parametric analysis method, they found that more than one-third of wage inequality is attributed to differences in social status. The authors also constructed hierarchical order of the circumstances by using regression tree algorithm. Das (2021) analysed the lack of robust conclusions about the association between inequality and economic growth by using 38th round (1983), 50th round (1993–1994), 61st round (2004–2005), 68th round (2011–2012) employment and unemployment survey and periodic labour force survey (2017–2018). This study used ex ante concept to calculate index of inequality of opportunity by applying Theil's T index in nonparametric set-up. 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.

However, there is a scope of further study in this area of research. In this study we have estimated unequal opportunities in earning for casual wage workers, regular salaried workers and self-employed workers with age 15 to 65 years by using periodic labour force survey (PLFS) data for 2017–2018, 2018–2019 and 2019–2020. In the earlier studies as referred to above, it was not possible look into different aspects of earning inequalities among self-employed workers because of lack of earning information for self-employed people in the employment and unemployment survey data used by them. Thus, analysis of unequal opportunities in earning among own account workers and employers in different occupations in self-employment status is the major contribution of this study. It provides the detailed analysis of unequal opportunity by applying ex ante approach of parametric method very similar to the methodology developed in Wendelspiess and Soloaga (2014). We use Shapley decomposition method to find out the relative contribution of gender, castes and parents' education to unequal opportunity in earning distribution. The decomposition analysis is important given the historical division of Indian society into different caste and religious groups, with some groups enjoying better opportunities than the others just because of their social inheritance.

3 Measuring Unequal Opportunity

This study uses Roemer's (1998) basic definition of equal opportunity in which individuals exerting the same effort are entitled to obtain the same earning. Differences in earning due to circumstances are ethically unacceptable and suggested to compensate in the literature by following the appropriate compensation principle.

We assume that earning of a person depends on person's endowments like level of education, work experience, job training, skill and other productivity-related factors (E) and on those factors which are beyond the individual's control like gender, castes and religion (C) and unobserved random factors (u):

$$y_i = g\left(C_i, E_i, u_i\right) \tag{1}$$

Here we are considering a finite population of discrete agents indexed by $i \in \{1, 2, .., N\}$, where N is large.

Earning differences occur because of the differences in E, C and u. Inequality between individuals with similar characteristics C, but differences in E is justified by the reward principle in the literature. However, inequality between individuals with the same E but differences in C is not ethically justified.

We define inequality of opportunity as that part of inequality which appears because of the differences in gender, castes and parents' background between individuals with the same levels of education, experience and other productive factors endowed by them.

In our study, C is exogenous variable in the sense that an individual has no control over them, but E is endogenous and depends partially on C:

$$E_i = E_i\left(C_i, \varepsilon_i\right) \tag{2}$$

For example, education level of a child partly depends on family background along with castes and ethnic factors.

Thus, Eq. (1) becomes

$$y_i = g\left(C_i, E_i\left(C_i, \varepsilon_i\right), u_i\right) \tag{3}$$

By following Wendelspiess and Soloaga (2014), we estimate the earning generating function (3) by applying OLS. The linear form of (1) and (2) is given, respectively, as

$$y_i = C_i^{'}\beta + E_i^{'}\gamma + u_i \tag{4}$$

$$E_i = C_i^{'}\delta + \varepsilon_i \tag{5}$$

Therefore, the reduced form of (3) is

$$y_i = \underbrace{C_i^{'}\beta}_{\text{direct effect}} + \underbrace{C_i^{'}\gamma\delta}_{\text{indirect effect}} + \underbrace{\gamma\varepsilon_i}_{\text{effort effect}} + \underbrace{u_i}_{\text{residual}} \tag{6}$$

or,

$$y_i = C_i^{'}\theta + v_i \tag{7}$$

where

$$\theta = \beta + \gamma\delta$$

and

$$v_i = \gamma\varepsilon_i + u_i$$

Thus, circumstances have a double effect on earnings: direct effect through the coefficient, β, and indirect effect through $\gamma\delta$. The distinction between direct and indirect effects of circumstances on welfare may matter, not only because they are of intrinsic interest, but also because they have sharply different implications for policy. As effort is endogenous, it is difficult to distinguish between the principle of compensation and the principle of reward.

The ex ante counterfactual distribution is simply the distribution of the predicted outcomes:

$$\tilde{Y}_{EA} = c_i^{'}\hat{\theta}$$

The explained variability of this regression model will capture both the direct effect of circumstances and the indirect effect that circumstances through their effect on effort.

The major limitation of this parametric method is that it provides the lower bound estimates of inequality of opportunity particularly when some circumstances are not observed in the data. We have used the methodology developed in Ferreira and Gignoux (2014) and extended by Wendelspiess Ch´avez Ju´arez and Soloaga (2014) for continuous variables in which this problem can be resolved to some extent and is used widely in empirical research on unequal opportunity.

The inequality index of $\tilde{Y}_{EA}$ is the inequality of opportunity. In this framework, circumstances and efforts are mutually independent, and total inequality is the weighted sum of inequality of opportunities, inequality of efforts and inequality due to unobserved determinants:

$$v(\ln y_i) = \beta_1' V(C_i)\beta_1 + \beta_2' V(E_i)\beta_2 + v(u_i) \tag{8}$$

where $v()$ stands for variances and $V()$ for variance–covariance matrices.

In this study, circumstances include gender, ethnicity and parental education:

$$C_i = \{C_{i,1}, C_{i,2}, C_{i,3}\} \tag{9}$$

$$C_{i,1} = (\text{male, female})$$

$$C_{i,2} = (\text{ST,SC,OBC,UC})$$

$$C_{i,3} = (\text{illiterate, primary,secondary,graduate})$$

We have also followed Roemer (1998) in treating effort as a continuous variable, while the vector C_i consists of three elements corresponding to each circumstance j (for individual i), with the typical entry being $C_{i.j}$. Furthermore, each element $C_{i.j}$ takes a finite number of values, x_j, $\forall i$.

This allows us to partition the whole sample into 32 Roemerian *types, i.e. population subgroups that are homogenous in terms of circumstances,* which are non-overlapping:

$$T = \{t_1, t_2, \dots, t_j, \dots, t_{32}\} \tag{10}$$

such that $t_1 \cup t_2 \cup \dots \cup t_j \cup \dots \cup t_{32} = \{1, \dots, \text{N}\}$, $t_l \cup t_{32} = \emptyset, \forall l, k$ and $C_i = C_j, \forall i, j | i \in t_k, j \in t_k, \forall k$. The maximum possible number of types is given by $\overline{K} = \prod_{j=1}^{32} x_j$.

The type specific earning distribution represents the set of earning which can be achieved by exerting different degrees of effort with the same circumstance. This type distribution is a representation of the opportunity set expressed in terms of earning for any individual endowed with given circumstances.

Let Nj be the number of persons in type j of the earning distribution Y,

Therefore, $\sum_{j=1}^{32} N_j = N$, N being the total number of persons in the sample.

The *type* distribution of Y is

$$Y_j = \left\{ y_{j,N1}, y_{j,N2}, \dots, y_{j,N_j} \right\}, j = 1, 2, \dots, 32 \tag{11}$$

The overall earning distribution or marginal distribution of advantages can be written as

$$Y_C = \left\{ Y_1, Y_2, \dots, Y_j, \dots, Y_{32} \right\} \tag{12}$$

In this study, we assume that effort is two-dimensional: person's education and work experience,

$$E_i = \left\{ E_{i,1}, E_{i,2} \right\} \tag{13}$$

$$E_{i,1} = \text{(illiterate, primary,secondary,graduate)}$$

$$E_{i,2} = \text{(with experience, without experience)}$$

Therefore, the whole sample can be partitioned into eight tranches:

$$\tilde{T} = \left\{ \tilde{t}_1, \dots, \tilde{t}_p \dots \tilde{t}_8 \right\} \tag{14}$$

Thus, the tranche distribution of earning is.

$$Y_m = \left\{ y_{1,m}, y_{2,m}, \dots, y_{j,m}, \dots, y_{32,m} \right\}, m = 1, 2, \dots 8 \tag{15}$$

The overall earning distribution,

$$Y_E = \left\{ Y_1, Y_2, \dots, Y_k, \dots, Y_8 \right\} \tag{16}$$

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 counterfactual distribution is constructed by replacing individual earning of those with same circumstances (*j*) and same degree of effort (*k*) with their mean income of $\left\{ y_{j,m} \right\}$. Then, a smooth distribution of the earning is constructed by taking the mean earning for each type,$\left\{ \overline{y}_j \right\}$, by replacing $\left\{ y_{j,m} \right\}$.

here $\overline{y}_j = \frac{1}{N_j} \sum_m y_{j,m}$, N_j is the size of type $t_{\mathrm{j},}$ j=1,2, …0.32; m=1, 2,…,8.

The mean earning of type j, $\overline{y}_j$, is used as a numerical measure of opportunity set faced by people in that type (Ferreira and Gignoux 2011). Inequality of opportunity presents if $\overline{y}_l \neq \overline{y}_h, \forall l, h | T_l \in T, T_h \in T$.

Inequality in this counterfactual distribution is the inequality of opportunity in ex ante approach:

$$IO = I\left(g\left(C, \overline{E}\right)\right) \tag{17}$$

Ferreira and Gignoux (2011) used the mean logarithmic deviation (MLD) of this counterfactual distribution as a measure of inequality of opportunity. In our study, inequality of opportunity is measured by following the similar methodology. This is an entropy class of inequality index and popularly known as Theil's L index, which provides a description of inequality in terms of simple statistical indices. The Theil's Index measures inequality by the extent to which an actual society deviates from a perfectly equal society. It is based on computing for everyone the ratio of their income share to their population share.

If individual *i* has an income y_i, there are *n* people in the sample, and average income in the sample is $\bar{y}$, then the general entropy measure is specified as

$$GE(\alpha) = \frac{1}{\alpha(1-\alpha)}\frac{1}{n}\sum_{i=1}^{n}\left[\left(\frac{y_i}{\bar{y}}\right)^{\alpha} - 1\right] \tag{18}$$

The parameter α in the GE class represents the weight given to distances between incomes at different parts of the income distribution, and can take any real value. With positive and large α, the index GE will be more sensitive to what happens in the upper tail of the income distribution.

By applying L'Hopital's rule, GE(0) is the Theil's L index giving the mean log deviation measure:

$$GE(0) = -\frac{1}{n}\sum_{i=1}^{n} ln\left(\frac{y_i}{\bar{y}}\right) \tag{19}$$

We segregate the whole sample into 32 mutually exclusive groups of persons on the basis of social status, gender and parent's education. The Theil's index has the desirable property of decomposability.

The Shapley decomposition, based on the well-known concept of Shapley value in cooperative game theory (Shapley 1953), is used to find out the relative contribution of gender, social status and parents' education to inequality of opportunity in earnings. The idea of the Shapley value is to compute the value of a function considering all the possible combinations of circumstances. The sample used in this study is partitioned into three subgroups. Now, the index of inequality of opportunity can be looked at as a function of the observed earnings,

$$\text{IOP} = f\left(x_{11} \ldots x_{N_1 1}, x_{12} \ldots x_{N_2 2}, \ldots, x_{13} \ldots x_{N_3 3}\right) \tag{20}$$

x_{ij} is earning of the ith person ($i = 1,..., N_j$) in subgroup $j = 1, 2, 3$.

Additive decomposition is made by considering the impact of inequality within subgroups, inequality between subgroups, ranking and relative size in each subgroup (see Deutsch and Silber 2007, for detail). By using Shapley decomposition, we can derive the marginal impact of each circumstance measuring the difference in the value of the inequality index corresponding to the observed situation and the reference one, where the income does not change with that circumstance.

4 Data

This study uses household- and personal-level information from periodic labour force survey (PLFS) in India. This survey was started in 2017–2018, and the data for third wave survey in 2019–2020 are available very recently in the public domain. It provides annual estimates of the key labour market indicators based on the usual status (US) and current weekly status (CWS) approach and also provides quarterly estimates of these indicators in the urban economy on the basis of the CWS approach. A rotational panel sampling design is being used in urban areas to generate quarterly urban estimates. Rotational panel facilitates to use the information contained in earlier occasions for capturing the dynamic behaviour of labour force characteristics over time. The rotational panel sampling of two years cycles is used first time in PLFS, 2017–2018, by the National Sample Survey Office (NSSO) in India. The PLFS in India uses "four-in-then-out" rotation design where the household units in a given panel in urban areas are interviewed for four consecutive quarters and are then dropped from the sample permanently. The schedule of enquiry has been collected from the sample households using computer-assisted personal interviewing (CAPI) method. Information is collected on the hours worked on each day of the reference week on the basis of current weekly activity status. Information on earnings from employment is provided on the basis of current weekly activity status. For the self-employed workers in current weekly activity status, gross earnings are recorded on the basis of earnings from the last 30 days. The PLFS does not provide any estimates using the current daily status. It, however, provides the measure of employment and unemployment of different types in an economy in a comprehensive manner.

We have constructed gender dummy by taking its value that equals 1 if a person is female and 0 for male. Caste dummies are created by using the categorical variable social status. In PLFS social status of the households is given in the form of Scheduled Tribes, Scheduled Castes, Other Backward Castes and Others. The social status category Others captures the people in upper castes, and we have taken this group as a reference. As there is no information separately for parents, head of the household is treated as a parent of the family members within the households. We have constructed four education dummies on the basis of general education level of head of the household and used them as parent's education in our empirical work. Earning information for casual wage workers is given on daily basis with hourly intensity, while earnings for regular salaried and self-employed people are given on monthly basis.

5 Empirical Findings

We have estimated relative measure of inequality of opportunity for earnings among working age people in urban India by using the methodology developed in Ferreira and Gignoux (2014) and extended further in Wendelspiess and Soloaga

(2014). In this method, we need to estimate first an OLS regression of earnings on circumstances as shown in Eq. (4). In this empirical exercise, gender, social status and parents' education are taken as circumstance variables. Using the estimated coefficients of the reduced form equation, counterfactual distributions corresponding $\tilde{Y}_{EA}$ have been obtained for urban areas for the consecutive three waves of PLFS data. This helps to decompose earnings inequality for working population in the urban samples into a component due to unequal circumstances (inequality of opportunity) and a residual component due to all factors other than the observed circumstances which may be "efforts," random elements or any other unaccounted factor. The log mean deviation of the predicted values of earnings obtained from this regression provides the absolute measure of inequality of opportunity. A relative measure of inequality of opportunity is obtained by dividing this absolute measure by the mean log deviation of the actual earnings available in the sample.

Table 1 presents Ferreira–Gignoux-type index of inequality of opportunity obtained from the counterfactual distribution of earnings among working age urban population. As earnings have no inherent scale, we have used inequality measure without considering scale. The estimates are made for workers of different types in 2017–2018, 2018–2019 and 2019–2020. The bootstrap standard errors are based on 100 replications and are nearly zero. The bootstrap standard errors suggest the robustness of the estimate. The index of unequal opportunity increased in the second wave survey in 2018–2019 for all types of workers as compared to the estimates from the first wave survey in 2017–2018, but it declined in 2019–2020 from the respective values in 2018–2019. The survey period of fourth quarter of 2019–2020 covers the beginning phase of COVID-19 pandemic during which a lot of restrictions were imposed that affected badly the employment conditions and people's movement. Thus, the fall of the index of inequality of opportunity in 2019–2020 may be because of job losses among the vulnerable part of the workforce in each type of employment during the lockdown phase of the economy. As is observed, the extent of unequal opportunity in earnings is relatively less in casual wage employment than in regular paid jobs and self-employment.

Table 1 Inequality of opportunity: urban India

	2017–2018	2018–2019	2019–2020
Regular salaried worker	0.26	0.29	0.25
	(0.008)	(0.005)	(0.006)
Self-employed worker	0.24	0.31	0.24
	(0.009)	(0.007)	(0.007)
Casual wage worker	0.18	0.19	0.16
	(0.016)	(0.010)	(0.009)
All workers	0.22	0.26	0.21
	(0.005)	(0.004)	(0.0040

Figures in parentheses are Bootstrap standard error

Source: Authors' estimate from PLFS data

To find out the relative contributions of gender, social status and parental education to inequality of opportunity, we have decomposed the index of inequality of opportunity by using Shapley method. The relative contributions of each circumstance variable, namely gender, social group and parent's education, are shown in Table 2. Parents' educational background plays a major role in unequal opportunity in earnings among regular salaried workers for whom the Ferreira–Gignoux relative index was the highest in each time point. The probability of getting regular salaried employment in Indian labour market is highly affected by person's education level which is influenced significantly by parent's educational background. Perhaps, this may be one possible reason why parent's education contributes more to unequal opportunity in earnings in the regular paid jobs. On the other hand, gender difference among workers is primarily responsible for unequal opportunity in earnings in casual employment and self-employment. While the difference in social identity in terms of castes among workers contributes a notable part to unequal opportunity in regular paid jobs, it has a negligible role in explaining this unethical part of earning inequality in casual employment.

India is a country with heterogeneous states of social, economic and cultural background. Thus, the relative roles of factors responsible for inequality of opportunity in employment and earnings are different in different regions. By using the same method as described above, we have calculated the index of inequality of opportunity and decomposed the index into three components for all major and small states and union territories in India for 2017–2018, 2018–2019 and 2019–2020. Tables 3 and 4 provide the estimates of inequality of opportunity and its decomposition between gender, social status and parental education for all workers. In 2019–2020, Telangana exhibited the highest and Kerala showed the lowest measure of unequal opportunity among working age people living in urban areas across the major states in India (Table 2). Other major states showing high unequal opportunity in urban location are Haryana, Delhi, West Bengal and Chhattisgarh. In smaller states, the extent of inequality of opportunity in earning was relatively low as compared major states. The relative positions of the states in terms of index of inequality of opportunity roughly remained the same in 2017–2018 and 2018–2019. The fourth sub-round of 2019–2020 (April to June 2020) covers the initial phase of the COVID 19 pandemic; thus, it captures the effects of pandemic and economic lockdown on employment and earning for different types of workers.

We have shown that inequality of opportunity in earning due to differences in parental education is the highest in the urban economy at the national level. The state-level results also suggest the similar phenomenon, but there is a wide variation of this part of inequality of opportunity across states. It was very high in the urban locations of Sikkim, Nagaland, Delhi and Chandigarh. Assam among the major states exhibited a very high contribution of differences in parent's education to unequal opportunity in earning in 2019–2020 (Table 4). In Kerala, differences in parent's education had the least effect on inequality of opportunity in earning in urban areas. In some states like Kerala, West Bengal, Gujarat and Tamil Nadu, gender difference among workers was the major factor for unequal opportunity in earning, and

Table 2 Shapley decomposition of IOP: all India

	2017–2018			2018–2019			2019–2020		
	Gender	Social status	Parent's education	Gender	Social status	Parent's education	Gender	Social status	Parent's education
Regular salaried worker	13.37	14.72	71.91	11.66	9.75	78.59	13.65	12.34	74.01
Self-employed worker	62.49	12.42	25.09	70.41	7.43	22.16	73.34	8.10	18.56
Casual wage worker	94.86	2.62	2.52	86.41	4.98	8.61	87.62	5.83	6.55
All workers	27.11	14.02	58.87	29.11	8.59	62.30	32.04	10.42	57.54

Source: As for Table 1

Table 3 Change in IOP for all workers by states in urban India

	2017–2018		2018–2019		2019–2020	
Jammu & Kashmir	0.26	(0.026)	0.25	(0.018)	0.20	(0.020)
Himachal Pradesh	0.23	(0.055)	0.34	(0.043)	0.22	(0.035)
Punjab	0.23	(0.022)	0.34	(0.019)	0.22	(0.019)
Chandigarh	0.45	(0.051)	0.31	(0.042)	0.30	(0.051)
Uttarakhand	0.23	(0.040)	0.30	(0.027)	0.21	(0.025)
Haryana	0.33	(0.027)	0.40	(0.019)	**0.32**	(0.023)
Delhi	0.28	(0.039)	0.31	(0.026)	0.31	(0.026)
Rajasthan	0.21	(0.023)	0.28	(0.017)	0.24	(0.019)
Uttar Pradesh	0.20	(0.018)	0.22	(0.015)	0.16	(0.013)
Bihar	0.23	(0.032)	0.23	(0.022)	0.19	(0.021)
Sikkim	0.13	(0.046)	0.19	(0.040)	0.13	(0.036)
Arunachal Pradesh	0.34	(0.035)	0.26	(0.030)	0.22	(0.040)
Nagaland	0.29	(0.046)	0.18	(0.031)	0.19	(0.027)
Manipur	0.15	(0.022)	0.23	(0.019)	0.22	(0.017)
Mizoram	0.06	(0.021)	0.12	(0.014)	0.15	(0.019)
Tripura	0.11	(0.032)	0.19	(0.027)	0.12	(0.023)
Meghalaya	0.15	(0.034)	0.14	(0.031)	0.17	(0.031)
Assam	0.22	(0.031)	0.30	(0.026)	0.15	(0.040)
West Bengal	0.26	(0.020)	0.33	(0.014)	0.29	(0.016)
Jharkhand	0.27	(0.032)	0.29	(0.023)	0.20	(0.033)
Odisha	0.21	(0.033)	0.31	(0.022)	0.27	(0.022)
Chhattisgarh	0.28	(0.030)	0.34	(0.021)	0.29	(0.033)
Madhya Pradesh	0.25	(0.024)	0.27	(0.014)	0.20	(0.015)
Gujarat	0.24	(0.034)	0.29	(0.020)	0.27	(0.017)
Daman & Diu	0.45	(0.170)	0.49	(0.081)	0.29	(0.082)
D & N Haveli	0.38	(0.158)	0.31	(0.059)	0.19	(0.070)
Maharashtra	0.35	(0.026)	0.32	(0.013)	0.27	(0.016)
Andhra Pradesh	0.31	(0.030)	0.30	(0.017)	0.22	(0.018)
Karnataka	0.30	(0.027)	0.33	(0.015)	0.28	(0.019)
Goa	0.19	(0.089)	0.29	(0.045)	0.24	(0.046)
Lakshadweep	0.18	(0.139)	0.18	(0.071)	0.17	(0.075)
Kerala	0.06	(0.021)	0.19	(0.013)	0.14	(0.013)
Tamil Nadu	0.24	(0.024)	0.33	(0.013)	0.24	(0.014)
Puducherry	0.29	(0.072)	0.19	(0.031)	0.24	(0.041)
A & N Island	0.26	(0.093)	0.17	(0.041)	0.17	(0.050)
Telangana	0.37	(0.039)	0.40	(0.017)	**0.35**	(0.019)

Figures in parentheses are Bootstrap standard error

Source: As for Table 1

the importance of gender became more relevant over time in those states. Difference in ethnicity among workers was the least responsible factor for unequal opportunity in earning in urban labour market in all states in India (Table 4).

Table 4 Shapley decomposition of unequal opportunity for all workers in urban areas

State name	2017–2018 Gender	Social group	Parent's education	2018–2019 Gender	Social group	Parent's education	2019–2020 Gender	Social group	Parent's education
Jammu & Kashmir	25.8	1.7	72.5	22.6	5.5	71.9	47.8	3.8	48.4
Himachal Pradesh	49.0	15.0	36.1	31.6	12.2	56.2	20.2	23.9	55.9
Punjab	31.0	27.9	41.0	39.3	13.2	47.5	37.1	18.9	44.0
Chandigarh	45.4	6.1	48.5	2.0	5.4	92.7	5.0	6.5	88.5
Uttarakhand	26.2	10.8	63.0	14.3	18.9	66.8	19.2	9.8	71.0
Haryana	19.8	24.1	56.1	17.8	22.8	59.4	7.7	17.2	75.0
Delhi	8.0	10.2	81.8	7.3	9.3	83.4	2.9	8.5	88.6
Rajasthan	34.4	9.3	56.3	35.4	7.5	57.1	46.2	11.4	42.4
Uttar Pradesh	6.4	18.6	75.0	16.9	11.2	71.9	17.1	12.2	70.7
Bihar	2.1	16.6	81.3	5.6	23.9	70.5	12.0	16.3	71.7
Sikkim	15.1	40.9	44.0	10.6	8.2	81.2	0.2	3.9	95.8
Arunachal Pradesh	1.7	12.1	86.1	7.3	19.8	72.9	5.5	23.7	70.9
Nagaland	34.4	31.9	33.7	3.6	37.4	59.0	0.1	8.5	91.4
Manipur	28.9	16.3	54.8	42.7	25.0	32.3	60.5	17.5	22.1
Mizoram	0.0	1.6	98.4	10.8	1.5	87.7	34.8	5.8	59.5
Tripura	13.5	36.2	50.3	6.3	7.2	86.5	38.3	11.5	50.1
Meghalaya	18.3	1.0	80.7	22.7	14.2	63.1	23.4	10.3	66.3
Assam	15.2	14.8	70.0	11.8	11.2	77.1	14.4	3.5	82.1
West Bengal	57.2	3.9	39.0	57.8	2.3	39.9	62.3	1.8	35.8
Jharkhand	16.3	4.8	78.9	17.0	23.6	59.5	31.8	14.6	53.6
Odisha	31.2	5.6	63.2	11.7	3.8	84.5	22.4	6.1	71.4
Chhattisgarh	42.4	13.2	44.4	20.9	17.0	62.2	14.9	18.4	66.7

Table 4 (continued)

State name	2017–2018 Gender	Social group	Parent's education	2018–2019 Gender	Social group	Parent's education	2019–2020 Gender	Social group	Parent's education
Madhya Pradesh	32.0	12.8	55.2	34.0	11.9	54.2	29.8	16.4	53.8
Gujarat	49.4	22.2	28.4	42.1	8.3	49.6	54.1	6.2	39.8
Daman & Diu	10.5	10.5	79.0	60.2	5.4	34.4	39.3	12.5	48.2
D & N Haveli	47.8	40.2	12.1	45.7	5.1	49.1	32.1	11.5	56.4
Maharashtra	20.9	17.8	61.3	21.8	11.8	66.4	25.5	10.4	64.0
Andhra Pradesh	21.2	13.1	65.7	41.9	8.2	49.8	40.5	4.6	54.9
Karnataka	53.9	11.1	35.0	22.6	8.7	68.8	27.0	14.6	58.4
Goa	17.0	25.9	57.1	50.6	11.5	37.9	5.9	7.3	86.8
Lakshadweep	60.5	1.5	38.0	3.3	0.0	96.7	27.1	9.7	63.2
Kerala	41.8	17.8	40.3	66.1	2.7	31.2	76.7	5.2	18.1
Tamil Nadu	53.9	6.6	39.5	42.6	5.2	52.1	53.4	6.2	40.4
Puducherry	18.6	9.0	72.3	12.6	11.6	75.8	28.2	16.3	55.6
A & N Island	36.0	23.0	41.0	40.3	13.2	46.5	23.3	5.9	70.8
Telangana	53.8	9.6	36.6	46.7	10.7	42.6	50.3	6.2	43.5

Source: As for Table 1

6 Conclusions

This paper presents the ex ante estimates of inequality of opportunity by using parametric method developed by Ferreira and Gignoux (2014) and decomposes it by using Shapley method with recently available PLFS data. In parametric analysis, however, the overall estimates are considered as lower bound because (though multiple circumstance variables have been taken) the possibility of existence of other circumstance variables, which are not observed, cannot be ruled out. For our analysis, we have subdivided the sample into 32 groups of 3 circumstance variables: gender, social status and parent's education. The empirical exercise of this study is restricted to analyse unequal opportunities in earnings for all types of workers in urban locations. The estimated results of this study point out that a substantial part of total earnings inequality is accounted by unequal circumstances. The estimates provide the relative role of gender, social status and parent's background in explaining unequal opportunity in urban India. The contributions of gender, social status and parental background are different in different states. In smaller states, the degree of inequality of opportunity in earning was relatively low as compared major states. It is observed that inequality of opportunity in earnings for all workers was the highest among regular salaried workers and the lowest among casual wage workers in 2019–2020. Self-employed workers are highly heterogeneous varying from street vendors to high-skilled professional.

One significant finding of this study is that parental education has an important role in reducing unequal opportunities in earnings particularly among workers in regular paid jobs. Parent's education is a decisive factor for attainment of higher levels of education of the individual and ultimately getting good job and better earnings. Thus, to reduce unethical part of inequality policy measures should be focussed on increasing opportunities in getting quality education by the children of the vulnerable parents. For the casual and self-employed workers, on the other hand, more than 90 per cent of unequal opportunity appeared because of gender difference among workers in casual employment in 2019–2020.

The importance of gender differences and difference in parental background in determining unequal opportunity as observed in our study is somehow dissimilar to observations of the past studies using different dataset (Deshpande, 2001; Kijima, 2006; Gaiha et al., 2007; Gang et al., 2007; Desai and Kulkarni, 2008). These studies have found that a significant portion of difference between the achievements (educational attainment or earnings) can be explained by the difference in social status of the individuals. The findings of the current study become pertinent if seen in the light of the affirmative action (in terms of reservation of seats in educational institutions and governmental jobs) for individuals belonging to lower social status categories. The study offers some support for the affirmative action. The analysis presented in the current study is a deviation from many conventional studies, in the way, that this study not only measures the earning inequalities for urban India but it also points out the roots behind such income inequalities.

In a country like India, the reasons for differences in gender–pay are more complex and can be related to socio-economic factors. Girl children from underprivileged social groups are sometimes held back of schools or made to drop out of school relatively early and are forced to join low paid activities for the survival of their families. Even many women in upper-caste families with high education are not allowed to join high-paid jobs for social, cultural and religious reasons. The unfairness and discrimination against women witnessed in social spheres get imitated on to economic spaces through direct, legitimate routes and also via the flexibility in perceptions among the representatives of the labour markets that rearrange to retain elements of gender imbalances.

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Declarations

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