IHD WORKING PAPER SERIES

WP 06/2022

Inequality of Opportunity in India: Concept and Measurement

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INSTITUTE FOR HUMAN DEVELOPMENT
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WP 06/2022

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Suggested citation

Mehta B.S & Dhote S, (2022). Inequality of Opportunity in India: Concept and Measurement. Inequalitrees Working Paper Series, N.X.

Published by:

INSTITUTE FOR HUMAN DEVELOPMENT
256, 2nd Floor, Okhla Industrial Estate, Phase-III
New Delhi - 110020
Tel: +91 11 41064676, +91 9871177540
E-mail: mail@ihdindia.org
Website: www.ihdindia.org

ISBN: 978-81-88315-82-6

INEQUALITREES

https://inequalitrees.eu/

A Novel Look at Socio-Economic Inequalities Using Machine Learning Techniques and Integrated Data Sources

PROJECT'S DESCRIPTION

The INEQUALITREES project aims to investigate the levels and main drivers of two key manifestations of socio-economic inequality across the globe: poverty and inequality of opportunity (IOp). This project adopts a multidimensional, interdisciplinary and cross-national approach, by analysing IOp and poverty in three key individual outcomes (education, income and health) in four countries (Bolivia, Germany, India, Italy), and integrating contributions from economics, sociology, geography and computer science. A key innovative feature of this project is the application of cutting-edge machine learning techniques to integrate and analyze large scale datasets from various sources, including national and international surveys, administrative and register data, as well as innovative data extracted from satellite images.

For details see https://inequalitrees.eu/

ACKNOWLEDGEMENTS

We would like to thank Professor Sandip Sarkar and Mr Oliver Rix for their useful comments and suggestions. Additionally, we are grateful for the comments received from conference audiences at the Indian Institute of Technology, Roorkee, and the Indira Gandhi Institute for Development Research in Mumbai

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CONTENTS

Abstract

There is a growing debate about the limitations of inequality of outcomes in explaining the widening income inequalities within countries across the world. In this context, scholars and public policy advocates are taking a keen interest in the measurement of inequality of opportunity (IOp), which is based on the philosophical concept of distributive justice. In this article, we discuss the evolution of the concept of IOpt and its measurement, and provide empirical results on IOp in India, based on data from the Labour Force Surveys conducted by the National Statistical Office (NSO). Our analysis shows that in India, around one-fifth of the consumption inequality and one-fourth of the income inequality result from an individual's unequal circumstances (such as Gender, Caste, Race, Parent's background, and Location of Residence). The findings based on Shapeley decomposition reveal that parental backgrounds i.e., education and occupation contribute the most to unequal opportunities for regular salaried employment, while gender plays a key role in explaining unequal earnings opportunity for casual wage employment and self-employment. Our regression inference tree based results also indicate that parent's education is the most important variable that determines income or consumption inequality, followed by the location (rural-urban), place of birth (region) and occupation of the parents.

Keywords: Equality of Opportunity, Machine Learning, Conditional Inference Trees

JEL CODES: D31, D63, F63

Inequality of Opportunity in India: Concept and Measurement

Balwant Singh Mehta and Siddharth Dhote[1]

1. INTRODUCTION

Inequality in all forms, whether economic, social or political has always been a matter of serious concern. Growing economic inequality in most countries across the world has attracted significant attention from policy makers and academics in the last three decades (Morelli and Rohner, 2015). As a result, several studies have been conducted to capture inequalities, mostly in the form of income or consumption expenditure. These studies often follow a welfarist approach to measure inequality, where inequality in the outcome is the main focus of the analysis. However, this classical approach has been criticised for not taking into account the multi-dimensional nature of the inequality generating factors (Dworkin, 1981a). This has triggered a philosophical debate around the concept responsibility sensitive egalitarian justice in the late twentieth century (Roemer, 1993, 1998). The Inequality of Opportunity approach splits inequality into fair and unfair parts, and brings about the question of individual responsibility in the domain of distributive justice. This prioritises analysis of inequality arising solely from the factors that are beyond subjective responsibility. As a result of this, the focus of inequality analysis has moved from 'inequality of outcome' to 'inequality of opportunity' in the recent years.

Inequality of Opportunity (IOp) offers a new way to distinguish between what might be considered 'good' and 'bad' inequalities in a society, which could be crucial for achieving higher economic efficiency as well as social cohesion. Unequal societies may hold back one segment of the population while favouring another. In this context, it is important to understand to what extent this relationship is driven by IOp. However, conventional approaches and existing sources of data have many limitations, making the measurement of IOp and identification of its correlates difficult. To solve the limitations of the traditional methods and generate more

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robust estimates, we propose to use Machine Learning (ML) algorithms. In this light, the first objective of this paper is to show how the emerging ML technique promises new and robust insights on IOp.

Another important concern, which has attracted significant attention in the recent years, is the widening inequalities in developing countries such as India. It is widely documented that the impressive economic growth achieved by India after the introduction of economic reforms in the 1990s has not achieved desirable results with regard to economic and social welfare. This has raised serious concerns about the adverse effects of widening inequality in India's growth process. It is also important to note that income inequality cannot be adequately controlled if the underlying IOp is not addressed effectively (Sharma, 2015). Several studies exist, which explore the inequality of outcome in India. While research on inequality of opportunity is gaining momentum across the world, literature on IOp in India is limited. Thus, the second objective of this paper is to measure and identify IOp generating factors using both conventional as well as ML algorithms in India. The findings of this paper can act as a guide to devise policies for improving equality of opportunity across the society.

The rest of the paper is organised as follows: Section 2 describes the evolution and theory of IOp; Section 3 provides information on methods and approaches; Section 4 presents the India based analysis; and Section 5 concludes the paper with some policy reflections.

II. THEORETICAL BACKGROUND: EVOLUTION OF IOP CONCEPT

It is important to take a pause and briefly discuss the evolution of the notion of IOp. Equality of opportunity is an ideal situation, the concept of which originated from the Principle of Distributive Justice. This principle has traditionally been anchored—explicitly or implicitly in the welfarist idea, within which equity assessments are formulated on the basis of the distribution of some individual achievement—welfare, utility or preference satisfaction across the population. An influential version of the welfarist tradition is the utilitarian approach, which uses an additive aggregation of individual achievements as the social objective function. However, the dominance of utilitarianism and welfarism— as the ethical basis for the assessment of social progress was previously critically challenged in political philosophy and normative economics.

An egalitarian view was suggested as an alternative to utilitarianism by Rawls (1958, 1971) in the form of the notion of primary goods such as basic liberties and rights, access to political and other offices, income, and wealth. He argued that after guaranteeing a system that maximises civil liberties, justice requires a set of institutions that maximise the level of 'primary goods' allocated to those who are worse off in the society and those that receive the least amount of these goods. According to egalitarianism, the equality of opportunity is an ethical value that enables members of the society to pursue their interests through fair and equal opportunities. The idea put forward by Rawls was rejected by Dworkin (1981a), as he claimed that different individuals may have different material needs and tastes. Therefore, achieving 'equality of welfare' may mean distributing different amounts of wealth or income to different individuals, and a commitment to egalitarianism cannot justify compensating for expensive tastes. Dworkin (1981b) also suggested a different notion of equality called 'equality of resources', where not only physical and tangible goods can be transferred among individuals, but biological and physical characteristics, genetic traits and talents etc., can too.

On the other hand, Arneson (1989) and Cohen (1989) found Dworkin's proposal, that holds individuals responsible for things that are beyond their control, to be problematic and suggested shifting the focus away from resources to opportunities. Arneson (1989) proposed an alternative 'equal opportunity for welfare', which prevails when every individual faces the same set of possibilities for satisfying his or her preferences. Cohen (1989) also proposed 'equal access to advantage' which is somewhat similar to Arneson and where 'advantage' not only includes but also goes beyond welfare. Sen (1985, 1992 and 1999) emphasises on a person's achievement or capability such as his/her 'being and doing' or 'functioning', followed by primary goods, or resources, or utilities as proposed by Rawls and Dworkin. However, the ability to achieve a functioning ('capability') combines the ideas of functioning and freedom, which is somewhat similar with the proposals of Arneson and Chohen (Motiram, 2018).

Nevertheless, these proposals do have in common the idea that an equitable society is not necessarily a society that makes all people equally happy, rich or educated. Rather, it is a society that guarantees for all its members an equal opportunity to attain the desired outcomes. Roemer (1998, 2002) finally conceptualised and provided a more precise definition of where an individual has been able to achieve an 'outcome' such as income or earnings, wealth, educational achievement, and good health as a result of two sets of factors. The first set of factors are within the control of the individuals, which they should be held responsible for— efforts (e.g., number of hours devoted to study or work, quality of the work supplied, occupational choices, etc.). The second set of factors includes factors that are beyond the control of the individuals, which they should not be held accountable for, called circumstances (e.g., family, socioeconomic and cultural background, ethnic origin, gender, age etc.) (Roemer and Trannoy, 2016).

The literature also discusses other issues such as various forms of luck or randomness and the consequences of uncertainty. A substantial literature has developed, exploring IOp in various contexts following the idea of Roemer and his collaborators across the globe. The empirical work which brought forward the method for estimating IOp in economic outcomes following the idea of Roemer and others includes Bourguignon et al. (2007), Ferreira and Gignoux (2008), Barros et al. (2009), Fleurbaey and Schokkaert (2009), Cecchi and Peragine (2010), Fleurbaey and Peragine (2013), Ferreira and Gignoux (2011, 2014), etc. In the next section, we turn to the concept and measurement of IOp by reviewing methods previously used, including those of the above-mentioned scholars.

III. MEASUREMENT OF IOP AND DATA SOURCES

For the measurement of IOp, two broad ethical principles, namely 'reward' and 'compensation' have been commonly used in the literature. The principle of reward seeks to preserve differential rewards that are the result of individual responsibility and efforts, while the principle of compensation holds that individuals should be compensated for circumstances outside their control (Fleurbaey, 1994). These principles are further refined into two broad sets: types and tranches. Types refer to groups of individuals who share the same circumstances or opportunity set, and tranches are understood as a group of individuals who exert the same degree of effort or are the same in the matter of responsibility (e.g., they made similar choices) (Peragine, 2004). In other words, 'within-type' inequality is caused by the differential exertion of effort, which is morally permissible, while 'between-type' differences in achievements are inequitable and morally unethical, and call for compensation. Roemer disregards the principle of reward or the 'within-type' inequality or tranches as an important ingredient of IOp. Hence, evidence on the measurement of IOp through the principle of reward is scarce, while the evidence on the principle of compensation is well established in the literature.

Differences stemming from the compensation and the reward principles are reflected in the two different perspectives called the ex-ante and ex-post approach, adopted to evaluate the extent of (in)equality of opportunity (Fleurbaey and Peragine, 2013). The ex-ante approach focuses on inequality between types, whereas the ex-post approach focuses on inequality between tranches. The difference in approaches arises due to a difference in opinion regarding the nature of the effort variable. However, due to the lack of consensus on the measurement of effort variable, the ex-post approach lacks popularity among academics and policymakers. This is likely to be the main reason why empirical applications focus mostly on the ex-ante approach, given that estimating efforts requires very strong assumptions (Fleurbaey and Peragine, 2013; Ramos and Van de gaer, 2016). We follow the empirical applications, and focus our discussion on the ex-ante approach of IOp.

3.1 Regression Approach

Several methods have been proposed to assess ex-ante IOp over the years. Regression approach became very popular and was widely used in studies of different countries. This approach relates the outcomes to circumstances by parametric or non-parametric regression methods. The regression method proposed by Ferreira and Gignoux (2011) is justified by its practical use in the recent empirical applications. This approach can be explained as y being an outcome variable of interest, such as earnings or income of an individual, and C as the matrix of circumstances beyond the control of the individual, such as race (social group), gender, parent's education and occupation, etc. This method relates the outcome variable with the vector of circumstances. We can describe this relationship with the expected conditional outcome as denoted by:

$$\hat{y}=E[y|C] \qquad [1]$$

This can be estimated in different ways according to the research question and the dependent variable. Ferreira and Gignoux (2011) used the outcome variable 'income' as a dependent variable and estimated the same equation with an ordinary-least squares (OLS) regression and with nonparametric methods by averaging over the types. Independent of the way, equation (1) is estimated. IOp is then computed using a common inequality measure I(.), which is applied to ŷ as denoted by:

$$\theta_a = I(\hat{y}) \qquad [2]$$

All variation in the vector ŷ is exclusively due to circumstances; hence, it refers to IOp. The best choice of the appropriate inequality measure depends on the scope of the analysis and on the dependent variable. Paes de Barros, de Carvalho, and Franco (2007) used the dissimilarity index, Ferreira and Gignoux (2011) used the mean logarithmic deviation, and Ferreira and Gignoux (2014) used the variance. Dividing the absolute inequality measure by the same metric I(.), applied to the actual outcome y gives a relative measure of IOp as denoted by:

$$\theta_r = \frac{I(\hat{y})}{I(y)}, \qquad [3]$$

Where, θ_r is IOp.

This last step is possible only when the inequality measure is equally defined for and y. This is not the case when the actual outcome is binary and is the estimated probability. The choice of the appropriate inequality measure is crucial and depends mainly on the outcome variable.

3.2 Decomposition of IOp Measure

It is important to understand to what extent all the circumstances affect inequality and how much each circumstance contributes to the total IOp. The decomposition is based on the well-known concept of the Shapley value in Cooperative Game Theory, which measures the contribution of each circumstance to the outcome, such as earnings. The idea of the Shapley value is to compute the value of a function considering all the possible combinations of circumstances. We do this by first estimating the inequality measure for all possible permutations of the circumstance variables (Shapley 1953). We then compute the average marginal effect of each circumstance variable on the measure of inequality of opportunity. This procedure is computationally intensive because 2^K (K=number of circumstances) must be computed. The Shapley decomposition has substantial advantages over other decomposition methods since it is order independent, and the different components equal the total value.

3.3 Machine Learning Algorithm

The conventional approaches discussed above suffer from many limitations, including that researchers have to decide which circumstance or effort variable to consider in the model. Discarding some relevant circumstance or efforts variables from the model limits the explanatory scope of these variables and leads to downward biased estimates. At the same time, including many circumstances or efforts variables leads to upward biased estimates (Brunori et al, 2019; Hufeetal, 2017; Ferreira and Gignoux, 2011). To overcome these limitations, Machine Learning (ML) algorithms are designed, which automatically learn from data and make responsive decisions.

The application of these methods has become popular in recent years, as they not only minimise the risk of arbitrary and ad-hoc model selection, but also provide a standard way to tackle the upward and downward biases in IOp estimation. The conditional classification and inferential regression trees belong to the class of supervised ML, which can be used for estimating IOp. Several empirical studies have used the ML algorithm to estimate IOp in recent years (Brunori et al, 2018, 2019; Brunori, Hufeand Mahler, 2018; Brunori and Neidhofer, 2020; Lefranc and Kundu, 2020).

Conditional inference regression trees provide predictions based on identifiable groups, which closely connect to Roemer's theoretical formulation of IOp. The application of conditional inference regression trees represents a substantial improvement over existing empirical approach to measure IOp. First, they minimise the risk of arbitrary and ad-hoc model selection and second, they provide a standardised way of trading off upward and downward biases in IOp estimations. In addition, the conditional inference trees are econometrically less complex and provide a handy graphical illustration that can be used for the straightforward analysis of opportunity structures. This makes the measurement of IOp more easily comprehensible to a large audience.

In a tree-based method, the algorithm chooses the relevant partitioning of the sample data in a non-arbitrary way through what is referred to as recursive binary splitting from the full set of available circumstances (Brunori et al, 2018). Recursive binary splitting is a type of permutation test, because it rearranges the labels on the observed data set multiple times and computes test statistics (p-value) for each of these rearrangements. It starts by dividing the full sample into two distinct groups based on one circumstance factor and then continues the same way for each split, potentially based on another circumstance, into more subgroups and so on. The criterion for the selection of splitting circumstances depends on the type of regression tree used. The conditional inference tree algorithm determines the splitting criteria in two stages: (i) selecting the initial splitting circumstance, and (ii) growing the opportunity tree. In other words, first it performs a hypothesis test (t-test) before each split to check whether equal opportunities exist within a sample or subsample. If the algorithm does not make a split, then one cannot reject the null hypothesis of equality of opportunity, where the p-value associated with circumstance C^* is greater than pre-specified significant level (α). Otherwise, it continues by setting the selected circumstance C^* as a splitting variable. Once the C^* is selected, it is split by the binary split criterion to grow the tree and generate visually interpretative opportunity trees in the hierarchical order of circumstance.

3.4 Data Sources and Variables

Our analysis is based on household level survey data from Employment and Unemployment surveys (EUS) (2004-05 and 2011-12), and Periodic Labour Force

Survey (PLFS) (2019-20) collected by Government of India's National Sample Survey Office (NSSO). The cross-sectional survey of these rounds is representative of the national and state level population. The outcome variables include household consumption expenditure, household total income or earnings, monthly wage income (regular and casual), regular salaried/wage income, self-employed income, and casual wage income. However, the earnings of self-employed individuals are not available for the years 2004-05 and 2011-12. The given weekly wage or earnings of causal and regular workers have been converted into monthly earnings before the analysis. The circumstance variables considered for the analysis are parent's education (no education, education up to primary, secondary and higher secondary level, and graduate and above), parent's occupation or job (high skilled, medium skilled, low skilled, unskilled), social group (Scheduled Caste, Scheduled Tribes, Other Backward Classes, and Others), gender (male/female), place of birth (north, east, central, north-east, south and west), and location (rural/urban). Individuals of working age (15-64 years) are included in the analysis. A total sample of 105,020 in 2019-20, 112,103 in 2011-12, and 149,909 in 2004-05 remains in the survey data, after dropping the cases where the parental background information was not available. These sample individuals consist of around one-third (35 per cent in 2019-20; 33 per cent in 2011-12; 33 per cent in 2004-05) of the total sample covered in these surveys.

IV. FINDINGS AND DISCUSSION

4.1 Characteristic of the Sample Population

The profile of the working age (15-64 years) population in the sample is discussed in this section with a focus on circumstances (i.e., location, zone (region), caste (social group), parental education and occupation) and outcome variables (i.e., consumption expenditure, total income, wage income, regular salaried income, casual labour income, and self-employed income). The majority of the sample population resides in rural India, though this has marginally declined from 73.6 per cent in 2004-05 to 68.5 per cent in 2019-20 (Table 1). Across the broad regions, the central region constitutes the highest share (26.2 per cent) followed by the south, east, north and west. The lowest share is in the north east (3.9 per cent). The household heads reported in the survey were mostly male, which dominates in the sample (71.7 per cent). Thus, while selecting the parental background, they are the obvious choice. In the social groups, OBC has the higher share (43.5 per cent) followed by Other/General Category (27.5 per cent), Scheduled Castes (20.5 per cent) and the Scheduled Tribes (8.5 per cent).

Table 1

Profile of Sample Population (in percentage)

		2019-20	*2011-12*	*2004-05*
Sector	Rural	68.5	70.2	73.6
	Urban	31.5	29.8	26.4
	Total	100.0	100.0	100.0
Region (Zone)	North	14.5	13.2	12.3
	East	19.5	20.7	20.3
	Central	26.2	24.5	24.0
	North East	3.9	3.5	3.7
	South	20.8	22.8	24.2
	West	15.1	15.3	15.4
	Total	100.0	100.0	100.0
Gender	Male	71.7	73.9	75.8
	Female	28.3	26.1	24.2
	Total	100.0	100.0	100.0
Social group	ST	8.5	8.0	7.9
	SC	20.5	19.1	19.6
	OBC	43.5	43.4	40.8
	Others (general)	27.5	29.5	31.8
	Total	100.0	100.0	100.0

Source: EUS, 2004-05 and 2011-12, and PLFS, 2019-20

In the year 2019-20, more than three-fourth (75.6 per cent) of the parents in the sample population were educated below the secondary level including 37.3 per cent illiterates. 24.4 per cent were educated to the level of secondary and above (Table 2). However, the share of parents with higher secondary level education (11.7 per cent in 2011-12 to 17.2 per cent in 2019-20), and graduates (4.5 per cent in 2011-12 to 7.2 per cent in 2019-20) has increased in the last two decades. Around half of the parents were engaged in low skilled, non-routine manual jobs (48.2 per cent), followed by elementary routine manual (25.7 per cent), non-routine cognitive high skilled (16.1 per cent) and routine cognitive medium skilled (16.1 per cent) jobs in 2019-20. Over the years, the parents' involvement in high skilled (11.8 per cent in 2011-12 to 16.8 per cent in 2019-20) and elementary jobs (18.5 per cent in 2011-12 to 25.7 per cent in 2019-20) has increased, while their share in the medium (13.1 per cent in 2011-12 to 10.0 per cent in 2019-20) and low skilled jobs (56.6 per cent in 2011-12 to 48.2 per cent in 2019-20) has declined in the last two decades, reflecting the phenomenon known as job polarisation.

Table 2

Parents' Education and Occupation Profile (in per centage)

		2019-20	*2011-12*	*2004-05*
Education	No Education	37.3	42.0	49.3
	Below Secondary	38.3	37.3	34.5
	Secondary/Higher Secondary	17.2	14.7	11.7
	Graduate and above	7.2	6.0	4.5
	Total	100.0	100.0	100.0
Occupation	Non-routine cognitive (High Skilled)	16.1	14.6	11.8
	Routine cognitive (Medium Skilled)	10.0	9.9	13.1
	Non-routine manual (Low Skilled)	48.2	46.6	56.6
	Routine manual (Elementary)	25.7	28.9	18.5
	Total	100.0	100.0	100.0

Source: EUS, 2004-05 and 2011-12, and PLFS, 2019-20

The average household Monthly Consumption Expenditure (MCE) was INR 10652 in 2019-20, with a significant difference between rural (8839 INR) and urban (14587 INR) locations (Table 3). The average MCE in real value has increased from 11391 INR in 2004-05 to 13173 INR in 2011-12, but has decreased to 10652 INR in 2019-20. One of the important reasons for the decline in MCE in 2019-20 may be the nationwide lockdown for a few months in 2020 to reduce the spread of COVID-19 pandemic. The average monthly income (17049 INR) of the households was substantially higher than average monthly consumer expenditure (10652 INR) in 2019-20.

Table 3

Average Monthly Consumer Expenditure and Income in Real Value[2] (in INR) in 2004-05, 2011-12, and 2019-20

	Rural	*Urban*	*Total*
	Average Monthly Consumer Expenditure		
2019-20	8839	14587	10652
2011-12	10758	18864	13173
2004-05	9863	15662	11391
	Average Monthly Income (Self-employed + Regular salaried + Casual labour)		
2019-20	13812	24078	17049

Note: The coverage of all these surveys is from July to June.
Source: EUS, 2004-05 and 2011-12, and PLFS, 2019-20

2. The consumer expenditure is converted from nominal to real values by using Consumer Price Index (CPI), CPI-agriculture labour for rural areas, and CPI-industrial workers for urban areas.

In the year 2019-20, the status of employment (by weekly status) shows that around half of the working age people in the sample were engaged in self-employed activities (49.2 per cent), followed by regular salaried job (29.4 per cent) and casual labour work (21.4 per cent) (Table 4). Over the years, the share of sample population engaged in regular salaried jobs (13 per cent in 2011-12 to 29.4 per cent in 2019-20) has increased substantially, while the share in casual labour (32.1 per cent in 2011-12 to 21.4 per cent in 2019-20) and self-employment (54.9 per cent in 2011-12 to 49.2 per cent in 2019-20) has declined during the same period.

Table 4

Status of Employment of Working Sample (in percentage) in 2004-05, 2011-12, and 2019-20

Status of Employment	*2019-20*	*2011-12*	*2004-05*
Self employed	49.2	50.2	54.9
Regular	29.4	18.2	13.0
Casual labour	21.4	31.6	32.1
Total	100.0	100.0	100.0

Source: EUS, 2004-05 and 2011-12, and PLFS, 2019-20

In 2019-20, the average monthly income from regular salaried job (15505 INR) was the highest, followed by self-employment (12133 INR) and casual labour work (7392 INR) (Table 5). There are substantial gender and locational differences visible in average income. Over the years, the average monthly regular salaried income has increased substantially from 11407 INR in 2004-05 to 15901 INR in 2011-12, but marginally declined to 15505 INR in 2019-20. On the other hand, the average monthly casual labour income has increased substantially from 3651 INR in 2004-05 to 6106 INR in 2011-12, and further to 7392 INR in 2019-20. In particular, the average income of the regular salaried population in the urban locations and for males has declined during the last decade which may largely be a consequence of the lockdown.

Table 5
Average Monthly Income in Real Value[3] (in INR) by Status of Employment in 2004-05, 2011-12, and 2019-20

	Location		*Gender*		*Total*
	Rural	*Urban*	*Male*	*Female*	
	Average monthly self-employed (SE) income				
2019-20	10214	17312	12475	6055	12133
	Average monthly regular salaried (RE) income				
2019-20	12849	17729	15756	13940	15505
2011-12	11500	18595	16283	12375	15801
2004-05	8979	13216	11842	8373	11407
	Average monthly casual labour (CL) income				
2019-20	7155	8549	7581	4865	7392
2011-12	5926	7062	6291	3987	6106
2004-05	3504	4586	3842	2291	3651

Source: EUS, 2004-05 and 2011-12, and PLFS, 2019-20

4.1 Inequality of Opportunity in India

In 2019-20, the inequality (mean long deviation) is almost similar in the case of total income (0.307) and wages (regular/casual) (0.291), while less in the case of consumption (0.160). On the other hand, the relative IOp is also relatively higher in the case of wages (0.265) than in income (0.241), and consumption (0.222). This reflects that 22 per cent of consumption inequality, 31 per cent of income inequality, and 29 per cent of wages inequality is due to the chosen set of unequal circumstances. These results corroborate with the earlier findings, which also show that relative IOp is higher in the case of wages and income compared to consumption (Singh, 2012; Lefranc and Kundu, 2020). The inequality increased both in the case of consumption and wages between 2004-05 and 2011-12, but declined in the recent decade (2011-12 to 2019-20). However, there has been an opposite trend in consumption and wage inequality in the period between 2004-05 and 2019-20, where the former is stable or marginally declined from 0.236 to 0.222, and the latter increased from 0.184 to 0.265. The analysis reveals that even though overall inequality in both consumption and wages has decreased substantially in the last two decades, the relative contribution of IOp is stable and increased considerably in the case of wages. This reinforces the theoretical argument that advocates a greater focus on IOp instead of outcome-based inequality.

3. The self-employed income, regular salaried income and casual labour income expenditure is converted from nominal to real values by using the Consumer Price Index (CPI), CPI-agriculture labour for rural areas, and CPI-industrial workers for urban areas.

Table 6

Inequality of Opportunity in Consumer Expenditure, Income and Wages

	Consumption			*Income*	*Wages*		
	2004-05	*2011-12*	*2019-20*	*2019-20*	*2004-05*	*2011-12*	*2019-20*
Inequality (MLD)	0.172	0.191	0.160	0.307	0.465	0.394	0.291
Relative IOp	0.236	0.235	0.222	0.241	0.184	0.272	0.265
	(0.0066)	(0.0099)	(0.0140)	(0.0069)	(0.0134)	(0.0152)	(0.0192)

Note: Figures in parentheses are Bootstrap standard error[4]
Source: Authors calculation from EUS, 2004-05 and 2011-12, and PLFS, 2019-20

The relative IOp in consumption expenditure and wage income has increased from 2004-05 to 2011-12, and decreased in the last decade between 2011-12 and 2019-20. On the other hand, the extent of relative IOp in income from regular paid jobs has increased consistently over the years, while the relative IOp has declined in income from the casual wage employment. Further, the wage or income inequality in regular jobs is the highest, followed by self-employment. It is the least in casual labour. An almost similar pattern is also observed in the case of relative IOp in income for regular salaried, self-employed and casual labour. Over the years, the relative IOp in wages or income in regular employment has increased from 0.163 in 2004-05 to 0.242 in 2019-20, while the relative IOp in wages in casual labour has remained almost stable between 0.153 and 0.162 during the same period. This reveals that most of the rise in income inequality is contributed by IOp in the regular salaried jobs.

Table 7

Inequality of Opportunity in Income/Wages by Employment Status

	Regular salaried			*Self-employed*	*Casual labour*		
	2004-05	*2011-12*	*2019-20*	*2019-20*	*2004-05*	*2011-12*	*2019-10*
Inequality (MLD)	0.500	0.457	0.306	0.269	0.186	0.155	0.117
Relative IOp	0.163	0.238	0.242	0.179	0.153	0.173	0.162
	(0.0129)	(0.0178)	(0.0235)	(0.0166)	(0.0093)	(0.01316)	(0.01449)

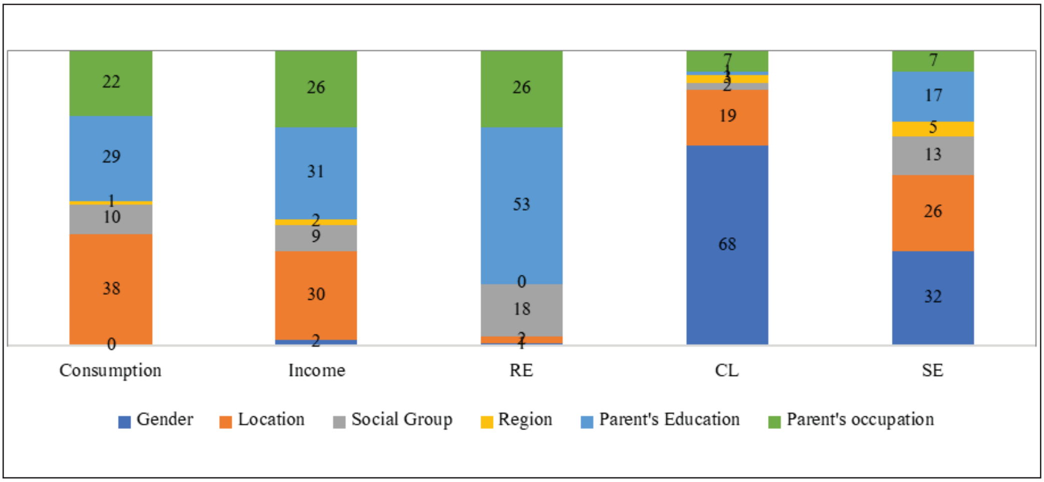
Note: Figures in parentheses are Bootstrap standard error
Source: Authors calculation from EUS, 2004-05 and 2011-12, and PLFS, 2019-20

4. The bootstrap standard errors are based on 100 replication and nearly zero, which suggest the robustness of the estimate.

4.2 Contribution of Factors

To find out the relative contribution of circumstances to IOp, we have decomposed the IOp using the Shapley decomposition method. The relative contribution of each circumstance variable is presented in Figure 1. The parental background (51 per cent), which includes education (29 per cent) and occupation (22 per cent), followed by location (38 per cent), are the key contributing factors contributing to consumption IOp. Similarly, parental background (57 per cent) and location (30 per cent) also play a key role in determining income IOp.

Figure 1
Shapley decomposition of Inequality of Opportunity in 2019-20



The parental background i.e., education and occupation contribute substantially higher in the case of regular salaried workers, where these two factors combined contribute around 80 per cent to the income IOp. The probability of getting a regular salaried job in the labour market is highly affected by individual educational level, which is influenced significantly by parents' education level and occupation. Perhaps, this may be one of the possible reasons why parents' education and occupation contribute more to unequal opportunity in income in the regular paid jobs (Das and Biswas, 2022). On the other hand, gender difference among workers is primarily responsible for unequal opportunity in income in casual wage employment (60 per cent), while gender (32 per cent) and parental education (17 per cent) play key roles for unequal opportunity in income in the case of self-employment. While the difference in social group or caste (social identity) among workers also plays a significant role in creating unequal opportunity in regular paid jobs (18 per cent) and self-employment (13 per cent), it has a negligible role in explaining this unethical part of income opportunity in casual wage employment. This reveals that parental background plays a significant role in income, consumption and earnings IOp in case of regular employment, while gender contributes most in the case of casual wage employment and self-employment.

4.3 Conditional Inference Regression Tree

Using mean log deviation (MLD), we find that the relative IOp using tree-based methods gives us estimates of consumption (0.253) and income IOp (0.232) slightly higher but very near to the parametric estimates as discussed above in Table 6. In the conditional inference trees, the terminal node of each tree allows us to visually represent a type, their respective conditional mean output, and the circumstance that is important in each outcome. The conditional inference regression tree for the consumption expenditure given in Figure 2 is discussed below as per the tree classifications.

The inference trees analysis reveals that parents' education is the most important circumstance that determines consumption IOp, as indicated by the initial node in Figure 2. It importance varies with the parents' level of education as for the individuals with parents having secondary or above educational qualifications, the occupation of the parents becomes the second most important circumstance determining consumption IOp. Among these individuals, those whose parents are in non-routine cognitive medium skilled jobs, and routine cognitive high skilled jobs have lower consumption IOp, while those whose parents are in non-routine manual low skilled jobs, and routine manual unskilled jobs have high consumption IOp.

On the other hand, for individuals with parents with below secondary level education or no formal schooling, the location (rural-urban) becomes the second most important circumstance determining consumption IOp. Those who are residing in rural areas tend to have higher consumption IOp compared to their counterparts in the urban areas. For those residing in the rural areas, consumption IOp in the central and eastern part of the country is higher than the north, north-east, south, and west, which consist of relatively less developed, and high poverty ridden states.

Further, individuals in the rural north, which includes agriculturally rich states such as Punjab and Haryana, tend to have lower consumption IOp compared to their counterparts in north-east, south, and west. Additionally, individuals in the rural north-east, south, and western parts of the country, whose parents are in non-routine cognitive medium skilled jobs and routine cognitive high skilled jobs, tend to have less consumption IOp than those whose parents are in non-routine manual low skilled jobs and routine manual unskilled jobs.

Similarly, the results of the conditional inference regression tree for the income or earnings are given in Figure 3. The result shows that parent's education is the most important circumstance that determines earnings or income IOp, indicated by the initial node in Figure 3. Individuals with parents having graduation and above education tend to have low income IOp compared to the individuals whose parents have education below graduation. On the other hand, individuals with parents having education below graduation or no formal schooling, location (Rural-Urban) becomes the second most important circumstance determining income IOp.

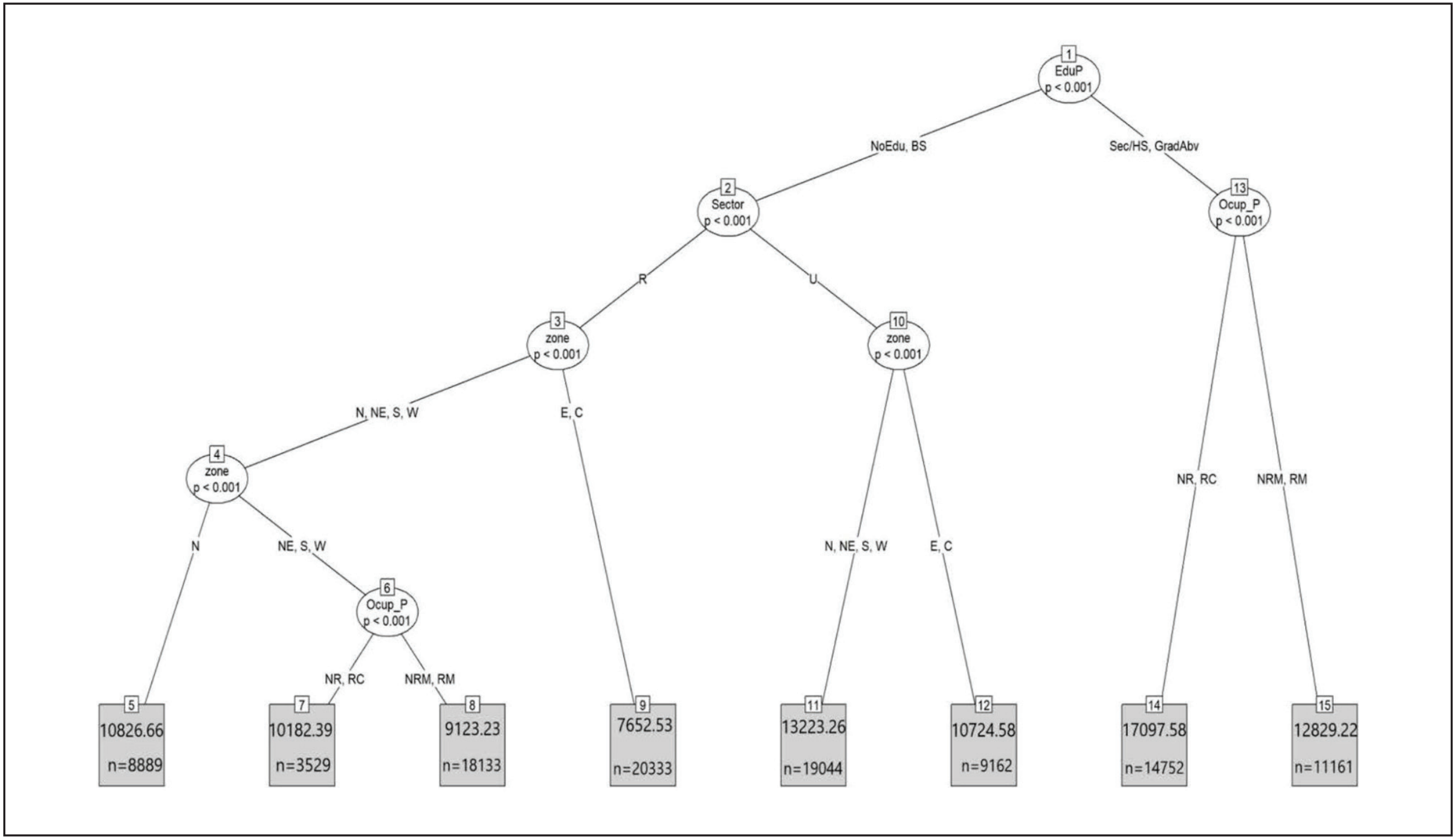
For the individuals residing in the urban areas, income IOp is comparatively less than those living in the rural areas. In the urban areas, income IOp is higher in the central and eastern parts of the country compared to the northern, north-eastern, southern, and western parts. In the rural areas, income IOp is higher in the central and eastern parts compared to the northern, north-eastern, southern and western regions.

Further, individuals residing in the north, north-east, south, and west rural parts of the country, whose parents are in non-routine cognitive medium skilled jobs and routine cognitive high skilled jobs have lower income IOp than those whose parents are in non-routine manual low skilled jobs, and routine manual unskilled jobs.

The conditional inference regression tree analysis reveals that parental education has turned out to be the most important circumstance factor followed by location for both consumption and income IOp. In addition, occupation is also equally important as location in the case of consumption IOP.

Figure 2

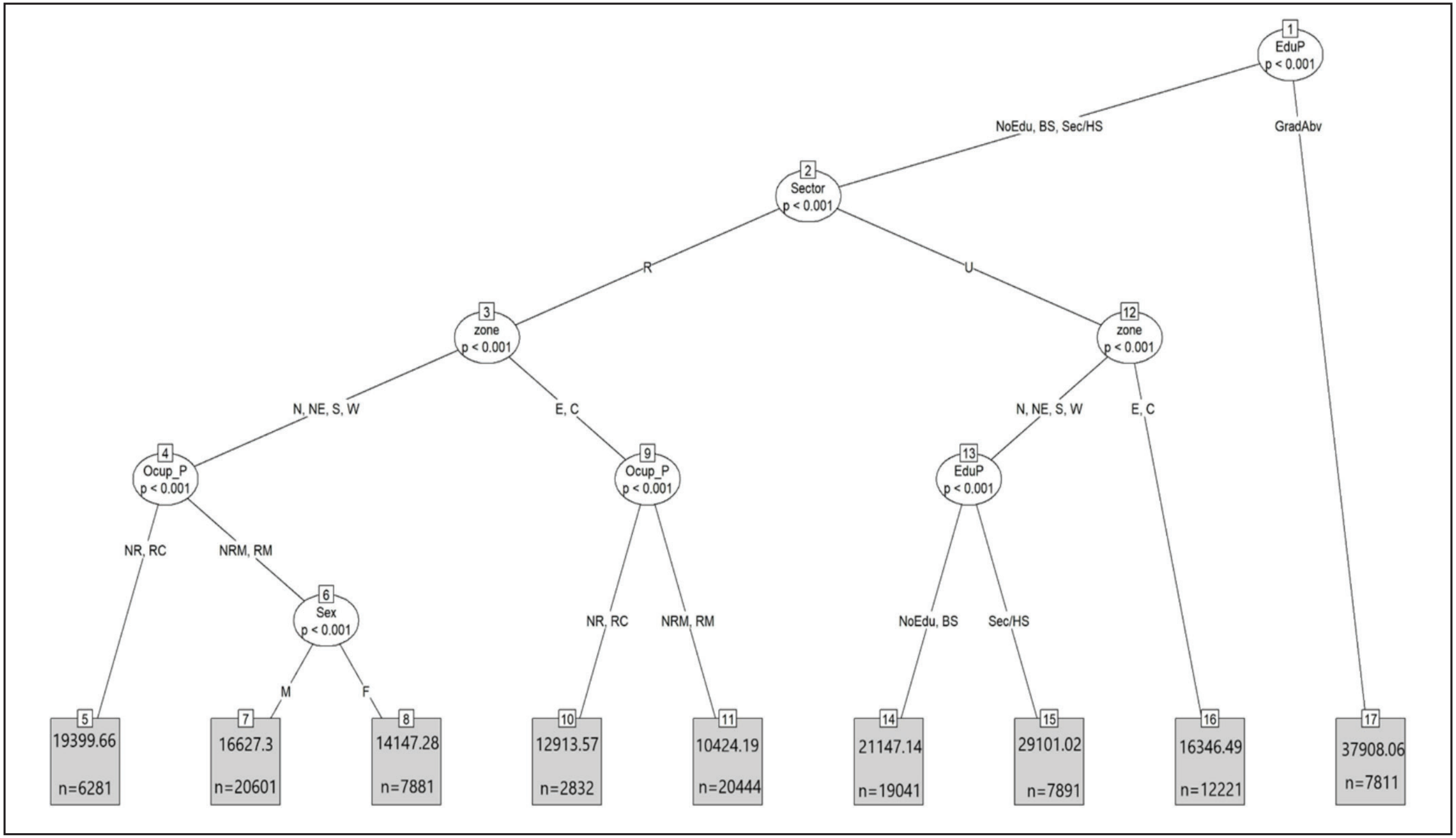
Monthly Consumption Expenditure Tree



R: Rural; U: Urban; N: North; NE: North East; S: South; W: West: E: East; C: Central; Sec/HS: Secondary/Higher Secondary; GradAbv: Graduate and Above; NoEdu: Illiterate or Nor Formal Schooling; BS: Below Secondary; NR: Non Routine Cognitive; RC: Routine Cognitive; NRM: Non Routine Manual; RM: Routine Manual M: Male F: Female

Figure 3

Conditional Inference Regression Tree for HH Earnings/Income



R: Rural; U: Urban; N: North; NE: North East; S: South; W: West; E: East; C: Central; Sec/HS: Secondary/Higher Secondary; GradAbv: Graduate and Above; NoEdu: Illiterate or Nor Formal Schooling; BS: Below Secondary; NR: Non Routine Cognitive; RC: Routine Cognitive; NRM: Non Routine Manual; RM: Routine Manual; M: Male F: Female

V. CONCLUSION AND WAY FORWARD

The analysis shows that around one-fifth of the consumption inequality and one-fourth of the income inequality is accounted for by unequal circumstances in the country. Overall, inequality in both consumption and wages has declined substantially. However, the relative contribution of IOp is stable in the case of consumption, while it has increased considerably in the case of wages. In light of this, public policy should focus more on IOp instead of outcome-based inequality. Further, the income or earnings IOp in regular employment is the highest and has increased significantly, while the same has declined in the case of wage employment during the last two decades. The ML algorithms provide improved results with more details on the important circumstances that contribute to income and consumption IOp. The analysis based on Shapely Decomposition reveals that the parental background i.e., education and occupation, contributes the most to unequal opportunities for regular salaried employment. Here, gender plays a key role in explaining unequal earnings opportunity for casual wage employment and self-employment.

Further, the regression inference tree based on the ML algorithm also indicates that parent's education is the most important variable that determines income or consumption inequality. This is followed by the factors — location (rural-urban), place of birth (regions) and the occupation of the parents. Hence, to reduce this unethical part of inequality, public policy should differ across locations and regions, with a special focus on access to quality education for the children coming from vulnerable backgrounds. More research on this topic is needed, integrating different data sources such as conventional survey-based data with non-conventional data (like satellite-images). t provide more robust results on the circumstances that contribute to IOp, which is otherwise not possible from a single source of data.

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