The Impact of Caste on Income Disparity in India Today. A Pan-India Panel Data Approach

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Abstract: India has enacted several affirmative action policies since the 1990s to benefit the lower castes. This paper investigates if caste still affect an individual's income in India today. Previous studies in this field have focused on specific regions or castes, and there is a dearth of pan-India empirical studies using panel data to investigate the relationship between caste and income. There is also a lack of studies that highlight the factors that help accentuate or ameliorate the caste-based income disparity in India. This paper addresses these gaps. The sample used for this paper is composed of respondents from all across India. Using the Indian Human Development Survey (IHDS) panel data, it is found that although the impact of caste on income has reduced, lower caste individuals 'income is still lower than that of their upper caste counterparts. The paper also finds evidence that the effects of caste on income are ameliorated in rural areas and that higher state-level GDP per capita and attainment of at least high school-level qualifications also contribute to reducing the impact of caste on income. Finally, this paper finds that the lower the caste, the stronger the ameliorating effect of attaining a high school-level qualification and state-level GDP per capita.

JEL Classification: J71, O15, D31.

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1. **Introduction**

The caste system is a community-based system of enforcement that regulates socio-economic privileges through social ostracism, violence, and economic penalties. The system broadly categorises individuals into four categories: priests (Brahmins), warriors (Kshatriyas), traders (Vaishyas), and cleaners (Shudras)**.** The so-called Untouchables (Dalits) and Adivasis (Tribal people) are considered to be at the very bottom of the system. For centuries, the caste system has been a regulator of economic life in India. However, since India's independence from British rule in 1947, several policies and laws have been enacted to bridge the economic gap between the upper and lower caste groups. One of the most prominent of them was the expansion of reserved categories in the 1990s, which attempted to redress past inequities against the lower caste groups (Thorat and Newman, 2017).

The reservation policy reserves seats in public educational institutions, government jobs, and legislative bodies for people belonging to the lower castes and socio-economically poor sections of society (also known as Other Backward Classes (OBCs)). Under the reservation policy, the untouchables are termed Scheduled Castes (SCs), whereas tribal people (Adivasis) are referred to as Scheduled Tribes (STs). Moreover, India has also experienced rapid economic growth since the 2000s, but caste-based discrimination is still prominent in the socio-economic landscape of the country. This leads to the research question of this study: after decades of the implementation of the reservation policy and economic growth, does caste still affect one's income in modern India? If yes, then which castes are the most disadvantaged, and what are the factors that exacerbate or ameliorate the caste-based income disparity?

India has experienced rapid economic development since the 2000s. the country accounts for around 16% of the global population, and 80% of the Indian population is Hindu. Moreover, around 70% of the Hindu population is categorised as OBCs, Dalits, or Adivasis (Kramer, 2021). Therefore, the impact of the caste system is widespread making it crucial to study the relationship between one's caste and income in modern India. Besides, if there is evidence of caste affecting one's income in modern-day India, then it is also worth investigating what factors aggravate the caste-based income disparity and what policies the Indian government can adopt to ameliorate, if not eradicate the problem.

The next section discusses the existing literature related to this research while identifying the literature gap. The Literature Review section is followed by the Empirical Model section, which contains a detailed discussion of the Hausman-Taylor model. Then the Data Description section highlights the salient features of the sample, followed by the Income Mobility and Inequality Decomposition, and the Results sections, which present the primary findings of the paper. The paper then suggests policy changes for the Indian government before discussing the conclusions.

2. **Literature Review**

There is plenty of literature on the association between caste and income. Deshpande (2000) examines the role of caste affiliation as a descriptor of intergroup disparity. Deshpande and Newman (2007) show that Dalits are less likely than non-Dalits to use family resources to pursue employment, in addition to having lower occupational expectations. A longer job search duration is also anticipated by Dalits (9.6 months on average for Dalit students against 5.25 months for non-Dalits). They also conclude that although the language of the hiring process is said to be based on merit, the interview practice appears to be biased in favour of upper caste students. For instance, upper caste students perceive the questions on the family background as being generally neutral, whereas Dalit students feel the same questions to be adversely structured against them.

Deshpande and Palshikar (2008) find evidence of a strong association between occupational mobility and caste in the city of Pune. The extent of mobility varies among different castes, where higher castes like the Maratha-Kunbis display consistent upward class mobility over four generations. Therefore, they can consolidate their position using social, cultural, and economic capital. Dalits (people at the very bottom of the caste hierarchy), on the other hand, move from lower levels of occupation to lower-middle-class levels, whereas Other Backward Classes (which fall into the lower caste category in this paper; in the caste hierarchy, they are above Dalits but not upper caste) show barely any to no upward mobility. They also discover that individuals from no caste group are immune to downward mobility.

Jodhka (2010) also finds evidence of caste-based discrimination faced by Dalit entrepreneurs in Panipat, Haryana, and Saharanpur, Uttar Pradesh. One may assume that industrialisation, the workings of a free market economy, and the resultant urbanisation would weaken, if not eradicate, the association of caste and income, leaving little room for caste-based discrimination, which could be highly inefficient. Furthermore, Jodhka and Newman (2010) discover what on the surface appears to be a meritocratic, impartial hiring process is permeated by a persistent and subtle language of caste and discrimination.

Deshpande (2011) suggests that discrimination coexists with a free market economy. Zacharias and Vakulabharanam (2011) find that SCs and STs have substantially lower wealth than the so-called forward caste groups, i.e., people belonging to the upper castes like priests and warriors, while the OBCs and non-Hindus occupy positions in the middle.

Vaid (2012) finds evidence of a weakening of caste-income association over time, especially in the middle of the caste hierarchy. In addition, according to Vaid (2012), individuals belonging to higher castes, who do not qualify for the government's reservation or affirmative action programs, tend to be heavily represented in the upper echelons of society. This includes professions such as doctors, lawyers, large business owners, farmers, and those employed in white-collar jobs. In contrast, SC (Scheduled Castes) communities who are eligible for reservations are under-represented in stable white-collar or business and farm ownership classes and remarkably over-represented in "lower income, less stable, temporary employment in the manual work categories, and lower agriculture as labourers.” Such a caste-class association can lead to income differences between the upper and lower-caste populations.

Vaid (2014) also mentions that although higher castes are not immune from downward mobility, they display a much weaker inheritance of parental class, whereas it is much harder for lower castes, especially SCs, to leave their class origins. Vaid (2014) further adds that while mobility is limited in extremely high and extremely low castes, it is comparatively more prominent in the middle of the caste hierarchy.

Thorat and Newman (2017) elaborate on the prevalence of caste-based social and economic exclusion. Lower caste groups, notably the Dalits, have faced significant challenges engaging in free market interactions, including entering labour markets, and are essentially denied basic human rights like equality before the law and freedom of expression. Moreover, restrictions on the movement of labour between occupations due to caste become a source of voluntary unemployment for higher-caste individuals and involuntary unemployment for their lower-caste counterparts. Higher caste Hindus typically prefer to choose a temporary exit from the market over entering a profession they view as "beneath them" or "polluting.". Lower caste untouchables, on the other hand, are restricted from claiming more prestigious occupations, which pushes them towards involuntary unemployment. Furthermore, Dalits are forced to take up jobs that are regarded as socially degrading, such as scavenging and cleaning sewers. Such a system of social and economic exclusion results in a disproportionate number of individuals at the bottom of the caste system suffering from poverty.

Bharti (2019) argues that wealth is concentrated among upper caste Hindus. Munshi (2019) finds evidence of convergence in education, occupations, income, and access to public resources across caste groups. Mushi (2019) attributes this convergence to affirmative action policies and caste-based networks, which could have played an equalising role by exploiting the opportunities that become available in a globalising economy.

According to Vaid (2014), most studies in this field have focused on specific regions or castes, and there is a dearth of pan-India empirical studies using panel data to investigate the relationship between caste and income. There is also a lack of studies that highlight the factors that help accentuate or ameliorate the caste-based income disparity in India. This paper addresses this gap. The sample used for this paper is composed of respondents from all across India.

3. Empirical Model

In this paper, caste, which is a time-invariant variable, is one of the variables of interest. However, the fixed effects model will eliminate such variables by demeaning them. Therefore, these variables of interest need to be separated from the pool of fixed effects. This paper uses the Hausman-Taylor model to construct the estimator. Suppose the standard setting of the fixed effects model is the following:

$$y_{it} = \boldsymbol{x}_{it}^{'}\boldsymbol{\beta} + \boldsymbol{z}_{i}^{'}\boldsymbol{\alpha} + \varepsilon_{it} \qquad (1)$$

The variables of interest are encapsulated in $\boldsymbol{z}_i$, but the fixed-effects model simply absorbs them through the demeaning process. Random effects treatment does allow the model to contain observed time-invariant characteristics, such as demographic characteristics. Hausman and Taylor (1981) suggests a way to overcome the first of these while accommodating the second. The model setting is the following:

$$y_{it} = \boldsymbol{x}_{1it}^{'}\boldsymbol{\beta}_1 + \boldsymbol{x}_{2it}^{'}\boldsymbol{\beta}_2 + \boldsymbol{z}_{1i}^{'}\boldsymbol{\alpha}_1 + \boldsymbol{z}_{2i}^{'}\boldsymbol{\alpha}_2 + \varepsilon_{it} + u_i \qquad (2)$$

The model classifies the independent variables into four categories. The time-variant variables $\boldsymbol{x}_{it}$ are divided into two groups, $\boldsymbol{x}_{1it}$ and $\boldsymbol{x}_{2it}$. $\boldsymbol{x}_{1it}$ refers to the K_1 variables that are time-varying and uncorrelated with u_i. While $\boldsymbol{x}_{2it}$ accounts for the K_2 variables that are time-varying and correlated with u_i. Similarly, the time-invariant variables $\boldsymbol{z}_i$ are divided into the exogenous group $\boldsymbol{z}_{1i}$ and endogenous group $\boldsymbol{z}_{2i}$ with lengths of L_1 and L_2 respectively. Table 1 illustrates the variable setting.

Table 1: Illustration of variables setting.

	Uncorrelated with $\boldsymbol{u_i}$	**Correlated with $\boldsymbol{u_i}$**
Time-variant	$\boldsymbol{x}_1$	$\boldsymbol{x}_2$
Time-invariant	$\boldsymbol{z}_1$	$\boldsymbol{z}_2$

The assumptions are standard and similar to those of the Random Effects model. It is assumed that the variance matrix of unobserved variables has no serial correlation and no distinct "random effects" or "exchangeable" structure. The assumptions are the following:

$$E[u_i|\boldsymbol{x}_{1it}, \boldsymbol{z}_{1i}] = 0, E[u_i|\boldsymbol{x}_{2it}, \boldsymbol{z}_{2i}] \neq 0$$

$$Var[u_i|\boldsymbol{x}_{1it}, \boldsymbol{z}_{1i}, \boldsymbol{x}_{2it}, \boldsymbol{z}_{2i}] = \sigma_u^2$$

$$Cov[\varepsilon_{it}, u_i|\boldsymbol{x}_{1it}, \boldsymbol{z}_{1i}, \boldsymbol{x}_{2it}, \boldsymbol{z}_{2i}] = 0$$

$$Var[\varepsilon_{it} + u_i|\boldsymbol{x}_{1it}, \boldsymbol{z}_{1i}, \boldsymbol{x}_{2it}, \boldsymbol{z}_{2i}] = \sigma^2 = \sigma_\varepsilon^2 + \sigma_u^2$$

$$Corr[\varepsilon_{it} + u_i, \varepsilon_{is} + u_i|\boldsymbol{x}_{1it}, \boldsymbol{z}_{1i}, \boldsymbol{x}_{2it}, \boldsymbol{z}_{2i}] = \rho = \frac{\sigma_u^2}{\sigma^2}$$

Under these assumptions, the OLS or GLS estimators of this model are inconsistent when the model contains variables that are correlated with the random effects. The Hausman-Taylor model proposes an instrumental variable estimator that uses only the information within the model. First, we obtain consistent estimators of $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ (fixed effects estimators) based on $\boldsymbol{x}_1$ and $\boldsymbol{x}_2$:

$$y_{it} - \bar{y}_i = \left(\boldsymbol{x}_{1it} - \bar{\boldsymbol{x}}_{1i}\right)' \boldsymbol{\beta}_1 + \left(\boldsymbol{x}_{2it} - \bar{\boldsymbol{x}}_{2i}\right)' \boldsymbol{\beta}_2 + \left(\varepsilon_{it} - \bar{\varepsilon}_i\right) \quad (3)$$

Equation (3) is the normal demeaning process. Through this equation, we get the within-estimator $\hat{\boldsymbol{\beta}}_{1w}$ and $\hat{\boldsymbol{\beta}}_{2w}$. The residual variance estimator from this step is a consistent estimator of σ_ε^2:

$$\hat{\sigma}_\varepsilon^2 = \frac{SSR}{N-n} \quad (4)$$

Then we form the within-groups residuals e_{it} and stack the group means of these residuals in a full-sample-length data vector:

$$e_{it}^* = \bar{e}_i = \frac{1}{T}\sum_{t=1}^{T}\left(y_{it} - \boldsymbol{x}'_{1it}\hat{\boldsymbol{\beta}}_{1w} - \boldsymbol{x}'_{2it}\hat{\boldsymbol{\beta}}_{2w}\right) \quad (5)$$

$$\bar{e} = \begin{pmatrix} \left(\bar{e}_1, \bar{e}_1, \dots, \bar{e}_1\right) \\ \vdots \\ \left(\bar{e}_n, \bar{e}_n, \dots, \bar{e}_n\right) \end{pmatrix}_{n\times T} \quad (6)$$

The next step is the normal Two-Stage Least Squares (2SLS) regression. We simply need to run an IV regression on $\boldsymbol{z}_1$ and $\boldsymbol{z}_2$with instrumental variables $\boldsymbol{z}_1$ and $\boldsymbol{x}_1$. Recall that $\boldsymbol{z}_1$ is assumed to be uncorrelated with u_i, therefore we only need to run a regression of $\boldsymbol{z}_{2i}$ on $\boldsymbol{z}_{1i}$ and $\boldsymbol{x}_{1it}$ to get the predicted value of $\boldsymbol{z}_{2i}$, $\hat{\boldsymbol{z}}_{2i}$, in the first stage. Finally, we regress $\bar{e}$ on $\boldsymbol{z} = \left(\boldsymbol{z}_1, \hat{\boldsymbol{z}}_2\right)$ to get consistent estimators of $\boldsymbol{\alpha}_1$ and $\boldsymbol{\alpha}_2$: $\hat{\boldsymbol{\alpha}}_1$ and $\hat{\boldsymbol{\alpha}}_2$. Since we run the 2SLS regression, we need the following key identification requirements:

K_1 (Number of variables in $\boldsymbol{x}_1$) $\geq L_2$ (Number of variables in $\boldsymbol{z}_2$)

Moreover, for large samples, feasible GLS (FGLS) is more efficient than OLS and available for this study. FGLS is also an improvement over the simple instrumental variable estimation of the model, which is consistent but inefficient. To find the weight for GLS, recall that in the second step, we can obtain the residual variance, say $\hat{\sigma}^{*2}$, which is a consistent estimator of $\sigma^{*2} = \sigma_u^2 + \frac{\sigma_\varepsilon^2}{T}$. It should also be noted that we have $\hat{\sigma}_\varepsilon^2$, the residual variance estimator from the first step, which is a consistent estimator of σ_ε^2. Then we can construct an estimator of σ_u^2:

$$\hat{\sigma}_u^2 = \hat{\sigma}^{*2} - \frac{\hat{\sigma}_\varepsilon^2}{T} \quad (7)$$

which provides an estimate of the weight for feasible GLS:

$$\hat{\theta} = 1 - \sqrt{\frac{\hat{\sigma}_\varepsilon^2}{\hat{\sigma}_\varepsilon^2 + T\hat{\sigma}_u^2}} \quad (8)$$

Now, the final step is a weighted instrumental variable estimator. The transformed variables for GLS are, as before when we first fit the Random Effects model:

$$\boldsymbol{w}_{it}^{*'} = \left[\boldsymbol{x}_{1it}^{'}, \boldsymbol{x}_{2it}^{'}, \boldsymbol{z}_{1i}^{'}, \boldsymbol{z}_{2i}^{'}\right] - \hat{\theta}\left[\bar{\boldsymbol{x}}_{1it}^{'}, \bar{\boldsymbol{x}}_{2it}^{'}, \bar{\boldsymbol{z}}_{1i}^{'}, \bar{\boldsymbol{z}}_{2i}^{'}\right] \quad (9)$$

$$y_{it}^{*} = y_{it} - \hat{\theta}\bar{y}_i \quad (10)$$

The instrumental variables are:

$$\boldsymbol{v}_{it}^{'} = \left[\left(\boldsymbol{x}_{1it} - \bar{\boldsymbol{x}}_{1i}\right)^{'}, \left(\boldsymbol{x}_{2it} - \bar{\boldsymbol{x}}_{2i}\right)^{'}, \boldsymbol{z}_{1i}^{'}, \bar{\boldsymbol{x}}_{1i}^{'}\right] \quad (11)$$

Finally, a 2SLS regression of y_{it}^{*} on $\boldsymbol{w}_{it}^{*'}$ with instruments $\boldsymbol{v}_{it}^{'}$ is done to obtain the estimator:

$$\left(\hat{\boldsymbol{\beta}}^{'}, \hat{\boldsymbol{\alpha}}^{'}\right)_{IV}^{'} = \left[(\boldsymbol{W}^{*'}\boldsymbol{V})\left(\boldsymbol{V}^{'}\boldsymbol{V}\right)^{-1}(\boldsymbol{V}^{'}\boldsymbol{W}^{*})\right]^{-1}\left[(\boldsymbol{W}^{*\prime}\boldsymbol{V})(\boldsymbol{V}^{\prime}\boldsymbol{V})^{-1}(\boldsymbol{V}^{\prime}y^{*})\right] \quad (12)$$

To fit this model into this research, the settings of the variables must be discussed. Cornwell and Rupert (1988) provide an illustrative example that could work as an excellent paradigm. They seek to capture the real return of school on wages where there are aspects of ability that are not observed. Therefore, a Random Effects estimator model for Panel Data could be appropriate. Nevertheless, there is a strong correlation between the observed person-specific aspects, in this case, years of education, and the unobserved factors of an individual. Table 2 illustrates their setting of variables.

Table 2: Variables setting: returns on schooling.

	Uncorrelated with $\boldsymbol{u_i}$	Correlated with $\boldsymbol{u_i}$
Time-variant	$\boldsymbol{x}_1$: WKS, SOUTH, SMSA, MS	$\boldsymbol{x}_2$: EXP, EXP2, OCC, IND, UNION
Time-invariant	$\boldsymbol{z}_1$: FEM, BLK	$\boldsymbol{z}_2$: EDU

In their setting, EXP refers to work experience, and WKS stands for weeks worked. OCC is a dummy variable for occupation and equals 1 if the individual is blue-collar. IND equals 1 if the individual works in the manufacturing industry, and SOUTH is a dummy variable for whether the individual resides in the South. SMSA is whether the individual lives in a city. MS stands for Married Status, and FEM equals 1 if the individual is female. UNION is a dummy variable for whether the wage was set by a union in a contract. EDU accounts for years of education. BLK is a dummy showing whether the individual is black.

Following a similar structure, this study divides the variables into three groups. RURAL is a dummy for whether the individual resides in a rural area. NADULTS refers to the number of adults in the household. JOB refers to the type of occupation and INDUSTRY accounts for the individual working industry. RELIGION includes the types of castes and religions. SEX refers to the gender of an individual and EDU accounts for years of education. ENG, MATH, and WRITING represent the individual test scores for English, Mathematics, and writing, respectively. Table 3 provides a simplified illustration.

Table 3: Variables setting: impact of caste on income.

	Uncorrelated with $\boldsymbol{u_i}$	Correlated with $\boldsymbol{u_i}$

Time-variant	$\boldsymbol{x}_1$: RURAL, MARRIED, NUMBER OF ADULTS,	$\boldsymbol{x}_2$: JOB, INDUSTRY
Time-invariant	$\boldsymbol{z}_1$: RELIGION/CASTE, SEX	$\boldsymbol{z}_2$: EDUCATION

However, due to the limitations in the source data, we are unable to fully capture the setting. Since we have more reliable individual-level data on years of education for both the years 2005 and 2012, this paper uses years of education instead of test scores for analysis. More specifically, to capture the non-linear effect of education on income, the *High School Graduate* dummy is constructed, which is 1 if an individual has attained at least 14 years of education.

4. Data Description

This paper uses the Indian Human Development Survey (IHDS) panel data from 2004-05 (IHDS-1) and 2011-12 (IHDS-2). The survey was conducted by the University of Maryland and the National Council of Applied Economic Research, Delhi. About 215,000 and 210,000 individuals were surveyed in 2005 and 2012, respectively. The IHDS-1 interviewed a nationally representative sample of 41,554 households with a total of 215,751 individuals; the IHDS-2 re-interviewed 83% of those households as well as the households that were split from the original households and were residents in the same locality. The sample covers 971 urban blocks and 1503 villages in 388 districts of India and is dispersed throughout 34 states and union territories. The survey collected data on several socio-economic and demographic variables, such as caste or religion, income, marital status, state of residence, and occupation. Table 4 includes the summary statistics for the key variables.

The summary statistics presented in Table 4 provide preliminary evidence of an income gap between the upper caste populations, i.e., those who belong to the Brahmin (Priest) caste or some of the other so-called high castes, and the lower caste populations. It is worth noting that both in 2005 and 2012, the upper castes constituted about 21% of the sample, which is close to the national figure of around 30% (Pew Research Centre, 2021). This paper uses annual household income per capita as a measure of annual individual income. So, hereafter, the term income will refer to household income per capita. In the years 2005 and 2012, the average income was INR 9,533.4 and INR 26,547.22, respectively. However, a sub-sample analysis indicates the caste-based income disparity. In 2005, the average income of the upper castes was INR 14,496.29, whereas the figure for the lower caste group was INR 8,216.58. By 2012, while the average income of the upper caste was INR 39,336.17, the lower caste population earned about INR 23,058.62 on average. Note that about 9% of the sample reported negative farm income, which resulted in negative total income for about 1% of the sample. Crop failures, exorbitant interest rates on informal sources of credit, and other high expenses are frequent sources of debate in India, so this estimate seems reasonable. However, due to the usage of natural log values of income, the negative income entries are eliminated from the analysis. Moreover, state-level GDP per capita data for the years 2004-05 and 2011-12, is collected from the Reserve Bank of India.

Table 4: Mean and Standard Deviation of key variables

Variables	**2005** **(n = 150,070)**	**2012** **(n = 150,070)**
Annual Household Income Per Capita (INR)	9,533.4 (14,170.4)	26,547.22 (47,724.14)
Annual Household Income Per Capita among upper castes (INR)	14,496.29 (20,447.31)	39,336.17 (68,715)
Annual Household Income Per Capita among lower castes (INR)	8,216.586 (11,613.7)	23,058.62 (39,422.29)
Lower Caste (1 if the individual is not Brahmin, High Caste or Forward Caste)	0.790 (0.407)	0.785 (0.410)
Adivasi (Tribals)	0.079 (0.270)	0.082 (0.274)
Dalit (Untouchables)	0.208 (0.406)	0.209 (0.407)
Other Backward Classes (OBC)	0.346	0.338

	(0.475)	(0.473)
Muslim	0.125 (0.331)	0.126 (0.332)
Christian, Sikh, and Jain	0.030 (0.172)	0.028 (0.165)
Rural (1 if the individual lives in a rural area)	0.7008 (0.457)	0.677 (0.467)
Female (1 if the individual is female)	0.476 (0.499)	0.476 (0.499)
High School Graduate (1 if years of education > 13)	0.048 (0.21)	0.059 (0.23)
Number of adults in the household	3.31 (1.744)	3.323 (1.657)
Married (1 if the individual is married)	0.499 (0.5)	0.51 (0.499)
Experience (Individual's age – 16 years)	14.25 (15.81)	19.35 (18.03)

5. Income Mobility and Inequality Decomposition

In this section, sub-sample t-tests and income variance comparisons are conducted to investigate income mobility and decompose income inequality, respectively. The results of the sub-sample tests are presented in Table A1 in the Appendix, where evidence for higher upward income mobility among individuals from upper castes compared to lower castes is found. The tests also find evidence for higher upward income mobility among individuals from urban areas as opposed to rural areas. However, the extent of income mobility in urban areas is different among upper and lower-caste groups. Both in urban and rural areas, individuals from upper caste groups enjoy, on average, a statistically significantly larger increase in income than individuals from lower caste groups. In these t-tests, however, both location and caste could be influencing the results. Although the analysis here is not identical to that of Deshpande and Palshikar (2008), evidence supporting their results is found, i.e., upper caste groups enjoy a higher level of income mobility. They, however, conclude that the overall incidence of upward mobility in the city of Pune is "not very large". However, in this sub-sample analysis, evidence for significantly higher income mobility in urban areas is found.

Furthermore, a comparison of income variance is used to investigate income inequality within the upper and lower castes. Tables A1.1 – A1.4 in the Appendix report Levene's robust test statistic to measure the equality of variances between the upper and lower caste groups and the two statistics proposed by Brown and Forsythe that replace the mean in Levene's formula with alternative location estimators. The first alternative replaces the mean with the median whereas the second replaces the mean with the 10% trimmed mean. The analysis shows that income inequality was higher among the upper castes in both 2005 and 2012. Using the same technique, it is found that income inequality has been on the rise between 2005 and 2012 for both upper and lower-caste populations. The increase in inequality between 2005 and 2012 is not surprising, as it is consistent with the rise in inequality in India over the past three decades. However, the higher and increasing inequality among upper-caste groups may be a result of the concentration of these communities' members in positions of economic and political power, which could widen the income disparity within their castes. The next section explores the causal relationship between caste and income.

6. Results

Our base model is as follows:

$$ln(\text{Annual Household Income Per Capita})_i = \beta_0 + \beta_1 (\text{Lower Caste dummy})_i + \beta_2 (\text{Rural dummy})_i + \beta_3 (\text{Gender dummy})_i + \beta_4 (\text{Number of Adults in the Household})_i + \beta_5 (\text{Marital Status dummy})_i + \beta_6 (\text{High School Graduate dummy})_i + \beta_7 (\text{State Level GDP per capita})_i + \beta_8 (\text{Years of Experience})_i + \beta_9 (\text{Years of Experience})^2{}_i + \varepsilon_i$$

Table 5 presents the estimation results. Model 1 shows that if one is a lower caste individual, i.e., if one does not belong to the Brahmin (Priest) caste or some of the other so-called high castes, then one's annual income is 21.1% lower than that of the rest of the population. The effect is not only economically significant but also statistically significant at the 1% significance level. Model 1 also provides evidence for a significant rural-urban income gap. People residing in rural areas have about 50.2% lower annual incomes relative to people residing in urban areas. This effect, however, is not surprising because urban areas provide more economic opportunities.

The interaction term between *Lower Caste* and *Rural* in Model 2 is included to separate the estimated effects of being a lower caste on income between rural and urban populations. Model 2 shows that the effect of caste on income is exacerbated in urban areas as compared to their rural counterpart. In urban areas, the income of a lower caste individual is 26.6% lower than that of individuals belonging to the upper caste groups. However, in rural areas, the income of a lower caste individual is 17.6% lower than that of the upper caste population. The strong caste-based networks of upper caste people in urban areas could have accentuated the caste-based income gap because there are more channels available there through which favouritism among upper caste people could impede upward financial mobility of their lower caste counterparts promoting upward financial mobility among fellow upper castes. However, in rural areas, due to limited overall economic opportunities, such caste-based networks may not necessarily manifest themselves in terms of higher income. This is one major factor that can explain why caste-based income disparity has decreased in rural areas.

Table 5: Regression Results | Independent Variable: *ln(Annual Household Income Per Capita)*

Covariates	**Model 1 (n = 294,925)**	**Model 2 (n = 294,925)**	**Model 3 (n = 294,925)**	**Model 4 (n = 294,925)**	**Model 5 (n = 294,925)**
Lower Caste	-0.211*** (0.005)	-0.266*** (0.008)	-0.211*** (0.005)	-0.393*** (0.010)	-0.209 (0.007)
Rural	-0.502*** (0.005)	-0.571*** (0.010)	-0.490*** (0.005)	-0.499*** (0.005)	-0.502*** (0.005)

Female	-0.051*** (0.005)	-0.050*** (0.005)	-0.044*** (0.005)	-0.051*** (0.005)	-0.051*** (0.005)
No. of adults	0.008*** (0.001)	0.008*** (0.001)	0.006*** (0.001)	0.008*** (0.001)	0.008*** (0.001)
Married	-0.241*** (0.006)	-0.241*** (0.006)	-0.237*** (0.006)	-0.240*** (0.006)	-0.241*** (0.006)
High School Graduate	0.163*** (0.012)	0.169*** (0.012)	0.294*** (0.019)	0.164*** (0.012)	-0.165*** (0.012)
State level GDP Per Capita (INR 10,000)	0.330*** (0.001)	0.330*** (0.001)	0.330*** (0.001)	0.290*** (0.002)	0.330*** (0.001)
Experience	0.029*** (0.005)	0.029*** (0.005)	0.028*** (0.001)	0.029*** (0.0005)	0.029*** (0.0005)
Experience^2	-0.003*** (8.75e-06)	2.99e-04*** (8.75e-06)	-2.79e-04*** (8.71e-06)	-2.96e-04*** (8.74e-06)	-0.003*** (8.77e-06)
Lower Caste * Rural		0.09*** (0.010)	-	-	-
Lower Caste * High School Graduate	-	-	0.108*** (0.021)	-	-
Lower Caste * GDP Per Capita	-	-	-	0.052*** (0.002)	-
Lower Caste * Experience	-	-	-	-	-0.0001 (0.0002)
Constant	8.42*** (0.009)	8.46*** (0.010)	8.41*** (0.009)	8.56*** (0.011)	8.42*** (0.008)

*- Robust Standard errors reported in parentheses. *** $p < 0.01$*

In Model 3, the interaction term between *High School Graduate* and *Lower Caste* is included to investigate how education affects the impact of caste on income. Model 3 shows that the caste-based income disparity is higher among those who have not attained high school-level qualifications. Among people with lower than high school level qualifications, the lower castes have a 21.1% lower income than the upper castes. Whereas, for those who did attain at least a high school level education, caste-based income disparity shrank to about 10.3%. This shows that attending at least high school level education, i.e., having 14 to 16 years of education, is beneficial for the lower caste population in terms of reducing the caste-based income gap. The result makes sense because, with at least a high school level qualification, individuals from lower caste backgrounds can secure better jobs and income opportunities, which can ultimately help them bridge the caste-based income gap.

In Model 4, the interaction term between *State Level Real GDP Per Capita* and *Lower Caste* is included to investigate how state-level GDP per capita affects the impact of caste on income. The model shows that every INR 10,000 (about US$ 188 as of 2012) increase in the state-level real GDP per capita reduces the caste-based income disparity by 5.2 percentage points. The result is statistically significant at the 1% significance level. Caste-based stereotypes and practises in states with a higher GDP per capita are less prevalent, thanks to the more robust public health and education infrastructure. This could lead to relatively better socio-economic conditions for people belonging to lower caste groups, thereby aiding them in shrinking the caste-based income gap.

Model 5 includes the interaction term between *Experience* and *Lower Caste*, added to investigate whether caste-based income disparity decreases with more years of working experience. Since we do not have data for actual working experience, the variable *Experience* is calculated by subtracting 16 years from an individual's age, which indicates an individual's potential number of years of working experience. The interaction term's coefficient is -0.0001 and is not significant at the 10% significance level. This result underscores the persistent nature of the disparity. Moreover, individuals with more years of experience are likely to belong to older age groups, potentially having started working several decades ago when the caste system was more prevalent. So, gaining more years of experience may not necessarily translate to a narrower caste-based income gap.

From the results discussed so far, it is evident that the upper caste groups enjoy a higher income compared to the lower caste groups. In this sub-section, we investigate which of the lower caste groups is most disadvantaged compared to the upper caste groups and how ameliorating factors like whether an individual is a high school graduate and state-level real GDP per capita affect the impact of caste on income for individual lower caste groups. Table 6 presents the results of Models 6, 7, and 8, in which the lower caste group is decomposed into its constituent sub-groups: Adivasi (Tribals), Dalit (Untouchables), Muslim, Other Backward Classes (OBC), the group of Christians, Sikhs, and Jains.

Table 6: Regression Results | Independent Variable: *ln(Annual Household Income Per Capita)*

Covariates	**Model 6 (n = 294,925)**	**Model 7 (n = 294,925)**	**Model 8 (n = 294,925)**
Adivasi	-0.287*** (0.009)	-0.294*** (0.009)	-0.581*** (0.018)
Dalit	-0.277*** (0.007)	-0.271*** (0.007)	-0.538*** (0.013)
Muslim	-0.201*** (0.008)	-0.196*** (0.009)	-0.283*** (0.015)
OBC	-0.190*** (0.005)	-0.193*** (0.006)	-0.359*** (0.113)
Christian, Sikh, and Jain	-0.011 (0.013)	-0.017 (0.014)	0.145*** (0.029)
Rural	-0.492*** (0.005)	-0.480*** (0.005)	-0.488*** (0.005)
Number of Adults	0.007*** (0.001)	0.005*** (0.001)	0.006*** (0.001)
Married	-0.241*** (0.006)	-0.237*** (0.006)	-0.238*** (0.006)

State Level GDP Per Capita (INR 10,000)	0.330*** (0.001)	0.329*** (0.001)	0.291*** (0.002)
Experience	0.029*** (0.0005)	0.028*** (0.0005)	0.029*** (0.0005)
Experience^2	-0.0003*** (8.74e-06)	-0.0002*** (8.70e-06)	-0.0002*** (8.73e-06)
High School Graduate	0.174*** (0.012)	0.295*** (0.019)	0.179*** (0.012)
Female	-0.050*** (0.005)	-0.045*** (0.005)	-0.050*** (0.005)
Adivasi * High School Graduate	-	0.410*** (0.045)	-
Dalit * High School Graduate	-	-0.03 (0.030)	-
OBC * High School Graduate	-	0.131*** (0.023)	-
Muslim * High School Graduate	-	0.036 (0.035)	-
(Christian, Sikh, and Jain) * High School Graduate	-	0.074* (0.041)	-
Adivasi * GDP Per Capita	-	-	0.090*** (0.005)
Dalit * GDP Per Capita	-	-	0.076*** (0.003)
OBC * GDP Per Capita	-	-	0.049*** (0.002)

Muslim * GDP Per Capita	-	-	0.018*** (0.004)
(Christian, Sikh, and Jain) * GDP Per Capita	-	-	-0.032*** (0.006)
Constant	8.43*** (0.009)	8.42*** (0.009)	8.57*** (0.011)

*Robust Standard errors reported in parentheses. *** p < 0.01, ** p<0.05, * p<0.01*

Model 6 shows that Adivasis have the lowest income relative to the reference group of upper castes, which is composed of Brahmins and other High Castes. The model shows that Adivasis' income is, on average, 28.7% lower than that of upper caste groups. The model also shows that Dalits, Muslims, OBCs, and the group of Christians, Sikhs, and Jains have 27.74%, 20.17%, 19%, and 1.1% lower income, respectively. The order almost perfectly matches each group's position in the caste hierarchy as well, i.e., the lower a group is in the caste hierarchy, the lower their income relative to the upper caste groups. This could be attributed to the fact that the lower a caste lies in the caste hierarchy, the worse the caste-based stereotypes and prejudices, which leads to worse socio-economic circumstances for the lowest of the caste groups, thus hindering their upward financial mobility. All the results are statistically significant at the 1% significance level, apart from those for the group of Christians, Sikhs, and Jains.

In Model 7, the interaction terms between the individual lower caste groups and the *High School Graduate* dummy are included to investigate how attaining at least high school level education affects the impact of caste on income for each lower caste group. Like Model 3, the model shows that attaining high school level education reduces the caste-based income disparity. However, it is again interesting to note that the lower a caste group is in the caste hierarchy, the stronger the ameliorating effect. For instance, for Adivasis, attaining high school level education reduces the caste-based income disparity by 41 percentage points. Whereas, for OBCs and Muslims, the statistic is 13 percentage points and 3.6 percentage points, respectively. The results make sense because caste-based stereotypes are strongest towards the lowest of the caste groups, which could deprive them of socio-economic upward mobility opportunities. However, if someone from the lowest of the castes attains at least a high-school level education, they can benefit the most from the government's affirmative action policies like reservation in university seats and government jobs. Hence, reducing the caste-based income disparity much more effectively among the lowest of the castes, such as the Adivasis.

In Model 8, the interaction terms between the individual lower caste groups and the *State Level of Real GDP Per Capita* are included to investigate how different levels of GDP per capita affect the impact of caste on income for each lower caste group. Model 8 shows that the lower the caste is in the caste hierarchy, the stronger the ameliorating effect. For Adivasis, every INR 10,000 increase in the real GDP per capita, on average, results in a 9.05 percentage points reduction in caste-based income disparity. Whereas for Dalits, OBCs, and Muslims, the statistics are 7.6 percentage points, 4.9 percentage points, and 1.8 percentage points, respectively. As mentioned before, caste-based stereotypes and practises in states with higher real GDP per capita could be less prevalent, and such stereotypes are the worst against the lowest caste groups. Therefore, the lowest of the castes, like Adivasis and Dalits, benefit more from an increase in the real GDP per capita of their states relative to other low-caste groups and minority religions like OBCs and Muslims.

Furthermore, the Chow test is conducted to test for a change in the impact of caste on income between 2005 and 2012, and Table A2 in the Appendix shows the results of the test. The test shows that the effect of caste on income has decreased, and the decrease is statistically significant at the 1% significance level. In 2005, people from lower caste groups had a 38.1% lower income relative to the upper castes which fell by 8.9 percentage points in 2012. Based on the results of Model 4, this decrease in caste-based income disparity could be attributed to the rapid economic growth in India between 2004 and 2012. According to the World Bank, during this period, which included the 2008 financial crisis, India's GDP per capita grew at an average rate of 5.3%. This economic growth promoted urbanisation and the expansion of overall public health and education infrastructure in India, which could have contributed to a less discriminatory socio-economic environment for people from lower caste groups, hence aiding them in bridging the income gap.

Finally, residual analysis for Model 1 shows that the residuals and the independent variables do not have any significant correlation, nor are the residuals statistically different from 0. This indicates that the unobserved variables do not have any significant explanatory power regarding the caste-based income disparity.

7. Policy Suggestions

Even in today's India, caste still plays a significant role in determining one's income. Based on the evidence found in this study, we suggest that the government of India promote quality public education infrastructure for the lower caste groups in the country as the impact of education on reducing the income disparity between the castes in India is clear. It is not surprising that achieving higher levels of education allows people from lower caste groups to be more productive, participate in the labour market with more valuable skills, and secure better jobs. People from the lower caste groups, however, also belong to the lowest income groups. But unfortunately, India's public education infrastructure, especially at the primary and secondary school levels, is inadequate (Tilak, 2018). On top of that, the Indian government has further cut spending on education in the last few years. (Chakrabarty, 2022). Therefore, instead of curtailing spending on education, the government must invest more in public education infrastructure, such as public schools and universities, so that people from the lowest income groups can afford quality education. The Indian government does have a target of spending 6% of GDP on education, but in the years 2021-22, 2020-21, and 2019-20, the spending has been 3.1%, 3.1%, and 2.8%, respectively (Chakrabarty, 2022).

Although the Indian government does provide reservation of seats at tertiary level educational institutions, we recommend that more be done for the upliftment of people from lower caste groups. To be more specific, the Indian government must ensure that people from lower caste groups get access to quality primary and secondary level education as well. Such basic education, along with the reservation of seats at tertiary-level education institutions, can give people from lower castes an opportunity for upward socioeconomic mobility. In the absence of a robust public primary and secondary-level education infrastructure, only relatively well-off people (primarily from higher castes) can afford such provisions. Such a disparity naturally leads to an underrepresentation of people from lower caste groups at tertiary-level educational institutions and reinforces a culture in which only people from upper castes enjoy higher education and, hence, better career and income prospects.

8. Conclusion

The caste system regulates the socio-economic lives of hundreds of millions of people in India. Individuals at the bottom of the caste hierarchy have faced social and economic exclusion for centuries. This paper finds that there appears to be significant evidence supporting that being from an upper caste positively affects one's income in India. The effect is also statistically and economically significant at the 1% significance level making the results of this study consistent with studies like Thorat and Newman (2007), Bharti (2019), Zacharias and Vakulabharanam (2011), Deshpande and Palshikar (2008), and Jodhka (2010), which found evidence for caste-class association or income disparity among lower and upper caste groups at regional settings. Moreover, this paper also finds evidence for the effect of caste on income being stronger in urban areas as compared to rural areas. The paper identifies that the lower a group's position in the caste hierarchy, the lower their income is relative to their upper caste counterparts. So, the Adivasis and the Dalits are two of the most disadvantaged communities among the lower caste groups, having 28.7% and 27.7% lower incomes, respectively.

Furthermore, this study finds that the impact of caste on income is less pronounced among individuals who have attained at least a high school level of education. This suggests that education can help reduce income disparities between upper and lower-caste groups. Apart from years of education, the study also identifies state-level GDP per capita as an ameliorating factor. Every INR 10,000 increase in state-level GDP per capita reduces the caste-based income disparity by 5.2 percentage points. Overall higher GDP per capita could lead to more conducive socio-economic circumstances for the lower caste communities, hence aiding their income levels. Besides, rapid economic growth in GDP per capita could have contributed to the reduction in caste-based income disparity in India between 2005 and 2012. Finally, it is also found that the ameliorating effects of education and state-level GDP per capita are stronger among the lowest caste groups, like Adivasis and Dalits, compared to other low caste groups and minority religions like OBCs and Muslims.

9. Appendix

Table A1: Two sample T-tests for income mobility, with unequal variances:

Hypotheses	T-Statistics
H_0 : Delta Income $_{urban}$ - Delta Income $_{rural}$ = 0 H_1 : Delta Income $_{urban}$ - Delta Income $_{rural}$ > 0	32.5*** (69,684.1)
H_0 : Delta Income $_{upper\ caste}$ - Delta Income $_{lower\ caste}$ = 0 H_1 : Delta Income $_{upper\ caste}$ - Delta Income $_{lower\ caste}$ > 0	25.74*** (37,942.7)
H_0 : Delta Income $_{upper\ caste}$ - Delta Income $_{lower\ caste}$ = 0 if rural = 0 H_1 : Delta Income $_{upper\ caste}$ - Delta Income $_{lower\ caste}$ > 0 if rural = 0	17.01*** (14,420.8)
H_0 : Delta Income $_{upper\ caste}$ - Delta Income $_{lower\ caste}$ = 0 if rural = 1 H_1 : Delta Income $_{upper\ caste}$ - Delta Income $_{lower\ caste}$ > 0 if rural = 1	18.43*** (26,606)

Delta Income = Annual Household Income Per Capita $_{2012}$ – Annual Household Income Per Capita $_{2005}$

Satterthwaite's degrees of freedom are reported in parentheses. *** p < 0.01, ** p<0.05, * p<0.1

Table A1.1: Income inequality comparison by caste for 2012.

Year = 2012	Std. Dev.	Frequency
Lower Caste	39,422.289	117,907
Upper Caste	68,715.002	32,163
W0: 2,734.55*** W50: 1931.60*** W10: 2,113.77***		

W0: Levene's robust test statistic to measure the equality of variances.

W50: Mean in the Levene's formula replaced with median.

W10: Mean in the Levene's formula replaced with 10% trimmed mean.

Income inequality being higher among the upper castes in 2012.

Table A1.2: Income inequality comparison by caste for 2005.

Year = 2005	Std. Dev.	Frequency

Lower Caste	11,613.699	118,600
Upper Caste	20,447.314	31,470
W0: 3,682.84*** W50: 2,847.79*** W10: 3,028.80***		

W0: Levene's robust test statistic to measure the equality of variances.

W50: Mean in the Levene's formula replaced with median.

W10: Mean in the Levene's formula replaced with 10% trimmed mean.

Income inequality being higher among the upper castes in 2005.

Table A1.3: Income inequality comparison by year among lower castes.

For Lower Caste group	Std. Dev.	Frequency
2005	11,613.69	118,600
2012	39,442.28	117,907
W0: 11,823.66*** W50: 8,001.75*** W10: 8,598.82***		

W0: Levene's robust test statistic to measure the equality of variances.

W50: Mean in the Levene's formula replaced with median.

W10: Mean in the Levene's formula replaced with 10% trimmed mean.

Rising income inequality in lower-caste population

Table A1.4: Income inequality comparison by year among upper castes.

For Upper Caste group	Std. Dev.	Frequency
2005	20,447.31	31,470
2012	68,715.00	32,163

W0: 3,397.79*** W50: 2,271.33*** W10: 2,498.35***

W0: Levene's robust test statistic to measure the equality of variances.

W50: Mean in the Levene's formula replaced with median.

W10: Mean in the Levene's formula replaced with 10% trimmed mean.

Rising income inequality in upper-caste population

Table A2: Chow Test | Independent Variable: *ln(Annual Household Income Per Capita)*

Covariates	**Model 1** **(n = 294,925)**
Lower Caste	-0.381*** (0.005)
Rural	-0.531*** (0.003)
Female	-0.026*** (0.003)
Number of adults	0.023*** (0.001)
Married	-0.094*** (0.005)
High School Graduate	0.626*** (0.008)
Year (1 if 2012)	0.675*** (0.007)
Year * Lower Caste	0.089*** (0.008)

State Level GDP Per Capita (INR 10,000)	0.128*** (0.001)
Experience	0.015*** (0.0004)
$Experience^2$	-0.00018*** (7.35e-06)
Constant	8.871*** (0.007)

Robust Standard errors are reported in parentheses. *** $p < 0.01$

Chow Test	Model 1
$H_0 : \boldsymbol{\beta}_{year*lowercaste} = \boldsymbol{\beta}_{year} = 0$ $H_1 : One of the \boldsymbol{\beta}_s \neq 0$	20,514.56*** (0.000)

Asymptotically correct p-values are reported in the parentheses

*** $p < 0.01$ for a two-tailed test

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