Impact of Indigenous tribes and castes on the income of households

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Abstract

This study aims to empirically test and discuss the impact of indigenous tribes and castes on the income of the households, within the Indian context. With the goal that no one should be left behind, SDGs (Sustainable Development Goals) are important for indigenous communities and people. Globally, Indigenous people find it challenging to achieve higher economic growth and aim for a decent standard of living due to a lack of livelihood, occupation, and means of living. These indigenous people face several conflicts in proclaiming their indigenous rights on land and other natural resources. In this study, the difference in difference methods has been used to assess the influence of caste and tribes through the PM Jan Jati Mission scheme during COVID-19 on household income in India. 3,322 households from CMIE People dx and Consumer Aspiration dx databases were used for the analysis. The data was collated from May to August 2019 as the pre-Covid-period, and May to August 2021 as the post-COVID-19 period. The findings revealed that during COVID, household income from both scheduled castes and tribes increased manifold as compared to the income of people from the upper class and category. During COVID-19 the Government introduced various schemes for the upliftment of the poor belonging to the castes and tribal communities.

Keywords: Self-Help Group, Social Inclusion, Indigenous Tribes

JEL Classifications: O21

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1. Introduction

Indigenous people have existed for ages, and have faced exclusion and skepticism due to the lack of employment and livelihood opportunities. The Indian constitution has earmarked these indigenous people as the 'scheduled tribes' (ST). In 1975, tribal groups were identified as the most vulnerable group, owing to which, a separate category was created for them based on the recommendation of the Dhebar Commission. Largely these groups have been plagued with various challenges, such as poverty, lack of land ownership, and poor health facilities. The Indian constitution highlighted the importance of homogeneity of people from the same clan and tribe (Verma, 1990), especially as India has more than 705 ethnic indigenous tribes that are officially recognized as Scheduled Tribes. Besides, India is also a signatory to the Declaration of the Rights of the Indigenous People. Through the theoretical lens of the Resource View, the indigenous people have been seeking redressal for the conflicts that they regularly face in asserting their indigenous rights (Ambagudia, 2019). Various socio-economic and political factors impact their 'social inclusion'. A unique scheme called the (Particularly Vulnerable Tribal Group), with an annual budget of Rs. 15,000 crores, was introduced for the well-being of the people from the indigenous tribes. This scheme aims to provide safe housing, clean drinking water, and sanitation. The study uses the difference in difference methods to measure the impact of the special scheme introduced during COVID-19 for scheduled castes and tribes on the income of the households. This paper thereby aims to discuss the impact of this scheme on the economic well-being of the Indigenous people and on the income of the households during COVID-19. In this study, Scheduled Castes (SCs) and Scheduled Tribes (STs), along with a few groups of lower caste people as the participants of this study. And COVID-19 period is the proxy for treatment, i.e., allocation of funds under the Particularly Vulnerable Group scheme.

2. Literature review

Indian society is known to be 'diverse; it may be described as a mosaic of various cultures, customs, and traditions, where the ethnic minority forms an essential part of the nationalistic identity. India has 573 different Scheduled Tribes, who live in different parts of the country. These tribes have their dialects, languages, customs, and rituals, as well as arts and performances. Globally, tribal groups have always been socially isolated and discriminated against; and Indian tribal groups aren't an exception. Extant research shows that the level of poverty is extremely high among these tribal groups, owing to which, they are the most vulnerable section of the society, with limited access to infrastructure and essential resources. They live as homogenous groups in remote forests and hilly regions (Allman, 2012). They are often exploited due to their socio-cultural backgrounds and lack of capitalistic mindset, despite the Indian Constitution & the Government giving them the guarantee of protection and welfare under articles 15(4), 46, 244(i), and 339 (Manojan, 2018). In fact, due to their social exclusion, these tribal groups find it extremely difficult to enjoy access to basic infrastructure, health, and education (Sonowal, 2008; Pidgeon, 2016; Ambagudia, 2011). During the 1990s, most of the literature highlighted that market interventions largely ignored the interest of the tribals, who are not part of the markets due to a lack of collateral. The tribal groups of the indigenous groups face a lot of issues in terms of inclusion.

2.1 Indigenous tribes

Indigenous people or Scheduled Tribes within the Indian parlance are referred to as Adivasis (tribal groups). According to India's National Sample Survey Organization (NSSO, 2000), the Adivasis comprise twenty-four percent of the rural populous of the Indian state of Odisha, representing approximately 9 percent of the total population. Dalits on the other hand, constitute approximately 20 percent of the rural populous, and 38 percent of low-income people. Largely, poverty encompassed about 30 percent of Indian minority communities. The Status of Adivasi Livelihood Report, 2021, examines the well-being of Adivasis in Jharkhand and Odisha, highlighting disparities with the non-Adivasi population in living standards, education, literacy, and income. Adivasi households demonstrate lower rates of matriculation compared to non-Adivasi households, with considerable differences among Particularly Vulnerable Tribal Groups (PVTG), Adivasis, and non-Adivasis in both Jharkhand and Odisha. Adivasi households, particularly women, face significant challenges with functional literacy, as indicated by the report's findings. The Adivasi households have lower average annual incomes compared to non-Adivasi households in both Jharkhand and Odisha, with sources of income including farming, wage work, salaries, pensions, and non-farm businesses. (Haan & Dubey, 2004). In his study, (Haan & Dubey, 2004) concluded that holding various characteristics constant, Dalits comprised nineteen percent, and Adivasis were ten percent more likely to be poor. (Kozel & Parker, 2003) Stated that the per capita consumption of the Dalits and Adivasi households was lesser than the majority population, owing to significant differences in ownership of assets and disparities in education. Thus, there is a need to go beyond the prescriptive models, and adopt a more transformative approach to uplift these indigenous groups of people, (Kabeer, 2006).

2.2 Social Exclusion

Based on the definitions and perspectives outlined, it is evident that social exclusion encapsulates a process wherein individuals or groups are barred from full participation in the society in which they reside. (Luhmann,1990) defined inclusion as the incorporation of the entire population into individual function systems, encompassing access to benefits and individual dependence on them. The complexity of social inclusion emerges from diverse European perspectives. In 1991, two core concerns for social inclusion were recognized: one about social democracy, focusing on inequality and opportunities, and the other from a social Catholic perspective, emphasizing community and family ties. The existing policy regulation emphasized the Anglo-Saxon tradition, highlighting constant competition within a fragmented society, leading to poverty and misery. Contrastingly, the European social model underscores social solidarity, aiming to integrate all individuals into the national, social, and moral fabric. Based on the current understanding, it appears that there are primarily two forms of social exclusion: one rooted in factors like origin, caste, and ethnicity, and another linked to individual capabilities. Additionally, social exclusion encompasses discrimination based on group identities, which undermines societal welfare. Through a social exclusion lens as defined by the United Nations Sustainable Development Goals (UNSDGs), it characterizes a state where individuals face limitations in participating fully in economic, social, political, and cultural domains, along with the processes reinforcing this state. (Levitas et al., 2007). Noted multiple attempts to define social exclusion, emphasizing its multi-dimensional, relational, and dynamic nature distinct from poverty. In the French Republican tradition, exclusion signifies a status of being outside the social contract that defines rights and duties. Contrastingly, social contract traditions uphold reciprocity and responsibilities, differing from social democracy or lineage traditions linking rights to social entitlements. Individuals face exclusion not solely based on their class position but also due to detachment from their social core. Social exclusion can be constitutively detrimental, like the absence of relational capabilities, or instrumentally driven, where societal factors such as caste, creed, and ethnicity lead to exclusion from social life and potentially result in poverty.

2.3 A ramification of social exclusion

Extant literature highlights the ramifications of social exclusion as rampant poverty for the masses, which includes characteristics such as income poverty, distance from the mainstream, and isolation from societal mechanisms to achieve redistribution of resources. Tribal or Indigenous people are more likely to have lower incomes and poorer physical living conditions, and are results of the discrimination, both at the social and institutional levels (Mohapatra, 2011). (Rao, 2018) highlighted that Indigenous people or tribals are pushed into poverty by exclusion from livelihood and income-generating activities, lack of education and financial literacy, caste discrimination, poverty, exploitation by money lenders, and lack of financial literacy. Financial exclusion of the tribal people is thereby worse among all the sections of society; moreover, owing to their financial exclusion they are also deprived of adequate representation in mainstream policy-making and politics at large (Karmakar et al., 2011). (Biswal & Jha, 2022; Sharma, 2016) their research highlights that the financial inclusion program, such as direct benefit transfer and funding should be redefined, redesigned, and realigned for vulnerable tribe groups The Indigenous groups and the tribes also suffer from the digital divide and lack of access to digital finance due to digital literacy (Nedungadi et al., 2018).

3. Research problem

Indigenous people or tribal people are excluded from society, as they have unique needs. For instance, they need loans much more frequently, albeit in small sizes, and at an extremely low rate of interest. Social exclusion is defined as the absence of social integration and lack of power. It is an outcome of the lack of social capital, which can be defined as the networks of social relations among the people characterized by norms of trust and reciprocity (Stone, 2001). Lack of social inclusion has been defined as lower levels of social trust and lack of reciprocity among group members (Wotherspoon & Hansen, 2013). These people constitute around 6% of the total global population. These people often lack formal recognition of their resources, such as land, territories, and natural resources (Gracey & King, 2009). They often suffer various social barriers and cannot participate in political and social processes and get access to social justice. These social and economic conditions lead to the poor's marginalization and exclusion from the mainstream. Indigenous people are more likely to suffer from various kinds of exclusion. Due to the lack of access to financial services, these indigenous tribes are unable to generate income. They suffer from a lack of livelihood opportunities. The purpose of this study is to evaluate how well during COVID-19 the PM Jan Jati Mission succeeded and the Venture Capital Fund scheme for indigenous tribes helped in improving the socioeconomic status and income levels of tribal households. The study will specifically examine how the mission's major initiatives—such as skill development, financial inclusion, livelihood assistance, and comprehensive welfare services aimed at tribal communities—are being implemented. The goal of the research is to determine how much these activities improve income, support tribal households' ability to maintain their way of life, and promote economic sustainability. Through the examination of these central research questions, the present study aims to offer significant perspectives on the efficacy of the PM Jan Jati Mission in promoting the economic welfare of tribal populations and to advise prospective improvements to policy, program implementation, and resource distribution to mitigate the socio-economic inequalities that tribal households encounter.

RQ1: What is the impact of caste and tribe on the income of the households in India?

RQ2: How do various caste-specific programs impact the income of households in India?

4. Research methodology

The data for the analysis was collected from Consumer Pyramid dx, Consumer People dx, and Consumer Aspiration dx. Notably, the panel data was created from the surveys of the Consumer Pyramid dx, and different analysis methods were used to establish the causal estimate through the panel data analysis, comprising a panel of 3,322 households. The data comprised the 17th and 23rd waves in the Consumer Pyramid dx, corresponding to May to August 2019 as the control group, and May to August 2021 as the treatment group. In experimental research, it is essential to ensure that there is no issue of self-selection bias in selecting the subjects for the treatment and control group. To analyze the impact of caste or tribe on the financial sustainability and income of the households, the entire sample was divided into treatment and control groups using kernel matching, and propensity score matching was used to calculate and test for the significance of the average treatment effect. The dataset is suspected to have time-invariant differences between the treatment and the control groups, as both are not homogenous.

4.1 Description of Variable

Household Gender

In our data, out of 3,322 households, there were households headed by women, while the rest were headed by men (certain approximations made for the household with equal or balanced gender distribution). In CPHS data, the distribution of households as men and women was taken to represent household characteristics better, and thereby explain its behavior in terms of income, expenditure, and borrowing patterns (Consumer Pyramids Household Survey, 2020). We also intended to look at the impact of the gender of the household in terms of the financial outcome.

Treatment or Government schemes

The study aims to evaluate the influence of the Pradhan Mantri Jan Jati Vikas Mission scheme on the income of tribal households. The treatment period selected is May to August 2021, coinciding with the implementation of the scheme during the COVID-19 pandemic, while the control period for comparison is May to August 2019. This comparative analysis seeks to assess the effectiveness of the scheme in enhancing the income levels of tribal households during challenging circumstances.

Poverty score

We generated a wealth score to measure the impact of poverty on household income. In this regard, we used the CMIE Consumer Pyramid database, the Aspiration dx survey, along with the list of questions that were included in the questionnaire, which is included below for reference:

Table 1. Questionnaire

1. How many household members are there in the family? Points and ranking for this question are given as follows: Eight Seven Six Five Four Three Two One **2. What is the general education level of the members of the group?** Primary or below or not literate Middle Secondary or higher No female head/spouse **3. Does the household possess a refrigerator?** No Yes **4. Does the household possess a washing machine?** Yes No **5. Does the household possess a television?** Yes No

6. Does the household possess a cooler?
Yes
No

7. Does the household possess a regular supply of water?
Yes
No

8. Does the household possess a regular supply of power?
Yes
No

9. Does the household possess a motorcycle, scooter, car, or jeep?
Yes
No

10. Does the household possess a GENSET?
Yes
No

In this study, additional data about the basic amenities available to respondents, such as water supply, power supply, access to T.V., a washing machine, Genset, and a car, was incorporated and scored using a specific mechanism. The scores derived from this process were then utilized to evaluate the impact of poverty on access to microfinance. Drawing from previous literature, Rhyne (2000) suggested that microfinance helps reduce inequalities among poor people, particularly in rural regions where the poorest individuals often lack collateral and the means to organize. These individuals typically require subsidized credit, a need that microfinance aims to address.

The study adopts a comprehensive approach, taking into account the impact of COVID-19-induced changes in poverty levels, often referred to as 'poverty shock,' on the borrowing capacity of self-help groups. The study hypothesizes that variations in the poverty score reflect the capacity of self-help groups to secure loans. Furthermore, it will utilize the Poverty Score proposed by C. Henry in 2003 to analyze the influence of changes in asset ownership on the ability to access loans through self-help groups. The treatment period for the analysis spans from May to August 2021, aligning with the period during the COVID-19 pandemic, while the control period for comparison is from May to August 2019. This meticulous approach aims to provide a comprehensive examination of the multifaceted impacts of poverty and asset ownership on microfinance and the borrowing capacity of self-help groups. It's noted that the poverty score is calculated based on the asset score data, which comprises information regarding various assets such as houses, refrigerators, coolers, washing machines, televisions, computers, cars, generators, tractors, cattle owned, and access to power and electricity, with the possession of a toilet serving as the final data point. Each asset is given equal weight in the score calculation process. Additionally, the poverty shock is determined as the disparity in asset ownership between the Control and Treatment periods. This method provides a quantitative measure of changes in household assets and serves as a key parameter in analyzing the impact of the treatment on poverty levels.

Poverty Score = (∑Houses owned + Refrigerators + Air conditioner + Coolers + Washing machine + television + computer + cars owned + two wheelers + genset + tractors + cattle + Power + Water + Toilet)

Income Household

The study has utilized the Income Pyramiddx to obtain a time series of a household's income, encompassing various sources such as wages, pensions, dividends, interest on savings, provident fund and insurance, and income from properties and other sources. The household income was used as a proxy for the total income, and the borrowing patterns were based on data from the Consumptiondx Pyramids. The income data, collected over a four-month cycle, was averaged to generate the average income for the timeframe. Furthermore, the study involved modifying the average income by calculating the logarithm of the income.

Education

'Household education' referres to the necessary qualifications a person had obtained. The composite categorization for the family was computed in the CMIE CPHS Survey depending on the education level of the individuals. A family's highest level of education was determined by the highest degree, whether it was graduation, matriculation, literacy, or illiteracy. We also utilized the binary classification of 0 for illiterate families (no members who can read and write) and others for persons who can read and write.

5. Results & discussion

5.1 Graphical Summary of the Data

A critical issue in causal inference is ensuring no self-selection bias in the participants chosen for the treatment and control groups. In our assessment, the treatment or implementation of various schemes for the social tribes was from May to April 2021. We used the Consumer Pyramid Household Survey to undertake propensity score matching to remove the sample selection bias caused by the obvious differences between the treatment and control groups. The Kernel Matching approach was used to match the treatment and control groups by using similar items in terms of their observable features. We intended to test the impact of borrowings from self-help groups on household income, wherein the households were chosen based on pre-treatment covariates, resulting in an unbiased estimate of the outcome Average Income of the family was independent of the assignment to treatment conditional on pre-treatment covariates. Initially, the number of variables in our study was noted to be substantial, and Kernel matching allowed us to match households based on a covariate chosen using the natural weighing method. Through the Kernel matching, we generated approximately 1,593 households that are upper-class households and these were matched to tribal households. Kernal matching for the data was undertaken based on various control variables such as poverty score, education, occupation, and region.

The table below displays all the control variables selected for matching. To collect some basic information about the relationship between caste, financing decisions, and income of the households, we propagated that tribal households that borrow from self-help groups have a lower income than the upper class.

RQ 1: What is the impact of caste and tribe on the income of the households in India?

We calculated the two-sample t-test to measure the difference in income between the tribal versus non-tribal households. To check for the impact of the caste category and tribe on household income, we formulated an alternate household. Our null hypothesis posited that the group means of income of the tribal household was not different from the income of the non-tribal household. A one-sided test was used, as we presumed that the tribe and scheduled caste negatively impact the household income.

The hypothesis is presented as (Ha: Difference between the income of the non-tribal and tribal household > 0), which implies that tribal households should have a higher income than non-tribal households. The line diff = mean (Non-Tribal) – mean (Tribal) helps analyze the data. The result is highly significant, and the displayed result is smaller than 0.01 (Pr (T> t)). Thus, we are clear that the group means are statistically different, and the sampling error cannot be the source of difference. However, this does not prove that the caste category is the only reason for low income. There might be some spurious correlation in the data.

Table 2. Results of t-test (Source: Author's calculation)

Group	Households	Mean Income	Std Error	UCL	LCL
Upper caste households	1593	2,19,426	3,912.65	2,11,751.70	2,27,100.70
Tribal households	1729	2,10,460	3,435.70	2,03,721.80	2,17,199
Difference		8,965.85			

Table 2 provides the result of the t-test that compares the mean of household income between groups belonging to Indigenous tribes (receiving scheme benefits) and those belonging to non-indigenous households. The difference between the mean income of tribal households, who have borrowed from SHG is noted to be significantly different from the income of the upper caste household at a 5% significance level.

t statistics = 1.72; p= 0.0420

Ha: Income of non-tribal households borrowed from self-help groups is not different from that of tribal households and is rejected at a 5% significance level.

T-test proves, that there is a statistically important difference in the household income of the upper caste category and the tribal category. Still, the results do not prove that the caste category is the only reason for the difference in the income of households. There might be other confounders such as poverty score, education, and occupation that might have a big impact on the income of the households, based on the existing theoretical frameworks in the domain of the theory of inclusion. To resolve the issue of confounders, probability-based propensity matching based on kernel matching was used to match the households that have access to social schemes for the marginalized and are tribal the treatment to the households that do not have access to any social scheme, as they belong to the upper category.

5.1.1 Testing for the Parallel Trends

For estimating the causal effects, the parallel trend assumption is the key assumption in the difference in difference method. The parallel trend assumption states that in the absence of treatment or access to social schemes for the marginalized or the tribals, the mean income of the untreated group would be independent of the observed treatment status. Thus, the two groups exhibit a parallel trend. The parallel trends assumption is extremely critical to ensure the internal validity of the difference in difference approach. Further, the violation of the parallel trends is critical for ensuring the internal validity of differences in different models. In this study we have checked the data for the existence of parallel trends and data validates the presence of parallel trends.

5.1.2 Propensity score matching

The study is intended to evaluate data to measure the influence of caste and financing decisions through self-help groups on the average income of borrowers while adjusting for confounders, such as age, education, occupation, and gender. Based on the theory of social inclusion of tribes, it is assumed that it is important to include the marginalized sections and indigenous tribes to facilitate sustainable development. Besides, the dependent variable (social classification), the education, gender, and occupation of the excluded tribes are chosen as covariates to measure the impact of the category on the income of the households.

There are various reasons why parametric standard regression should not be used to analyze the impact of endogenous (non-random) policies, such as self-help group allocation based on attributes such as preliminary information about the other members in the group. The parametric regression analysis has several flaws. One possibility is that the members of caste categories and lower sections might be demographically different from members of upper-caste social groups. These distinctions or selection bias might have a substantial impact on the desired outcomes. To address the self-selection bias, the matching of the households in the treatment and control groups was done using kernel density and propensity score matching. The propensity score generates the probability of receiving support under the tribal schemes based on various covariates such as income, gender, and education. Further, the robustness checks for the kernel density matching were done using visual inspection through kdensity graphs and plots, evaluating the impact of varying bandwidth on matching results and assessing the validity of results by resampling the data using bootstrap analysis.

For this study, a nonparametric weighting approach, which balances the covariates between treatment groups by Kernel Mean Matching (KMM) with Mahalanobis distance kernels, is used. Kernel matching is a kind of propensity score matching (PSM) that matches treated subjects to a weighted average of all controls. Further, a wider bandwidth was used for matching the treatment and control group households, to provide a wider comparison and better matching. The covariates and the social demographic variables such as gender, education, and occupation were checked for multicollinearity using VIF. The results substantiated that there is no multicollinearity in the data.

Members who borrow from the self-help groups generally do not have any collateral; generally, each member doesn't know the other member's creditworthiness. (Berhman et al.,2004) Discussed the drawbacks of parametric regression. As a result, respondents in the participating group may be vastly different from those in the non-participant group. Matching methods were used to determine the differences between the groups. We utilized the Kernel Matching approach to assign respondents to this study's control and treatment groups. Using the Kernel Matching technique, we estimated the ATT (Average Treatment Effect on Treated and Nave Average Treatment Effect). The statistics computation shows that both of these statistics do have a high significance level on a 5% confidence interval. The Multivariate Distance Matching (MDM) approach is one of many possible methods for matching the treatment and control groups based on various algorithms. This metric is based on matching the treatment and control groups, using a distance metric that evaluates the proximity of observations in the multivariate space of X observations used in strategy.

5.1.3 Matching statistics

After the description, we started with the matching. Ben Jann's Stata program kmatch was used, which implements a fast and robust form of kernel-matching based on region, gender, and poverty score. *kmatch ps caste i.region i.education i.occupation i.gender (income), ate at atc vce(boot, reps(500))*

Table 3. Results of ATE, ATT & ATC (Source: Author's calculation)

Income	Coefficient	S.E.	T	P>t
ATE	-8,922.72	5,218.37	-1.71	0.087
ATT	-8,652.93	5,210.71	-1.66	0.097
ATC	-9,215.56	5,238.14	-1.76	0.079

*ATT (Average treatment effect of treated), ATE (Average treatment effect), ATC (Average treatment effect of control)

Table 3 provides the results of the average treatment effect (impact of financial support for Indigenous tribes on income), the average treatment effect of control, and the average treatment effect of treatment. As given in Table 3 ATE (Average treatment effect) is -8,922.72. The interpretation is that the tribal households borrowed from SHG (Self-help groups) have income lesser than the upper households borrowed from the SHG (Self-help groups) by Rs. 8,922.72. ATC (Average Treatment effect for control) implies that households in the group are upper caste, and have borrowed from SHG

(The control group). The results of the analysis show that if these households are tribal and borrow from the SHG, then their income would be Rs. 8,652.93 less than the present. This is the counterfactual effect. The other statistical measure is the ATT, which is the average treatment effect for the treated; thus, households that are tribal in reality, and have counterfactual, i.e., but are assumed to be upper caste, and they borrow from SHG, then their income would be Rs. 9,215.56 lesser than the upper caste households borrowing from the self-help groups.

5.1.4 Diagnostics

After the estimation of the ATE (Average Treatment Effect) and ATT (Average treatment of treated), it was found that the caste category and access to the schemes for the lower caste category had a significant impact on the income of the households. To check for whether the models hold or not, various diagnostic tests were carried out, such as checking for common support and the use of density graphs.

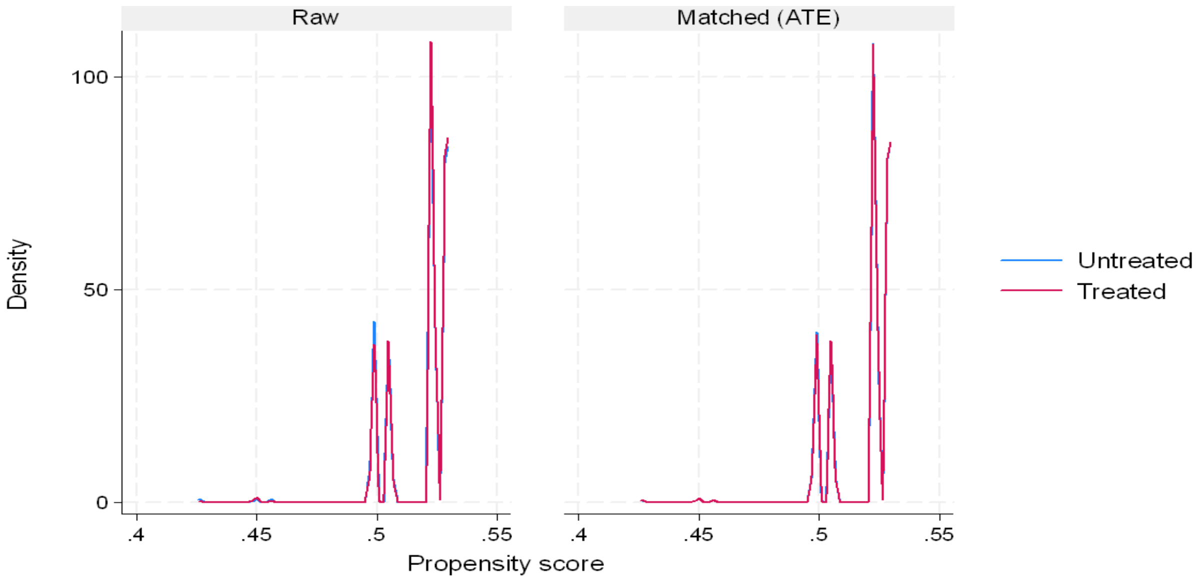

Figure 1. K-density plots (Source: Author's calculation)

As per the Figure 1 density plots, the matched data after the analysis is a single line, without any overlap with the untreated data. Thus, the analysis proves that the common support is extremely good and matching is accurate. The cases that are not matched are dropped from the analysis. Further to robust the results of matching, concerning the omitted variable, the Rosenbaum bounds method is used to simulate how unobserved factors impact the matching of treated and untreated households for analysis.

5.1.5 Bootstrapping to account for the standard errors

As we control for certain confounders, we could argue that this is a causal effect and that caste is the cause of this difference. However as there are no standard errors, we do not know if this difference is statistically significant (albeit large). We can get these values using a bootstrap method of resampling. The computer repeatedly draws a random sample of the households and calculates the effects. Then the average is shown. This is a valid and useful statistical technique.

Table 4. Results of bootstrapping (Source: Author's calculation)

INCOME	Coeff.	S. E	Z	P>z	LCL	UCL
ATT	-8652.93	4950.155	-1.75	0.08	-18355.06	1049.195

Table 4 provides the results of bootstrapping. The results of Table 4 indicate this statistic is highly significant (the p-value is smaller than 0.010) at a 10% significance level. Usually, we would say that any result be low 0.05 is substantial, which means we can reject the null hypothesis, assuming that our observed coefficient equals zero.

5.1.6. Rosenbaum bounds

Matching relies on observational data; therefore, we cannot test how well we can approximate causal effects in our findings. However, we can see how robust our results are concerning omitted variables. These variables are not included in the data, as they are not measured (for example, psychological constructs like intelligence or motivation), which might introduce spurious correlations and undermine our findings. Rosenbaum's bounds aim to simulate how vital these unobserved factors must be to undermine the effects we found with matching. Therefore, they are a type of sensitivity analysis.

Table 5. Results of Rosenbaum bounds analysis (Source: Author's calculation)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	4.30E-10	4.30E-10	-18559.2	-18559.2	-22552.3	-14700.4
1.25	0	0.015959	-28351.4	-7543.31	-33568.2	-716.247
1.5	0	0.862529	-37561.3	2447.68	-43574.7	8923.82
1.75	0	0.999937	-46857.5	10299.6	-51469.7	17456.7
2	0	1	-54575	20290.6	-58919.1	27447.7
2.25	0	1	-58919.1	27447.7	-66076.2	32680
2.5	0	1	-65731.8	31628.3	-72552.3	40065.1
2.75	0	1	-71857.5	35471.2	-77561.3	45290.6
3	0	1	-74477.1	42456.7	-82543.3	52447.7

Table 5 provides the results of the Rosenbaum-bound analysis. It calculates results for gamma values between 1 and 3 in steps of 0.25. Gamma refers to the strength of the unobserved factor that influences the chance to be part of the treatment group. We checked the sig-level until the value was larger than 0.05, and thereby above the normal significance level. The critical value seemed to be around 1.25, as the value crossed the threshold. Therefore, we conclude that even if an unobserved factor influences the chance of being part of the treatment in contrast to being part of the control in a relation of 1.25 to 1, we would still find a significant result. Table 5 provides the results of the Rosenbaum analysis. Notably, the confidence limits gave us an approximation of the range of the size of the effect we would still find then (-33,568.2 to -716.24, measured in grams). Largely, this seems like a robust result as this unobserved factor would need to influence our treatment status strongly.

R.Q. 2: The caste, through various social schemes and poverty scores, has an impact on the average income of the households

The Consumer Pyramid household survey from May Aug 2019 represented the control group, and May-August 2021 referred to the treatment group. The change in the income of the households due to the households' caste is expressed in the form of the following empirical strategy. Yit represents the metric variable, the dependent variable that denotes the households' income. The independent variables, on the other hand, include the region, which is a binary variable, i.e. 1 if the region is rural & 0 if the region is urban. Tribal served as a binary variable with a value of 1 if the household is tribal and 0 if the household is upper caste. The wealth score is the metric variable that signifies the assets owned by the household. Education is a binary variable that takes the value 1 if the household is educated, and 0 otherwise; occupation again, is a binary variable too that takes the value 1 if the household is artisan and 0 otherwise.

$$Y_i\,(\text{log income}) = \alpha_i + \beta_1\,\text{Occupation. Caste Category} + \beta_2\,\text{Poverty Score} + \beta_3\,\text{Caste Category} + \beta_4\text{Region} + \beta_5\,\text{Gender} + \beta_6\,\text{Occupation} + \beta_7\,\text{education} + \text{Constant}$$

Table 6. Impact of caste on the income of the households (Source: Author's calculation)

Log Income	Coefficient	Std Error
Rural Region	-0.000	0.98
Tribal	-0.046**	0.075
Tribal*Artisan	0.027	0.441
Wealth score	0.013***	0.000
Female-headed household	-0.046***	0.026
Education	0.317***	0.006
Occupation	0.052***	0.046
Constant	11.73***	0.000
R square	0.496	

Rural region is a binary variable, 1 rural, 0 urban. *Tribal* is a binary variable, 1 tribal, & 0 non-tribal. *Occupation* is a binary variable; 1 artisan 0 non-artisan *female-headed households* women-dominated (1) or non-women-dominated (0).

Table 6 provides the details of the impact of the caste on the households' income. From the analysis of the tribal households that borrowed from the self-help groups have negative income compared to the upper caste households that borrowed from the self-help groups. Tribal households that had artisans had a higher income than upper caste households that were non-artisans; although the impact was insignificant. Women-headed households had lower incomes as compared to men-headed households. Educated households had a higher income as compared to uneducated or illiterate households, or households with all illiterate members. Thus, we conclude that tribal households, who are artisans and are provided aid by the government under various schemes, such as Jan Jati Mission, do have higher incomes. Thus, welfare and state policy measures do tend to have a positive impact on the households' income.

RQ 3: Caste and related welfare programs have an impact on the financing decision of households

The research paper aims to analyze the impact of caste and tribe on the financing decisions of households. These are the households that have already borrowed money from the self-help groups. The data show that as compared to the upper caste, tribal households were less likely to borrow from the banks. Due to various welfare schemes, such as DAY NRLM (Deen Dayal Antodaya National Rural Livelihood Mission), tribal households with artisans were more likely to borrow from a bank and less likely to borrow from non-banking finance companies. Households that had higher wealth scores, and thus possessed more assets were less likely to borrow from shops and moneylenders. Furthermore, artisan households, not covered under the tribal schemes, were more likely to borrow from banks. On the other hand, they were less likely to borrow from shops, while some still were dependent on moneylenders. Higher-income households were more likely to borrow from traditional sources like banks and non-banking finance companies. Due to the approachability of households borrowing from self-help groups, a moneylender was still a preferred option. Notably, households borrowing from self-help groups generally lacked good credit records, and banks were at times unwilling to lend to such households. In this scenario, the moneylender, who has information about the creditworthiness of the households, seems like a preferred option.

Table 7. Results of the probit analysis to determine the impact of the caste on the financing decisions of the households (Source: Author's calculation)

	Banks	MFI	NBFC	Shops	Moneylender
Poverty score	-0.005	-0.005	-0.002***	-0.067***	-0.052***
Log income	1.514***	1.525***	0.818***	0.151	1.079***
Tribal*Artisan	0.690***	0.690***	-0.838**	0.059	-0.261
Tribal	-0.321	-0.316	0.296	-0.031	-0.207
Rural region	1.291***	1.284***	-0.792***	0.528***	0.230
Occupation	0.783***	0.793***	0.450	-0.667***	0.452***
Gender	-0.272**	-0.275**	-0.086	0.195	0.108
Constant	-21.772***	-21.90***	-13.667***	-2.733***	-15.482***

Binary variable: Rural region 1 rural, 0 urban. *Tribal* 1 tribal, & 0 non-tribal. *Occupation* 1 artisan 0 non-artisan *female-headed households* women-dominated (1) nonwomen-dominated (0). Poverty score denotes wealth & logincome income

Table 7 provides the details of the probit analysis to determine the impact of the caste and tribes on the financing decision of the households.

6. Contribution to Literature

By exploring the impact of the interaction of caste categorization and occupation on household income, this paper for the first time brings to the fore the issue of empowering marginalized sections of society through social schemes and welfare initiatives, targeted at artisans and skilled labor. Earlier studies have discussed the impact of caste on income, but none of the studies has looked at the complex interaction between social inclusion through self-help groups and special schemes for artisans and entrepreneurs. The study further explores the impact of interaction between caste and membership of social groups on the financial behavior of households. As per the Resource-based view (RBV), scarce resources are allocated as per the rules of society, which may be flawed and lead to inequities. From a critical realism perspective, devoid of social rules and class biases, the group lending should allocate resources to the marginalized and lower sections of society. But that does not happen in reality and the state interventions in the form of welfare schemes such as PM Jan Jati Mission have a vast impact on the wealth and livelihood of marginalized sections of society, (Ashraf, 2020; Padhan & Prabheesh, 2021). For the first time, the study establishes the impact of marginalization through social categorization and access to group lending on the financing choices and future behavior of the members of the group. The study further contributes to the existing knowledge by highlighting that the occupation and possession of collateral and wealth have a large impact on the financing choices of the household. Whether a household borrows from a formal finance channel or an informal channel depends on the occupation and caste classification of the household.

7. Conclusion

Based on the discussion thus far, we conclude that the tribal households, who borrowed from the self-help groups, do have lower income than upper caste households. Moreover, tribal artisan households that borrowed from self-help groups have a higher income than the non-tribal groups, which are not artisans. Due to various social welfare activities, tribal households, borrowing from self-help groups are more likely to borrow from banks. However, if bank credit is unavailable, such households are likely to borrow from the moneylenders. Furthermore, households with higher incomes are more likely to borrow. Thus, welfare schemes do seem to have a positive impact on the borrowing habits of households. Due to various social schemes, tribal artisan households have a higher propensity to borrow from traditional sources, such as banks and non-banking finance companies, and are less likely to borrow from shops and moneylenders. Dastkar Sashatikaran Yojna, Ambedkar Hastshilp Vikas Yojana, Handicrafts Mega Cluster Mission (HMCM), and Jan Jati Vikas mission are some of the initiatives that the Indian government has undertaken to support the artisan households borrowing from the self-help groups. These initiatives do have a positive impact on the financing choices of artisan households. Largely, while these artisan tribal households borrow more from banks, artisans who are not covered under the tribal schemes are still dependent on the moneylenders.

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