# Income Transfer Policies and Aggregate Welfare: Evidence from India*

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June 2026

**Abstract**

The impact of income transfers on aggregate welfare depends on the marginal propensity to consume and marginal utility. However, many countries make transfers contingent on observable social and demographic characteristics. What is the relative impact of identity-based transfers vis-a-vis transfers based purely on economic criteria? In this paper, we develop life-cycle models for four different caste groups in India and derive their MPC estimates. We use these estimates to assess the increase in aggregate welfare under counterfactual income transfer policies such as UBI, progressive transfers, and different variants of redistribution. Progressive transfers improve aggregate welfare the most, while redistribution based on social and economic characteristics outperforms redistribution based only on either of the criteria.

JEL Codes: E21, H23, H31

Keywords: Consumption, Savings, Wealth, Redistribution, Households

*We would like to thank the participants at Annual Conference of Economic Growth and Development, ISI, Delhi, 2023; attendees at the seminar series in IIM Bangalore; attendees at the seminar series in IIFT Kolkata.

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# 1 Introduction

Cash transfers are commonly used to improve consumption and welfare around the world (Hoynes and Rothstein, 2018; Banerjee et al., 2019; Ghatak, 2015, 2023). Economic rationale demands that households with high marginal propensity to consume (MPC) receive the transfers. However, due to information constraints, cash transfers are contingent on verifiable characteristics of the recipients. In several countries, policy-makers use information on demographics to determine eligibility of transfers. For eg; in India, under-privileged social groups, also known as lower caste groups, are the main beneficiaries of several welfare programs. If social exclusion correlates closely with economic deprivation, then such schemes may improve welfare. On the other hand, a socially underprivileged household with a low MPC or low marginal utility will experience only a minor consumption and welfare gain due to income transfers. Thus, *prima facie*, it is unclear how well do identity-based income transfer policies perform vis-a-vis transfers contingent on purely economic characteristics.

This question is of extreme importance in India, a country with widespread and cross-cutting social and economic inequities. Owing to historical injustices and continuing deprivation, the Government of India runs several cash transfer programs for the under-privileged caste groups, categorized as Scheduled Castes (SCs) and Scheduled Tribes (STs) (Desai and Dubey, 2012). However, recent debates have focused on the extent of correlation between social identity and economic deprivation in India.[1] Vaid (2012) shows that while the under-privileged caste groups in India have low economic mobility, the privileged groups also experience substantial downward mobility. Thus, whether social identity alone should serve as the marker for redistributive policies remains an open and policy-relevant question in the Indian context.

In this paper, we estimate the welfare effects of income transfer policies, where the eligibility criteria varies by economic and social characteristics. Our first step is to estimate MPC for Indian households. Several methods exist for estimating MPC.

[1] See the following: https://www.thehindu.com/opinion/lead/indias-destiny-not-caste-in-stone/article2913662.ece

These include using a natural experiment (Fagereng et al., 2021; Agarwal and Qian, 2014), eliciting responses through a survey (Albuquerque and Green, 2023; Jappelli and Pistaferri, 2014) or using semi-parametric restrictions on consumption-income evolution (Blundell et al., 2008). We develop a lifecycle model with a CRRA utility function $((c_t)^\alpha + \delta(c_{t+1})^\alpha + \cdots + \delta^{T-t}(c_T)^\alpha)$. The model delivers an optimal relationship between current consumption, savings, and present discounted value of expected lifetime wealth, and a closed-form consumption function. Following Irvine (1981), we substitute the PDV of expected lifetime wealth with predicted current wealth as a semi-parametric flexible function of covariates, such as occupation, education, age of the household head, etc. Using Generalized Methods of Moments (GMM) (Hansen and Singleton, 1982), we estimate the model separately for each of the caste groups separately. This estimation process provides us with caste-specific coefficients $\alpha$ and $\delta$. Using the consumption function, we obtain the the corresponding MPC for each household as the derivative of consumption with respect to income.

Our estimates for the discount rate, $\delta$, fall between 0.962 and 0.971 across the four caste groups, which is similar in magnitude to the estimates used in recent studies (Thasni et al., 2025). The value of $\alpha$ for the under-privileged groups, Scheduled Castes and Scheduled Tribes, is 0.947 and 0.892, respectively, which are significantly higher than the values for the *General* caste groups (0.854). We find that the average MPC is 0.683, and the median is 0.775. Consistent with theoretical predictions and previous literature, MPC declines with consumption level (Mariger, 1987; Kimball, 1990; Carroll and Kimball, 1996; Kaplan and Violante, 2014). We also find that MPC is higher for younger household (denoted by the age of the household head). This result is consistent with cross-country evidence on rising saving rate with aging population (Loayza et al., 2000b,a). Jain and Goli (2022) record similar evidence using panel of states in India.

Interestingly, the MPC of socially under-privileged households is higher compared to General-caste groups, across all consumption levels. Two potential reasons could drive such a variation in MPC across castes. First, caste groups may vary in their access to financial products, compelling some to save less, and hence, consume more. These differences may arise either due to supply-side frictions with

lower access to high-return instruments for some caste groups, or demand-side gaps such as lower financial literacy. A vast literature on financial inclusion in India records these empirical facts (Fisman et al., 2011). In our data, we also find that the average interest rates for the privileged groups, *General*-caste, are marginally higher. Alternatively, caste groups may also vary in their occupational and income preferences as reflected in the estimated coefficients, $\alpha$ and $\delta$.

To assess the relative contribution of these factors, we re-compute MPC of SC households through two imputations. First, we replace SC coefficients with *General*-category coefficients keeping interest rates unchanged. Second, we increase the interest rates faced by all SC households by a magnitude of the mean difference between *General* and SC interest rates, keeping $\alpha$ and $\delta$ unchanged. On imputing the interest rates, we find that average SC MPC falls from 0.795 to 0.744, indicating a moderate role of financial inclusion in consumption-saving behavior. Upon imputing the coefficients, the differences in SC MPC General MPC nearly vanish. Specifically, average SC MPC falls to 0.583, which is much closer to the average General MPC of 0.529. This exercise informs us that the caste-wise variation in MPC appears to be largely driven by variation in the estimated coefficients. What economic properties determines these coefficients? As our theoretical framework does not explicitly model endogenous occupational choices, it is likely, therefore, that the coefficients reflect the unmodelled occupational and income risks faced by different caste groups. Oh (2023) records that individuals in India tend to choose occupations consistent with their own caste identity. Thus, labour market evolution may play an important role in consumption-saving behavior of Indian household over and above financial inclusion.

How will the welfare of such a population respond to different income transfer policies? We simulate counterfactual consumption and lifetime utility for five cash transfer schemes. First, we consider Universal Basic Income (UBI) where every household receives 10% of the average monthly consumption, equivalent to Rs. 1122. Second, under progressive transfer scheme, the cash amount varies inversely with consumption level, while the total expenditure remains the same as under UBI. We then consider three variants of budget-neutral redistribution based on the socio-economic indicators used for targeting. In the first variant, each household

receives the difference between their transfers from the progressive scheme and the flat UBI transfer of Rs. 1122. Thus, the transfer to household with below median consumption are funded by the tax on the remaining households. The second redistribution variant relies only on social group identifier, where uniform tax on all *General* caste households funds transfers of Rs. 1122 to all socially under-privileged households (SC, ST and OBC). In the last variant of redistribution, we consider both economic and social backwardness measure. Specifically, SC, ST, and OBC households in the below-median consumption bracket receive a transfer of Rs. 1122 funded by a uniform tax on General caste households above the median consumption level.

One time progressive transfers increase welfare, measured by the total lifetime utility of all households, by 0.676% compared to an increase of 0.656% under UBI. This result is consistent with the findings from the literature. Hanna and Olken (2018) shows that targeted transfers deliver larger welfare gains than universal programs because the poorer households with high MPC receive much larger amounts. Under the first redistribution scheme, welfare increases by only 0.022%. On the other hand, redistribution contingent solely on social identity (variant 2) improves aggregate welfare by 0.031%. Finally, transfers which account for both social and economic deprivation (variant 3), improve welfare by 0.072%. Our results show that a cash transfer scheme accounting for social and economic deprivation improves welfare by more than three times the magnitude when we consider only the economic criteria and nearly twice when we account for only the social status. This result indicates a substantial overlap between social and economic deprivation. If only the socially under-privileged groups were poor, then the welfare impact across three redistribution schemes would not vary significantly.

We conduct several robustness checks and goodness-of-fit tests. First, we conduct an out-of-sample cross-validation test where we repeatedly estimate our model on a randomly drawn 80% of the sample 100 times, and compare predicted and actual consumption for the remaining 20% of the data each time. The distribution of t-statistics of the difference in predicted and actual consumption indicates a close fit on the out-of-sample data, thereby validating our model. Second, our choice of instruments for GMM satisfy an *ex-post quasi-first stage* exclusion restriction

(Berry et al., 1996; Berry and Haile, 2021). Finally, to assess the external validity of our results, we show that the state-level MPC is negatively related to a measure of state-level savings rate from an external source.

Estimates of MPC are common for developed countries (Evans, 2005; Crawley and Theloudis, 2024). For the Indian economy, similar estimates come from semi-structural work using data from decades ago (Ramanathan, 1968; Vakil, 1973; Laumas and Laumas, 1976; Townsend, 1994). We use a more recent representative Indian household data on savings and consumption to derive parameter estimates of a CRRA utility function, and the MPC for each household. Evaluating welfare under counterfactual policies requires robust and latest estimates of these parameters.

Recency is not the only advantage of our study. Several recent papers have derived uniform, economy-wide MPC estimates for India using macro-economic aggregates (Guimaraés, 2010; Bose and Bhanumurthy, 2015; Mundle et al., 2011; Thasni et al., 2025). For a large country like India, single, economy-wide estimates from aggregate indicators mask the heterogeneity along social, demographic, and economic dimensions. Hoff (2016), Desai and Dubey (2012), and Deshpande (2007) show that caste alone can be a strong determinant of life outcomes. Oh (2023) finds experimental evidence where workers reject labour market returns if the task does not align with their caste identity. Fisman et al. (2011) show how shared social identity between borrowers and lenders in India facilitates financial market transactions. Recent evidence reveals higher financial market frictions for underprivileged caste groups in India (Tiwari et al., 2022; Goraya, 2023; Garg et al., 2025). We use our caste-specific utility functions to evaluate a wider range of of cash subsidy programs. The household-level MPC variation can be crucial in determining the relative cash subsidies required to meet the minimum standard of living.

The use of cash transfers to reduce poverty began in Mexico and Brazil, followed by most of the Latin American countries (Parker and Todd, 2017). In India, government assistance mostly occurred through in-kind transfers of food grain and fuel (Khera, 2011). Owing to rapid expansion in bank account penetration and digi-

tal technologies in the last decade, cash transfers have become the more common policy tool for providing social assistance in India (Ghatak, 2023). In 2025-26, the Government of India transferred nearly USD 7.8 billions through a wide variety of schemes such as pension programs and income support to farmers. However, concerns have also been raised on indiscriminate use of cash transfers, initiating a debate on optimal design of these schemes. We contribute to this debate by simulating the change in consumption and welfare under various forms of income transfers. Redistribution based purely on social identities may not have the desired impact in India as social and economic status may not be fully correlated; some socially privileged but economically poor households may receive a tax, thereby reducing welfare.

While our counterfactual simulations provide impacts on welfare impacts, income transfer policies also vary in the monetary and non-monetary costs (Banerjee et al., 2019). These include costs for collecting and verifying information on social and economic indicators used for targeting, implementing the transfers and reducing inclusion and exclusion errors. Incorporating these elements of income transfer schemes is beyond the scope of the paper. However, the results on welfare change provide one half of the equation, thereby throwing partial but crucial light on the debate.

# 2 Theoretical Model

A household consumes $c_t$ in each period $t$ and lives till $T$. Its inter-temporal utility is

$$E(U(c_t, c_{t+1}....c_T)|I_t) = (c_t)^\alpha + E[\delta(c_{t+1})^\alpha + .....\delta^{T-t}(c_T)^\alpha|I_t]$$

where, $I_t$ is the information set of the household at time $t$. The household's budget constraint in period $t$ is:

$$c_t + k_t = y_t$$

where, $k_t$ is net-savings of the household. $y_t$ is the income.

Most lifecycle models adopt one of two approaches for the income generating process (Meghir and Pistaferri, 2011). In the first approach, income evolves exogenously (Meghir and Pistaferri, 2004), which can either be stochastic (Blundell et al., 2008) or non-stochastic (Kopczuk and Lupton, 2007). We assume income to be non-stochastic, which makes our approach closer to Kopczuk and Lupton (2007)'s. In the second approach, income is determined endogenously through households' choices such as labour hours and human capital investment (Low et al., 2010). Modeling an endogenous income process can be helpful when cash transfers discourage recipients from seeking work or investing in higher education. In India, cash transfers are unlikely to disincentivize human capital investment or labour market effort. Varshney et al. (2018) finds negligible impact of employment guarantees in rural labour markets in India. Therefore, we model an exogenous income evolution process.

Households use savings from each period $t$, $k_t$, to consume in the terminal period, $T$. These savings can either be positive or negative. A positive $k_t$ accrues to the household by rate of savings, $R_t$. On the other hand, a negative $k_t$ depresses future consumption by the opportunity costs, which can either be equal to the savings rate, $R_t$ if the household has no consumption loan, or borrowing rate, $R_{b,t}$ if the household has consumption debt. Thus,

$$c_T = R_t^{T-t}.k_t + R_{t+1}^{T-t-1}.E[k_{t+1} + ...R_{T-1}.k_{T-1}|I_t]$$

where, $R_t = R_{b,t}$ if $k_t < 0$ and household has consumption debt. Otherwise, $R_t$ is the savings rate.

The household solves the following problem

$$MaxU(c_1, c_2, k) = (c_t)^\alpha + E[\delta(c_{t+1})^\alpha + .....\delta^{T-t}(c_T)^\alpha|I_t]$$

subject to

$$c_t + k_t = y_t \,\forall\, t$$

$$c_T = R_t^{T-t}.k_t + R_{t+1}^{T-t-1}.E[k_{t+1} + ...R_{T-1}.k_{T-1}|I_t]$$

Using $\lambda_{t+j}$ and $\lambda_T$ as the Lagrangean multipliers for budget constraints in period $t+j$ and period $T$, respectively, we obtain the following first-order conditions with respect to $c_{t+j}$, $k_{t+j}$ and $c_T$[2]:

$$\delta^j.\alpha.(c_{t+j})^{\alpha-1} = \lambda_{t+j} \tag{1}$$

$$\lambda_{t+j} = R_{t+j}^{T-t-j}.\lambda_T \tag{2}$$

$$\alpha.\delta^{T-t}.(c_T)^{\alpha-1} = \lambda_T \tag{3}$$

Equations 1, 2 and 3 deliver $c_T = (\delta.R_t)^{\frac{T-t}{1-\alpha}}.c_t \, \forall t$. Using the terminal period budget constraint, we obtain

$$R_t^{T-t}.k_t + R_{t+1}^{T-t-1}.E[k_{t+1} + ...R_{T-1}.k_{T-1})|I_t] = (\delta.R_t)^{\frac{T-t}{1-\alpha}}c_t$$

The above equation delivers a relationship between consumption today and the aggregate savings in the terminal period. We can observe savings, $k_t$, consumption, $c_t$ and interest rates, $R_t$, faced by households. From age of the household head, we can infer the time till terminal period $T-t$. The second term on the left side, $E[k_{t+1} + ...R_{T-1}.k_{T-1})|I_t]$, is the expected present discounted value of terminal wealth of the household. We denote this by $w^*$. The optimal per-period consumption-savings equation can be written as:

$$(R_t^{T-t}.k_t + R_{s,t}^{T-t}.w^*) = (\delta.R_t)^{\frac{T-t}{1-\alpha}}c_t \tag{4}$$

where, $R_t = R_{b,t}$ if $k_t < 0$ and household has consumption debt. Otherwise, $R_t$ is the savings rate faced by the household.

[2]For ease of exposition, we drop the expectations operator.

## 2.1 Structural Parameters

By substituting $k_t = y_t - c_t$ from period $t$'s budget constraint in equation 4, we obtain a closed-form solution of consumption as a function of income:

$$c_t = \frac{y_t + w^*}{1 + (\delta)^{\frac{T-t}{1-\alpha}}.R_t^{\frac{(T-t)\alpha}{1-\alpha}}} \tag{5}$$

Equation 5 provides us with the marginal propensity of consumption.

$$\frac{dc_t}{dy_t} = \frac{1}{1 + (\delta)^{\frac{T-t}{1-\alpha}}.R^{\frac{(T-t)\alpha}{1-\alpha}}}$$

Since the income process is non-stochastic, our MPC estimates reflect the consumption response to a fully-anticipated, one-time change in income.

## 2.2 Lifetime Value Function and Aggregate Welfare

A household's lifetime utility is

$$\Sigma_{j=t}^{T} \delta^{j-t}.(c_j)^{\alpha}$$

Assuming $R_{t+j} \approx R_{t+j+1} = R$, then the Euler equation can be written as $c_{t+j+1} = c_{t+j}(\delta.R)^{\frac{1}{1-\alpha}}$. We write the lifetime utility as a function of current consumption:

$$\Sigma_{j=t}^{T} (\delta.R^{\alpha})^{\frac{j-t}{1-\alpha}}.(c_t)^{\alpha}$$

$$(c_t)^{\alpha} \frac{(\delta.R^{\alpha})^{\frac{T-t}{1-\alpha}} - 1}{(\delta.R^{\alpha})^{\frac{1}{1-\alpha}} - 1}$$

Since $c_t = \frac{y_t + w^*}{1+(\delta)^{\frac{T-t}{1-\alpha}}.R^{\frac{(T-t)\alpha}{1-\alpha}}} = MPC_i(y_{it} + w^*)$, we can write lifetime utility function

of household $i$ as $(MPC_i(y_{it} + w_{it}))^{\alpha} \frac{(\delta.R^{\alpha})^{\frac{T-t}{1-\alpha}}-1}{(\delta.R^{\alpha})^{\frac{1}{1-\alpha}}-1}$. Aggregate welfare is the total of lifetime utilities over all households:

$$\mathcal{W} = \Sigma_i (MPC_i(y_{it} + w^*))^{\alpha} \frac{(\delta.R^{\alpha})^{\frac{T-t}{1-\alpha}} - 1}{(\delta.R^{\alpha})^{\frac{1}{1-\alpha}} - 1} \tag{6}$$

# 3 Data and Summary Statistics

Several papers use panel data to estimate consumption response to income shocks (Browning and Collado, 2001; Evans, 2005; Blundell et al., 2013). Blundell et al. (2008) provides a panel-data based technique for decomposing MPC into permanent and transitory components, which most of the literature follows (Theloudis, 2017, 2021). Arellano et al. (2017) extends it to account for heterogeneity in income shocks.

For the objective of our study, we face two limitations when using Blundell et al. (2008)'s technique. First, being a semi-parametric approach, it does not allow counterfactual simulations. Second, in India, CPHS is one of the only panel datasets on consumption and savings of households. While it has found widespread use, Somanchi (2021) demonstrates that the CPHS undercounts the marginalized and underprivileged households in the country. Despite attempts at bias correction after altering the sampling weights in CPHS, Dreze and Somanchi (2023) show that such readjustments remain inadequate in accounting the poorer households. Further, the bias of under-representation "*may have increased over time*" (Dreze and Somanchi, 2023).

Given these concerns, we use the All India Debt and Investment Survey (AIDIS) 2019 for our analysis—a nationally representative survey of savings and wealth accumulation behaviour of Indian households. The following explains the construction of the key variables for our analysis:

- Consumption ($c_i$): AIDIS reports the monthly household consumption expenditure on durable and non-durable goods, and imputed value of home production. We use the sum of all three, defined as the usual monthly con-

sumption expenditure, as our measure of consumption.

- Savings ($k_i$): AIDIS records the opening and closing balance of savings across various financial assets, such as Fixed Deposits, savings accounts, current accounts, post-office, pension funds, cooperative banks, etc. We use the difference between the aggregate of closing and opening balance of savings across as $k_i$.

- Time to retirement ($T - t$): We use the winsorize the age of the household head as $t$. For terminal period $T$, we use the maximum of the winsorized age of household head. $T - t$ is the time to retirement.

- Interest Rate ($R$): AIDIS reports the interest rates on loans but not the savings rate across financial assets. We collect this information from the Reserve Bank of India. Our proxy for $R$ is the weighted average of interest rates across all financial assets, where the weights are the share of total savings in a financial asset. If a household has consumption loan, we use the lending rate as reported in AIDIS.

- Proxy of Expected Present Discounted Wealth ($\hat{w}_i$): To obtain $\hat{w}_i$, we regress current wealth of the household on the following: occupation status, education category, age of the household head, household size, district fixed effects, whether the household is rural or urban (sector), and interactions between education and age, education and age, occupation and sector, and education and sector.

Table 1 reports the summary statistics by caste groups. *General*-caste group has the highest consumption, savings, wealth and weighted average interest rate on investment avenues. Thus, economic well-being varies by caste groups, necessitating caste indicator as a target for income transfer policies. However, the average values mask substantial heterogeneity. Figure 1 and 2 plot the distribution of log of consumption and log of wealth, respectively, for each caste. In both figures, we find the distribution for *General* caste (dashed yellow) stochastically dominating all other caste groups. ST group has the lowest consumption levels, while SC have the lowest wealth. We also find substantial overlap in these indicators across caste groups. Thus, caste is not the only differentiator of economic well-being.

Exploring appropriate income transfer policies, hence, becomes crucial.

Table 4 shows the share of savings in different financial assets by each of the four caste groups. *General*-caste groups place a higher share of their savings in higher interest rate venues such as Term deposits or Fixed income deposits. Thus, *General*-caste households have access to more lucrative financial assets. This could be due to either endogenous portfolio choice based on risk aversion or financial market frictions faced by under-privileged caste groups (Fisman et al., 2011).

Table 2 describes other characteristics of the households. The winsorized age of the head of household ranges from 21 to 80, with an average of 48.5. General caste households are the smallest but also have the highest age of the household head. ST households are the youngest as seen in the distribution of $T - t$ (Figure 3). Table 3 describes education level of different caste groups. SC and ST households have the highest propensity of being not literate.

# 4 Econometric Model

We rewrite equation 4 as:

$$\frac{R_i^{T-t}.k_i + R^{T-t}.E(w_i^*|I_t)}{c_i} = (\delta.R_i)^{\frac{T-t}{1-\alpha}}$$

$E(w_i^*|I_t)$ remains unobservable to the econometrician. For the household, this object varies by the relevant information set at time $t$. For eg; salaried households may have stable expectations on wealth evolution as opposed to households engaged in entrepreneurship. Education may also play a role in wealth evolution.

To proxy $E(w_i^*|I_t)$, we follow Irvine (1981) which shows the use of cross-sectional data in estimating lifecycle models. Specifically, we regress current wealth on several observable characteristics such as occupation, location, education and region. We use the predicted wealth, $\hat{w}_i$, from this regression to substitute for $E(w_i^*|I_t)$. This approach allows us to use the explainable variation from this regression to

capture the variation in the expected PDV of wealth. The unexplained variance in wealth is assumed to be idiosyncratic and exogenous to household's decision, though we acknowledge that the residual may still capture unmodelled heterogeneity.

Our econometric specification now becomes:

$$\log(\frac{R_i^{T-t}.k_i + R_i^{T-t}.\hat{w}_i}{c_i}) = \Phi.(T-t).\log(\delta.R_i) + \kappa.X_i + \mu_i \tag{7}$$

where, $\Phi = \frac{1}{1-\alpha}$. $X_i$ consists such covariates such as religion, household size, education, and household type, which is an interaction of occupation and location of the household.

## 4.1 Estimation

Estimation of caste-specific values for $\alpha$ and $\delta$ follows a semi-grid search method:

1. For a particular caste group G, we pick a value of $\delta_G \in (0, 1)$.
2. Starting from this value of $\delta_G$, we estimate equation 7 using GMM to obtain $\Phi_G$.
    - If $\Phi_G > 1$, or equivalently, $\alpha < 1$, we retain this as one of the candidate solutions.
    - If $\Phi_G < 1$, or equivalently $\alpha_G < 1$, we discard that solution.
3. We define the solution set as those values of $\delta_G$ for which $\Phi_G > 1$. For each $(\delta_G, \Phi_G)$ in the solution set, we compute the following criterion function.

    $$Q(\delta_G, \Phi_G; G) = [\frac{1}{N}\Sigma_i z_i \mu_i]' W.[\frac{1}{N}\Sigma_i z_i \mu_i]$$

    where, $W$ is the weighing matrix and $z_i$ is the instrument.

    The combination of parameters from the solution set which minimizes the criterion function is chosen as the optimal solution for that caste group. Es-

timator of $Q(\delta_G, \Phi_G; G$ is asymptotically consistent, asymptotically normally distributed and efficient if the $W$ is the Hessian (Amemiya, 1983, 1985).

Since we estimate the models for each of the four caste groups separately, we obtain eight parameters—four each for $\delta$ and $\alpha$. We adjust the standard errors for heteroscedasticity within districts.

## 4.2 Identification

Hall (1978) shows that consumption evolves as a random walk under some restrictions on the Euler equation. Thus, "*lagged consumption should be an exogenous variable*" in forecasting models. However, Hall (1978) also acknowledges that the results are contingent on the constancy of interest rates across individuals and over time. In our context, interest rates may remain stable over the short term, but may vary across individuals due to varying portfolio choice, financial market frictions and search costs for consumption goods. For example, a household which can search more intensely may obtain lower prices, thereby saving more. These factors may remain unobservable to the econometrician. Therefore, we use the instrumental variable approach to estimate equation 7.

### 4.2.1 Instruments

As instruments, we use indicators for households' access to pension and insurance schemes promoted by the Government of India in recent years. These schemes are *Pradhan Mantri Jeevan Jyoti Bima Yojana*, *Pradhan Mantri Suraksha Bima Yojana* and *Atal Pension Yojana*. The first two are insurance schemes, and the latter is a pension plan. Financial literacy in India is low, but the government's push for such schemes has given an impetus to financial inclusion. This has resulted in exogenous variation in access to saving instruments. Table 5 provides descriptive statistics on the share of households with various insurance and pension schemes. Nearly 3-4% of households have insurance coverage, while pension scheme penetration is small.

To test the relevance of the instruments, we regress the interest rate faced by each household on these instruments. Table 6 shows the results. Each regression con-

trols for education, religion, social group, household size, district fixed effects and whether the household is in rural region. The coefficients on the instruments remain significant in all the models, indicating their relevance after holding constant several observable covariates.

We will test for the overidentifying restriction on instruments by computing Hansen's J-statistic (Sargan, 1958; Hansen and Singleton, 1982). This statistic has a $\chi^2$-square distribution with the null hypothesis that the moment restrictions imposed by the instruments are satisfied. In other words, the J-statistic informs whether the moment restrictions in the empirical specification hold for the given parameter value. We will also regress the residuals from GMM on the instruments to test a *quasi-first stage* exclusion restriction (Berry et al., 1996; Berry and Haile, 2021).

### 4.2.2 Inference

A final technical and important point requires a discussion here. While GMM estimation will yield consistent, efficient and normally distributed estimate of $\Phi_G$, we are truly interested in $\alpha_G (= \frac{\Phi_G - 1}{\Phi_G})$. This estimate will be a ratio of two normally distributed random variables. Díaz-Francés and Rubio (2013) show that if $X$ and $Y$ are normally distributed and the coefficient of variation of $Y$ is less than 0.1, then the distribution of $\frac{X}{Y}$ can be approximated by a normal distribution with mean $\frac{E(X)}{E(Y)}$ and variance $(\frac{\sigma_Y}{E(Y)})^2((\frac{\sigma_X}{\sigma_Y})^2 + (\frac{E(X)}{E(Y)})^2)$. We verify that this condition is satisfied in our analysis.

# 5 Results

For each value of $\delta_G$ for a caste group, GMM estimation of equation 7 provides us with an estimate $\Phi_G$. Figure 4 shows the estimated $\Phi_G$ against $\delta_G$ for each of the four caste groups.

All values of $\delta$ for which $\Phi > 1$ or $\alpha < 1$ are feasible solution candidates. Figure 5 shows the criterion functions against different values of $\delta$ for General, OBC, SC and ST groups, respectively. We choose that value of $\delta$ and thus $\alpha$, which minimize

the criteria function.

Table 7 shows the final estimated parameters of the utility function. Column 1 shows $\delta$ against the corresponding $\Phi$ in In column 3, we report $\alpha$ obtained from $\frac{\Phi-1}{\Phi}$. GMM estimation allows inference on $\Phi$. To derive the standard error for $\alpha$, we use the approximation properties from Díaz-Francés and Rubio (2013). Column 5 reports the criterion function, which serves as the measure of fit for the estimation. We fail to reject the over-identifying restrictions for the instrument for ST, OBC and General, as seen by the p-value of the J-statistic in column 7. For SC, the null of over-identifying restriction is not rejected at 90% confidence interval as the p-value is 0.0964.

## 5.1 Estimates of MPC

Table 8 provides summary statistics for the overall MPC, and for each caste group separately. The average value is 0.683 with a median of 0.775. The 25th and 75th percentiles are 0.5 and 0.971, respectively. As expected, due to their relative prosperity in India the General caste group has the lowest MPC of 0.529, whereas the SC community has the highest MPC of 0.795. MPC is higher in rural areas, which are poorer on average, and hence, consume a larger proportion of their income.

Figure 6 plots MPC against the consumption level of the households for different caste groups. MPC declines with higher consumption for all caste groups. Further, at each consumption level, MPC for socially disadvantaged groups, SC, is higher than for the General caste households. A negative relationship between MPC and household prosperity is well-recorded in the literature on lifecycle models (Carroll and Kimball, 1996). Financial market frictions restrict poorer households from high-return assets, which compels them to save less and consume a higher proportion of their incomes.

Figure 7 plots the MPC estimates of different groups against the age of the household head. Here as well, MPC is higher for SC compared to others at each age level. We find that MPC falls with age. This result may occur because younger households earn less, thereby consuming a bigger share of their incomes. As house-

holds grow old, some expenses, such as childcare, fall. Loayza et al. (2000a,b) find evidence for this result worldwide. For India, Jain and Goli (2022) find that the growth in working-age population explains the rise in per-capita savings from 2001 to 2018, and the variation in the working-age population across states explains nearly a quarter of their per-capita savings.

## 5.2 Decomposing Variation in MPC

We find significant variation in MPC across caste groups, regardless of consumption level and age of the household head. What could explain these differences?

One possible explanation could be due to the supply-side or demand-side frictions in financial markets. Specifically, under-privileged households may remain excluded from accessing high return yielding financial assets. Fisman et al. (2011) find evidence of how cultural proximity affects financial market transactions in India. Goraya (2023) documents evidence of low financial inclusion of under-privileged groups. Poor financial literacy of under-privileged social groups can also be critical in their exclusion from financial markets. Such households may not have sufficient incentive or knowledge on savings in high-returns venture, thereby consuming a bigger share of their income. Alternatively, caste-wise variation in MPC could be due to varying preferences as reflected in the coefficients $\alpha_G$ and $\delta_G$.

To understand the relative contribution in MPC variation across caste groups, we conduct two imputations. First, we compute the MPC by replacing its $\alpha$ and $\delta$ with General-caste's $\alpha$ and $\delta$, keeping everything else unchanged. Second, we increase the rate of returns for SC households to match the distribution of General-category's rate of return and re-compute the MPC, *ceteris paribus*. For each imputation, we then check how close the SC MPC approaches General category's MPC. With the latter imputation, we can assess how much does portfolio choice of SC households affects their MPC. The former imputation measures the contribution of preferences.

Table 9 reports the SC MPC values under the two imputations. We also report the actual SC MPC and General category MPC. After imputing the coefficients, the

average MPC for SC drops to 0.583 from 0.795. Imputing rate of returns brings SC MPC to 0.744. Figure 8 plots the actual SC MPC (red circles), SC MPC with General category's interest rate (green squares), and SC MPC with General category's $\alpha$ and $\delta$ (blue triangles). Thus, we find that preferences contribute significantly to MPC variation.

If preferences explain MPC variation across castes, then what determines the preference parameters? Preferences may not be entirely exogenous but shaped by socio-economic conditions such as the occupational choices of households. As $1-\alpha$ measures the degree of risk aversion, differences in coefficients may reflect income and occupation risks. For eg; SC households may be present in occupations which influences their risk aversion, and thus, saving-consumption behaviour. Historically, the Indian society has associated castes with occupations (Hoff, 2016). Oh (2023) shows that individuals in India may forego employment opportunities which are inconsistent with their caste identity. We are unable to fully model an endogenous income evolution or labour market choice. We acknowledge this limitation of our approach which stems from genuine data constraints.

# 6 Income Transfer Policies

An income transfer policy provides a level of transfer, $t_i$, to each household $i$. We use our parameters to assess the counterfactual impact of income transfer policies on the overall consumption and aggregate welfare. From equation 5, we can write counterfactual consumption for a transfer, $t_i$, is

$$c_i(t_i) = MPC_i(y_i + \hat{w}_i + t_i)$$

Let $\mathbf{t}$ be the vector of transfers, $t_i$, under an income transfer policy. From equation 6, counterfactual aggregate welfare with $\mathbf{t}$ is

$$\mathcal{W}(\mathbf{t}) = \Sigma_i (MPC_i(y_i + w_i + t_i))^{\alpha_G} . \frac{(\delta.R^{\alpha})^{\frac{T-t}{1-\alpha}} - 1}{(\delta.R^{\alpha})^{\frac{1}{1-\alpha}} - 1}$$

We consider the following income transfer policies:

**Universal Basic Income** : In our baseline case, each household receives 10% of average monthly consumption expenditure. This amount is Rs. 1122.2, denoted by $t^{UBI}$. Ghatak and Muralidharan (2021) suggest a transfer of Rs. 144 per person per month as a UBI grant, which is nearly Rs. 500 per month per household. Current income transfer policies such as *PM-KISAN* have a similar level of grants. Thus, our transfers are similar or larger than the ones proposed elsewhere.

**Progressive Transfers** : UBI guarantees a positive transfer to all households. However, Hoynes and Rothstein (2018) find that UBI do not generate a meaningful impact on welfare unless they become prohibitively expensive. Therefore, we consider a progressive scheme, where poorer households receive a higher transfer. Given $N$ as the population size, $t^{UBI} * N$ is the total budget of the UBI transfer scheme. Under the progressive scheme, household $i$ receives transfer $t_i^P$

$$t_i^P = (\frac{\frac{1}{c_i}}{\Sigma_i(\frac{1}{c_i})}) * t^{UBI} * N \tag{8}$$

where, $c_i$ is the pre-transfer consumption level of household $i$. Thus, a household receives a share of the total UBI budget where the share is inversely proportional its consumption level. Such a scheme can deliver a higher welfare with the same budget as UBI since poorer households have higher MPC and marginal utility.

**Redistribution** : UBI and progressive transfers can vary in the welfare impact but are equally costly for the policymaker. We consider a redistributive scheme where positive transfers to some households are funded by taxes to others. While such a transfer policy can lower the monetary costs for the policymaker, suppression of consumption and savings on the taxed households will lower the aggregate welfare. We consider the following redistributive transfer policy for each household $i$:

$$t_i^R = t_i^P - t^{UBI} \tag{9}$$

where, $t_i^P$ and $t^{UBI}$ are progressive and UBI transfers, respectively. $t_i^R > 0$ if $t_i^P >$

$t^{UBI}$; i.e. transfers are likely to be positive for households with lower consumption level.

**Redistribution based on social and economic characteristics** : Income transfer policies can vary not only in their costs and welfare impact but also in the information required for implementation. Due to the inverse relationship between transfers and consumption level under progressive and redistribution policies, households have an incentive to misreport consumption. If inferring the true consumption level is difficult, progressive and redistributive transfers can become prohibitive to implement. Therefore, we consider the following variants of redistribution schemes based on relatively more easily observable socio-economic characteristics.

- Social Group-based Redistribution: First, we consider redistribution transfers based purely on social identity. All socially disadvantaged groups (SC, ST and OBC) receive a transfer of Rs. 1,122. These transfers are funded by uniform tax on all General caste households. The tax amount is Rs. 2681.
- Socio-Economic Redistribution: Second, we make transfers of Rs. 1,122 to all socially disadvantaged households below the median consumption level. The transfers are funded by a uniform tax on all households from the General caste with above-median consumption. Since the recipients are now a smaller proportion of the population, the tax amount under this scheme is Rs. 636.
- Gender-based Redistribution: Third, we make transfers of Rs. 1,122 to all female-headed households, funded by a uniform tax on all male-headed households, equal to only Rs. 170.83. The only requirement in this scheme is the gender of the household head.

We summarize the key features of the transfer policies in Table 10. Under UBI, each household receives the same amount with minimal information requirements, but the policy requires an external funding source. The progressive transfer scheme has the same monetary costs as the UBI, but requires information on the consumption level of each household. Redistribution also requires the same information as the progressive transfer scheme, but has no direct monetary costs compared to

UBI or progressive transfers.

Redistribution schemes based on social and economic characteristics require less information for implementation and impost no monetary costs. For example, variant 2, socio-economic redistribution, requires information on the households' caste identity and consumption bracket (above or below the median). In contrast, variant 3 requires information on the gender of the household head. Through these three policies, we address the debate on the evolution of welfare schemes in India. Many existing policies in India specifically target the socially disadvantaged groups, which the first variant reflects (see chapter 4 of Rahman and Pingali (2024)). The emphasis on a caste-centered approach to social welfare policies in India has further deepened. Recently, the Government of India has announced the next population census to record a more granular social identity of each individual along with the usual economic characteristics [3]. Such information can assist in redesigning welfare policies to address social and economic deprivation jointly (Omvedt, 2010). The second variant captures this approach, as the economic and social conditions of the household determine transfers. Finally, the third variant reflects a gendered approach to social welfare schemes.

## 6.1 Counterfactual Consumption

Figure 9 plots the consumption change across households under the UBI, progressive, and redistributive schemes. While the impact of UBI on consumption (blue curve) appears flat, progressive and redistributive schemes create substantial variation. Specifically, consumption by poorer households increases more under progressive and redistributive schemes, compared to UBI. However, more affluent households decrease their consumption under redistribution as they are subject to taxes.

In Figure 10, we conduct a similar analysis for the three variants of redistribution based on socio-economic characteristics. The social class based redistribution has a much steeper profile against consumption level compared to socio-economic based redistribution. Thus, a redistribution transfer scheme accounting only for social

[3] See Government approves Caste Census in India.

under-privileged status imposes a stronger tax as well as a higher transfer.

Table 11 provides summary statistics on the change in consumption under different income transfer policies. The average consumption change is Rs. 837 under the progressive transfer scheme, followed by Rs. 766 under UBI. Further, the distribution of consumption change is more dispersed under the progressive scheme While both the schemes incur same expenditure, transfers are inversely proportional to consumption or directly proportion to MPC levels under the progressive scheme. Thus, households with a higher propensity to spend receive a higher amount, thereby increasing the variance of consumption expenditure.

Total expenditure for the four types of redistribution remains zero but they create vastly different impact on consumption expenditure. Specifically, under classic redistribution, the average consumption change is only Rs. 35.22 whereas the median expenditure declines by Rs. 92. Social group based redistribution, where the transfers to under-privileged groups are financed by a uniform tax on all privileged households, improve average consumption by Rs. 173.46 with a median effect of Rs. 749.12. Such vast differences can be attributed to poor overlap between social and economic deprivation. Thus, SC, ST and OBC households do not necessarily have higher MPC. The disjointed nature of economic and social under-privileged status indicates the need for accounting both types of deprivation when designing income transfer policies.

## 6.2 Counterfactual Welfare

Income transfer policies impact households in two ways. Households which receive a positive transfer improve consumption and utility depending on their MPC. Taxed households suffer the opposite effect. These two forces serve to counteract the impact on overall welfare—sum of lifetime utilities of all households. The net impact on welfare depends on relative marginal utilities of households. To aggregate the impact of income transfer policies, we measure the percentage change in welfare before and after income transfers. Table 12 provides the results.

**Income transfers based on economic characteristics** UBI increases aggregate welfare by 0.656%. Most welfare schemes continue for longer durations with transfers or benefits delivered in each period. Progressive transfers and redistribution increase aggregate welfare by 0.676% and 0.022%, respectively. Considering that this impact on sum of lifetime utilities arises due to a one-time transfer, it is relatively large.

**Income transfers based on sociodemographic characteristics** Social group-based redistribution, where transfers are contingent only on the social group of the beneficiary, decreases aggregate welfare by 0.031%. Socio-economic redistribution transfers cash based on the joint eligibility of social and economic conditions. All SC, ST, and OBC households with consumption below the median level receive a transfer of Rs. 1,122, funded by a uniform tax on all General group households with consumption above the median level. This policy increases aggregate welfare by only 0.072%. Finally, gender-based redistribution (variant-3) has a negative but negligible effect, reducing overall welfare by -0.008%.

## 6.3 Discussion on Counterfactual Welfare Gains

The optimality of a transfer scheme depends on the direct monetary costs of the scheme and information collection costs to assess beneficiary status. Hoynes and Rothstein (2018) and Ghatak (2023) argue that UBI would exert a substantial fiscal cost unless other schemes are withdrawn. UBI creates a smaller impact compared to the progressive scheme but has lower costs in identifying and monitoring the targeting indicator, which is consumption in our case. The redistribution policy may have similar information and administration costs as the progressive scheme, it imposes zero budgetary costs. We are unable to estimate such non-monetary costs of implementing these welfare schemes. However, our results provide a range of such costs under which UBI may become Pareto optimal.

To overcome information asymmetry in welfare schemes, redistributive transfers are conditioned on observable and easily verifiable social and economic characteristics. In India, such information is routinely recorded in several databases (Omvedt, 2010). If social and economic status were perfectly correlated, such a

tax would only be imposed on the relatively well-off, ensuring aggregate welfare change remains high. However, we find that transfers based on both social and economic deprivation have nearly thrice the impact than transfers based only on economic deprivation (Redistribution) and twice the impact than targeting only on social deprivation. Thus, social and economic statuses do not overlap completely in India. Many General caste households may be impoverished and thus may have a high MPC. At the same time, some SC households may be economically well-off. Thus, welfare policies focusing only on social characteristics while overlooking the relative economic status of the recipient may be suppressing aggregate welfare.

# 7 Robustness Checks

## 7.1 Out-of-Sample Cross Validation

The criterion function provides the measure of fit of the GMM estimation model. To further understand the goodness of fit of the model, we conduct an out-of-sample cross validation exercise. Specifically, for each of the four caste groups, we estimate our model on 80% of the data. Using the estimates of the parameters from this sub-sample, we predict consumption for the remaining 20% of the test data as per the equation 4:

$$\hat{c_i} = \frac{R^{T-t}.(k_i + w_i^*)}{(\delta.R)^{\frac{T-t}{1-\alpha}}}$$

As a measure of fit, we conduct a t-test on the difference between the demeaned value of the predicted and actual log consumption on the test set. We repeat this exercise 100 times, each time randomly drawing 80% of the sample, thereby obtaining 100 t-statistics. In figure 11, we plot the distribution of t-statistics. Most t-statistics value fall between critical value for rejecting the test at 5% confidence interval level (dashed red vertical lines). Figure 12 plots the distribution of p-values from the t-test, where the red vertical line is at 0.05. Most of the p-values are well above the rejection threshold. Thus, for most of the test set, our predicted

consumption correlates closely with actual consumption. Thus, for most of the out-of-sample test set, predicted and actual consumption are statistically similar.

## 7.2 External Validity

As a test of external validity of the exercise, we compare the MPC estimates of each state against a metric of the state's savings from an external data source. A higher MPC estimate should be associated with lower per capita savings in the state, implying a negative relationship between these two variables. As a metric of per-capita savings, we compute the ratio of aggregate saving deposits in scheduled commercial banks in each state to the state's population. Figures 13 plots log of per-capita savings on the y-axis against the average MPC of each state on the x-axis. The relationship is downward sloping, validating our model against external data.

## 7.3 Validity of Instruments

For instruments to be valid, the exclusion restriction should be satisfied. Specifically, conditional on the observable covariates, the instruments, $z_i$, should be exogenous to the residual term from the estimating equation. To assess the validity of instruments, we follow Berry et al. (1996) by regressing the estimated residuals from the GMM estimation on the instruments. Berry and Haile (2021) term this as *"ex-post" quasi first-stage* validation. Table 13 reports the results of a regression of the GMM residuals on each of the instruments in columns 1, 2, and 3. In column 4, we include all three instruments. Each regression controls for the household characteristics, which include household type, religion, social group, household size, and education of the household head. The coefficients on the instruments are insignificant in columns 1 and 2. Household adoption of the public insurance scheme is uncorrelated with the unexplained terms from the GMM estimation. The coefficient on the pension scheme adoption is, however, significant. Given that our equation is over-identified with three instruments, we can conclude that the exclusion restriction is satisfied.

# 8 Conclusion

Income transfer policies are commonly used world over. However, merely transferring income is not the end goal but a means to improve consumption and subsequent welfare. Understanding the links between income, consumption, and welfare requires knowledge of structural parameters of the economy. In this paper, we develop lifecycle models for different caste groups in India using a nationally representative household-level dataset. Our model accounts for heterogeneity in interest rates and demographic factors such as age of the household head. We derive household-level MPC estimates.

We simulate consumption and welfare under different counterfactual income transfer policies. A targeted scheme, where transfers vary inversely to consumption level, increases welfare by 0.676%. UBI scheme, where each household receives a constant transfer, increases welfare by 0.656%. A redistribution scheme, where taxes on wealthier households provide funds for poorer households, increases welfare by only 0.022%. The choice between these three schemes will be contingent on their monetary costs, among other factors. Our results show that holding constant the budget, a progressive transfer generates 9% more welfare than UBI. If the budget constraints are binding, however, the tax-funded redistribution scheme is dominated substantially by other schemes.

Implementing income transfer policies also requires collecting and assessing the eligibility criteria for beneficiaries. In India, indicators of group identities, such as castes, are routinely collected by administrators for several welfare programs. Being easily verifiable, such welfare programs are less likely to suffer from information asymmetry. However, the welfare effect of transfers based on caste status depends on the correlation between social and economic deprivation. We find that when transfers to all socially under-privileged caste groups come from taxes on the General caste group, aggregate welfare improves by 0.031%. On the other hand, the impact on aggregate welfare is nearly twice as high when socially and economically backward groups receive transfers and only the above-median consumption General caste households are taxed. Thus, transfer schemes sensitive to social and economic characteristics dominate those contingent on only one of the factors.

This result indicates that social and economic under-privileged statuses in India do not overlap entirely, and may be cross-cutting. Many General caste households may be economically backward, so taxing them reduces aggregate welfare. At the same time, many socially under-privileged households may be economically well-off, who do not experience sufficient consumption and utility gains upon receiving a transfer.

Income transfer policies do not affect welfare only through consumption. They may have productivity externalities by reducing the incentives of recipient households to participate in labour markets (Guner et al., 2023). Alternatively, households may utilize the transfers to invest and upgrade entrepreneurial activities. One may extend the life-cycle models to include proxies of labour market decisions using survey-to-survey imputations (Elbers et al., 2003)and simulate the output consequences. We leave these exercises for future work.

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# 9 Figures

Figure 1: Distribution of Log of Consumption

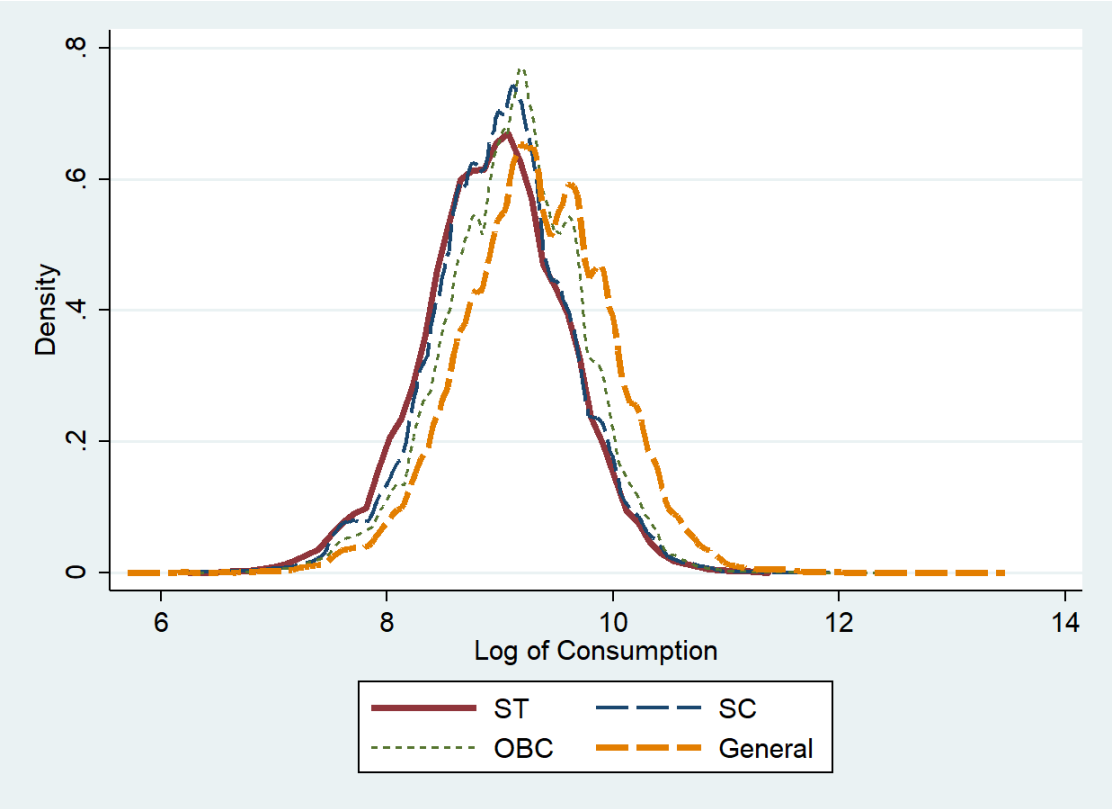


Figure 2: Distribution of Log of Wealth




Figure 3: Distribution of Time to Retirement by Caste-wise

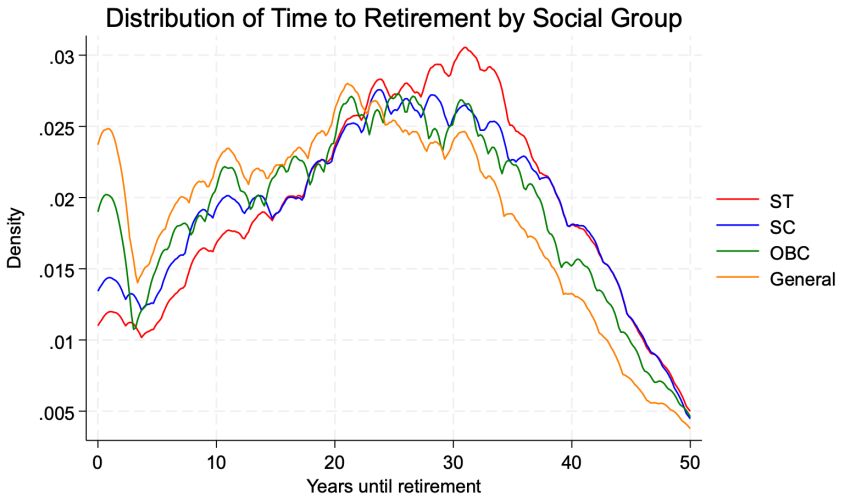
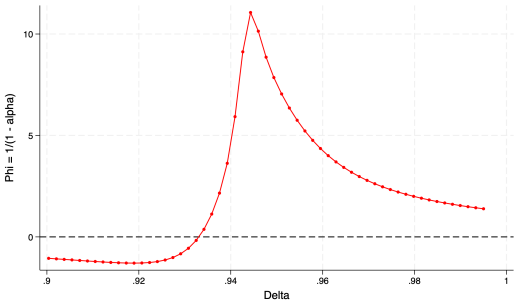
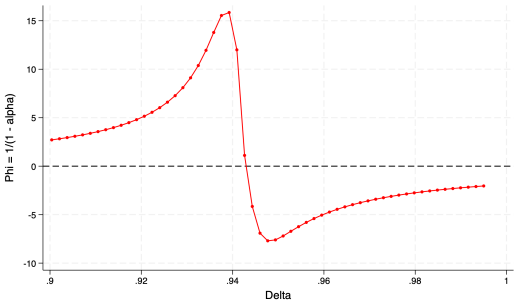


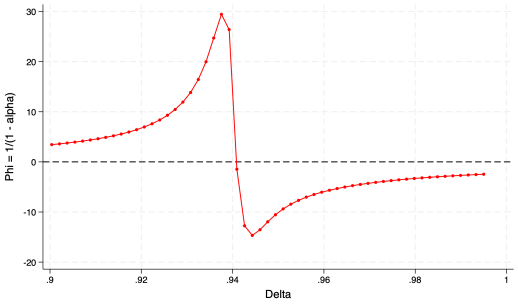
Figure 4: Value of $\Phi$ and $\delta$ for four caste groups



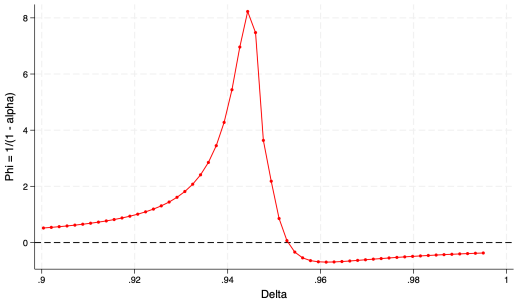

General




OBC

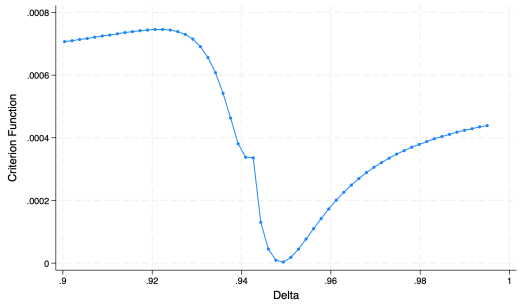



SC

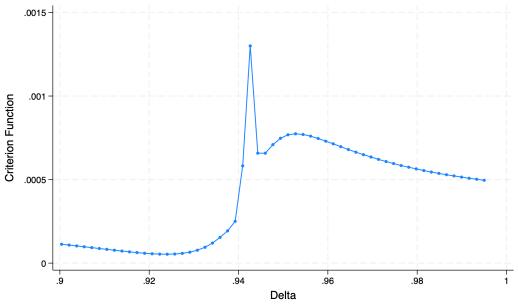



ST

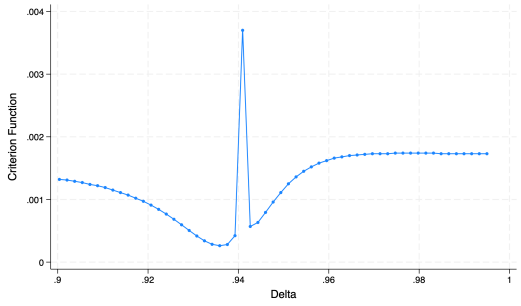
Figure 5: Criterion Function and $\delta$ for four caste groups



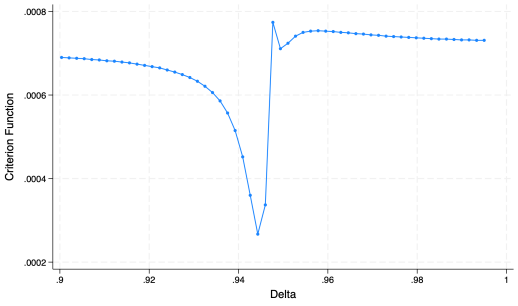

General




OBC




SC




ST

Figure 6: Marginal Propensity of Consumption and Consumption Expenditure

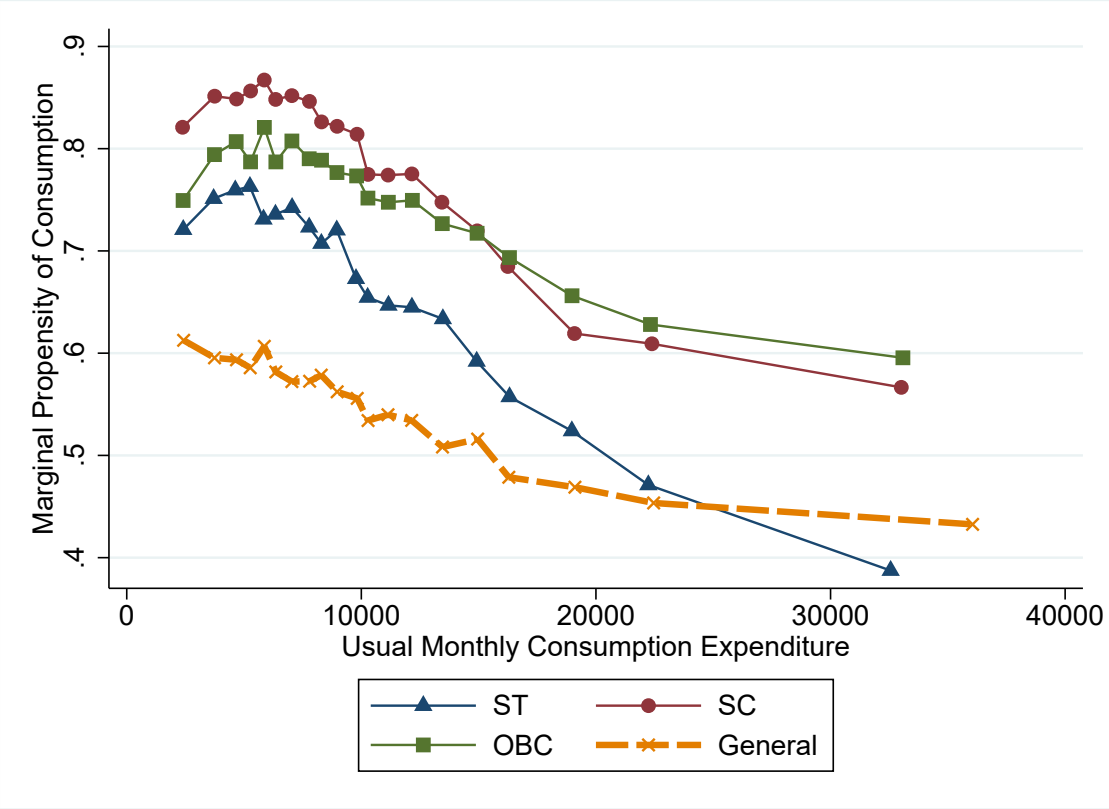


Figure 7: Marginal Propensity of Consumption and Age of Household Head

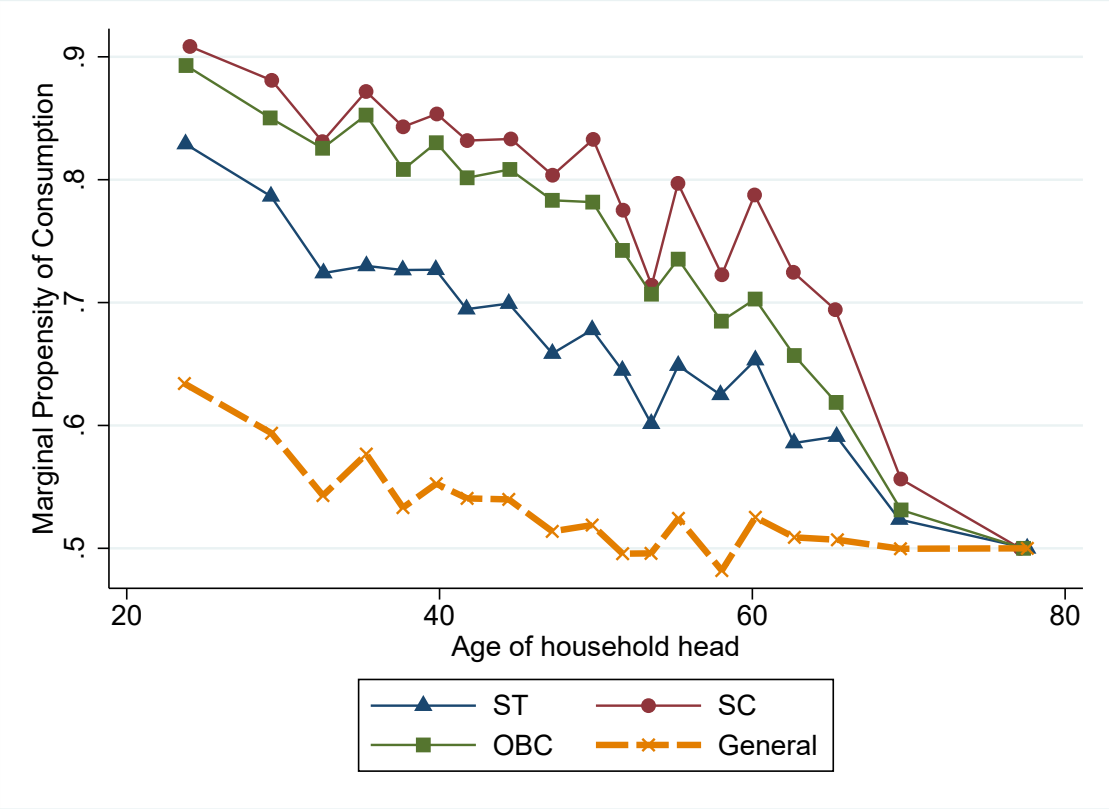


Figure 8: Imputed and Actual SC Marginal Propensity of Consumption

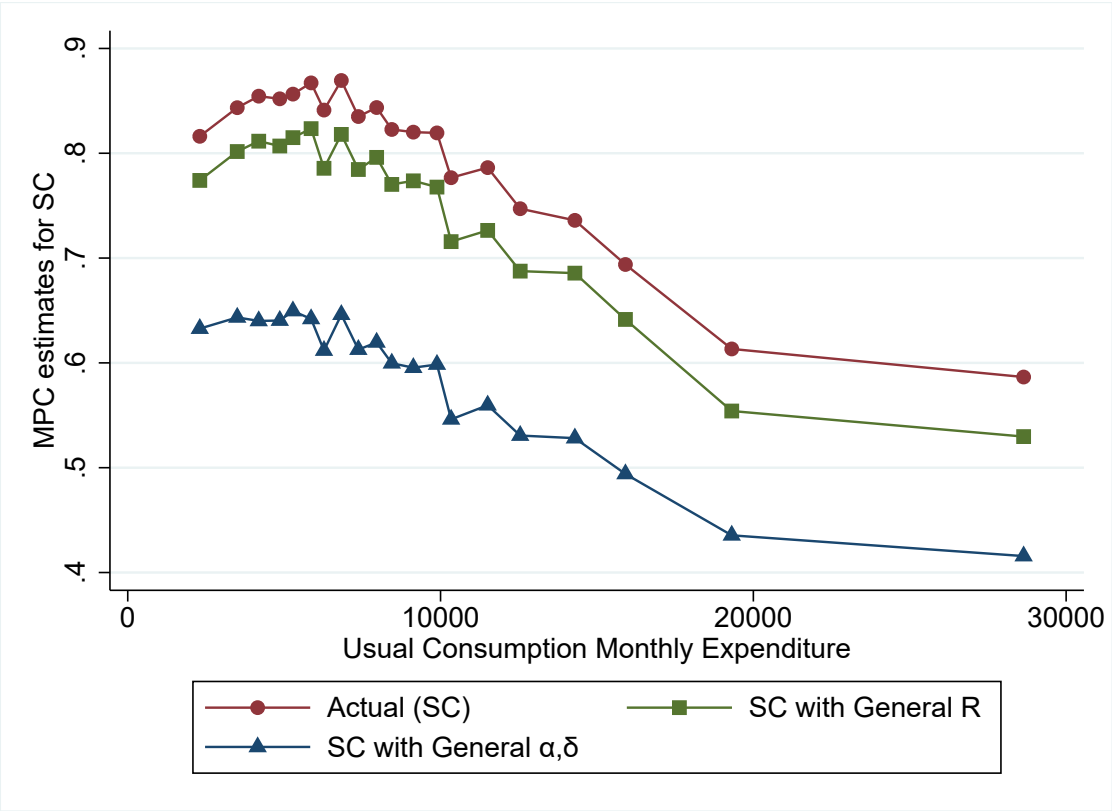


Figure 9: Consumption Change under UBI, Progressive and Redistributive Schemes

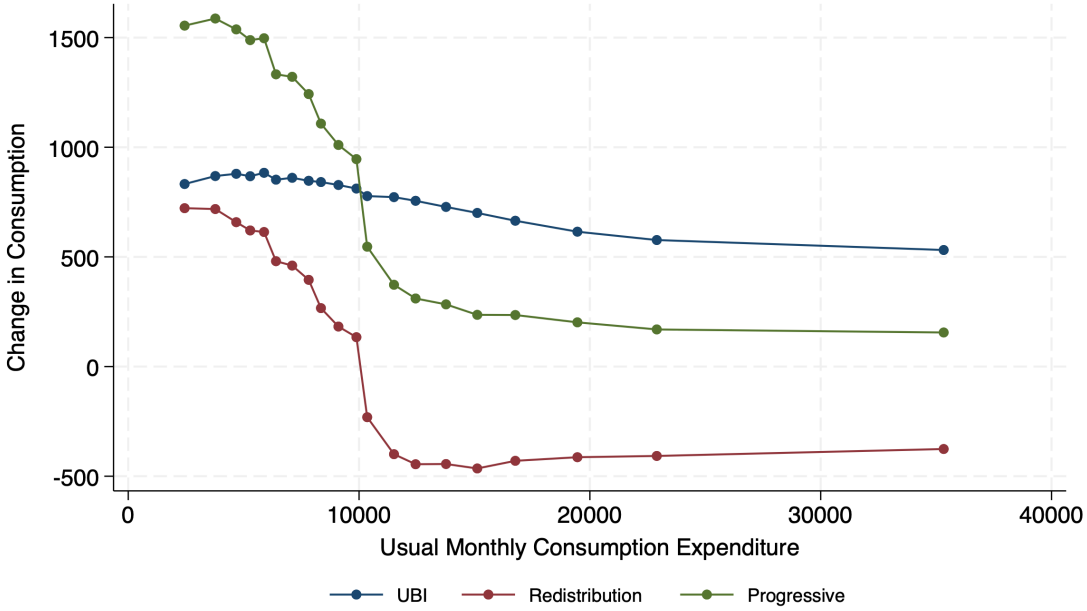


Figure 10: Consumption Change under Redistribution based on Socio-Economic Characteristics

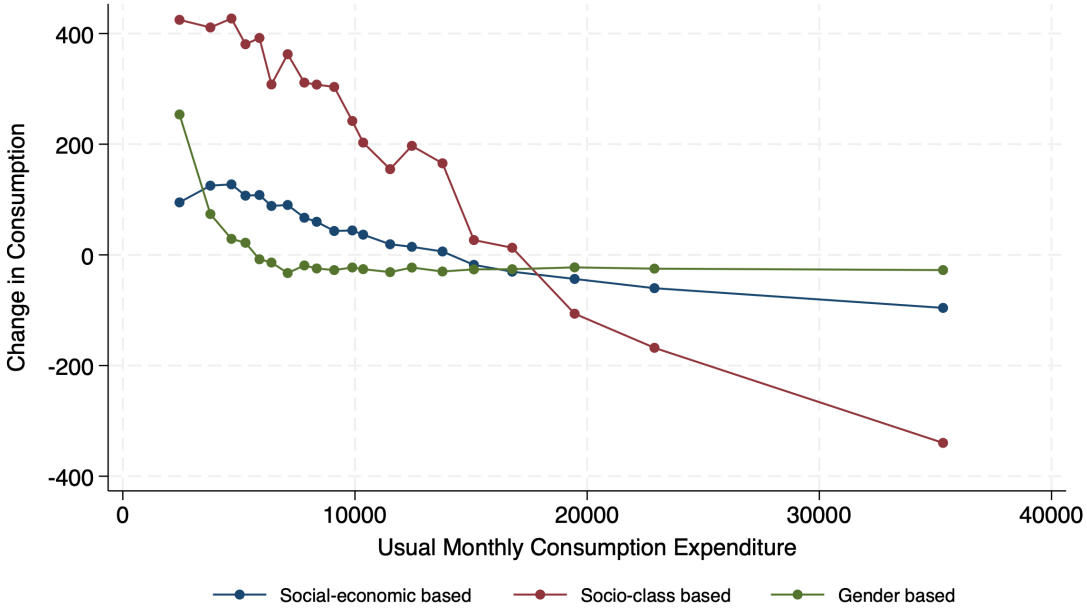


Figure 11: Distribution of t-statistics from out-of-sample Cross Validation Test Set

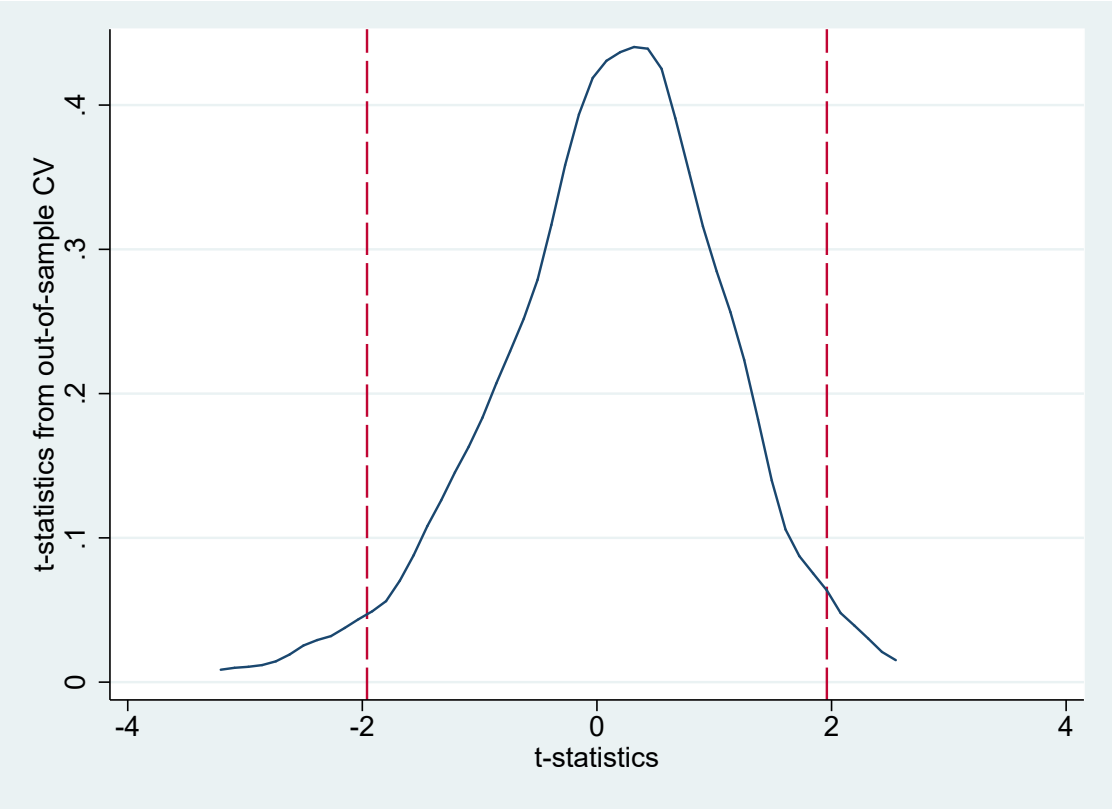


Figure 12: Distribution of p-value from out-of-sample Cross Validation Test Set

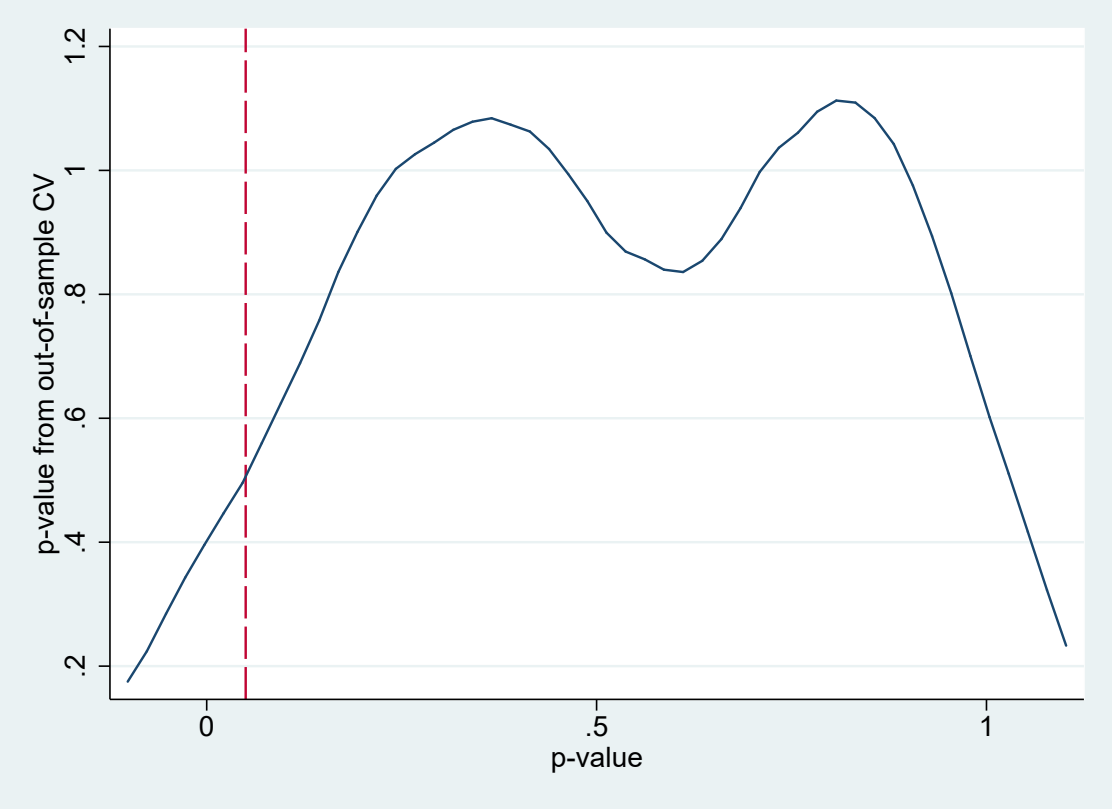
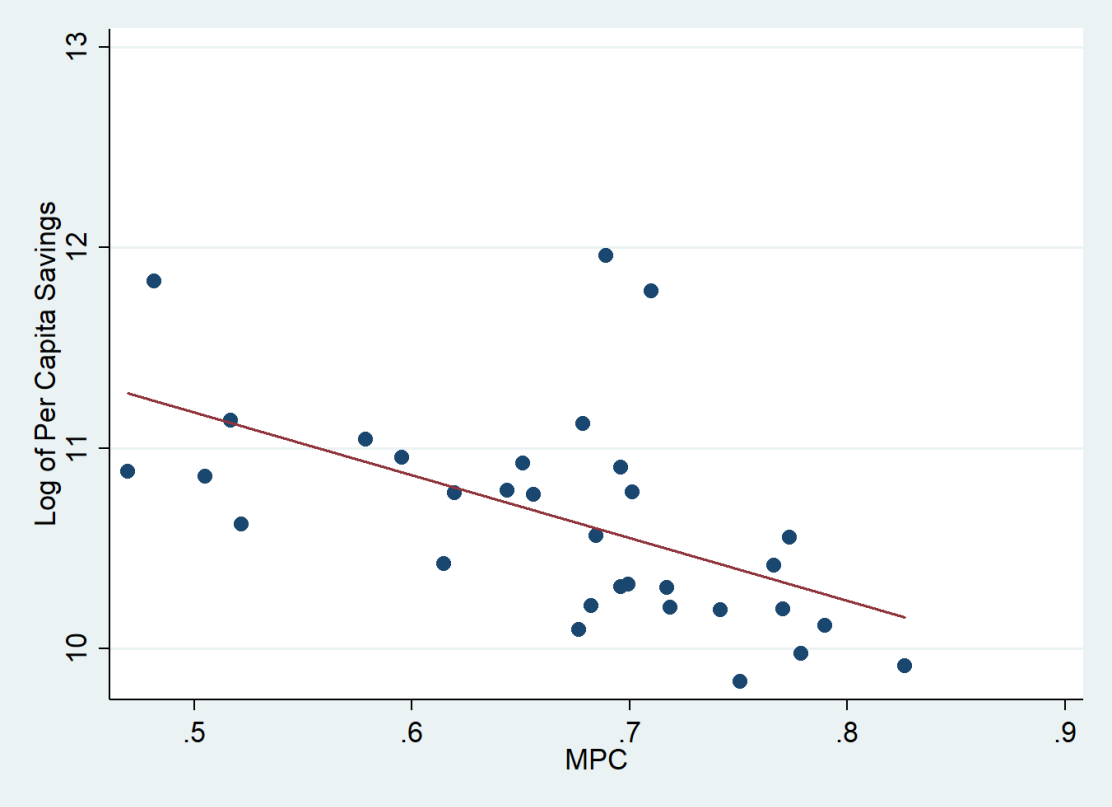


Figure 13: State-wise Log of Per-capita Savings and MPC



# 10 Tables

Table 1: Savings, Consumption, and Interest Rates by Social Group

| Social Group | Savings | Consumption | Wealth | Interest rate | Obs. |
|---|---|---|---|---|---|
| Scheduled Tribe | 14151.37 | 9229.23 | 219417.5 | 1.0296 | 15,821 |
| Scheduled Caste | 8230.508 | 9645.39 | 127295.8 | 1.0295 | 18,586 |
| Other backward Castes | 8274.082 | 10730.58 | 167734.9 | 1.03 | 46,560 |
| General | 26228.24 | 13652.86 | 443624 | 1.032 | 33,615 |
| All | 14867.58 | 11204.57 | 256314.7 | 1.0307 | 115,857 |

Table 2: Household Characteristics by Social Group

| Social Group | Average Age of Household Head | Average Household Size | Proportion with Land Ownership |
|---|---|---|---|
| Scheduled Tribe | 46.196 | 4.444 | 0.984 |
| Scheduled Caste | 47.145 | 4.252 | 0.954 |
| Other Backward Castes | 48.482 | 4.292 | 0.966 |
| General | 50.397 | 4.131 | 0.944 |

Table 3: Education Level Distribution by Social Group (Percentage of Households)

| Education level | Social Group | | | | |
|---|---|---|---|---|---|
| | ST | SC | OBC | General | Total |
| Not Literate | 33.39 | 36.54 | 27.17 | 16.65 | 26.46 |
| Literate | 9.15 | 9.21 | 8.13 | 6.56 | 7.99 |
| Primary | 14.82 | 14.06 | 14.23 | 11.46 | 13.47 |
| Middle | 15.47 | 15.57 | 16.36 | 14.75 | 15.64 |
| Secondary | 10.68 | 10.27 | 13.98 | 16.76 | 13.74 |
| Higher Secondary | 7.50 | 6.46 | 8.16 | 11.49 | 8.77 |
| Diploma | 0.59 | 0.88 | 1.31 | 1.63 | 1.24 |
| Graduate | 7.18 | 5.39 | 8.29 | 15.51 | 9.78 |
| Post graduate | 1.22 | 1.62 | 2.37 | 5.20 | 2.92 |
| Total | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |

*Note*: The values represent the percentage of households within each social group with the corresponding education level.

Table 4: Share of Savings in Financial Assets by Caste groups

| Savings Instrument | ST | SC | OBC | General |
|---|---|---|---|---|
| FD or Term deposit | 1.24 | 0.90 | 1.18 | 2.53 |
| Fixed income deposits | 0.05 | 0.10 | 0.08 | 0.17 |
| Interest-free loans | 0.63 | 0.37 | 0.61 | 0.66 |
| NPS and pension | 1.12 | 0.75 | 0.70 | 0.91 |
| PPF | 2.91 | 2.16 | 2.15 | 3.17 |
| Savings | 41.07 | 43.29 | 42.92 | 41.13 |
| Savings or FD in PO | 2.52 | 3.34 | 3.71 | 4.67 |
| Cash in hand | 46.61 | 46.86 | 46.11 | 44.03 |
| Current account | 3.85 | 2.24 | 2.55 | 2.72 |
| Total | 100 | 100 | 100 | 100 |

Table 5: Share of Households with Financial Inclusion Schemes

| | Mean |
|---|---|
| Jeevan Bima Yojana | 0.034 |
| | (0.182) |
| Suraksha Bima Yojana | 0.0414 |
| | (0.199) |
| Atal Pension Yojana | 0.0046 |
| | (0.0682) |
| Observations | 114,582 |

Table 6: Relevance of Instruments

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Jeevan Bima Yojana | 0.185*** | | | 0.068* |
| | (0.037) | | | (0.037) |
| Suraksha Bima Yojana | | 0.239*** | | 0.169*** |
| | | (0.032) | | (0.034) |
| Atal Pension Yojana | | | 1.040*** | 0.950*** |
| | | | (0.120) | (0.122) |
| Observations | 114582 | 114582 | 114582 | 114582 |
| $R^2$ | 0.037 | 0.038 | 0.039 | 0.039 |
| Adjusted $R^2$ | 0.031 | 0.032 | 0.033 | 0.033 |

Regression of interest rates on participation in financial inclusion schemes. Each regression controls for education, religion, social group, household size, district fixed effects and whether the household is in rural region. Standard errors are adjusted for heteroscedasticity within districts.

Table 7: Estimated Parameters of the Utility Function

| | $\delta$ | $\Phi$ | $\alpha$ | Criterion FN | J stat | p-value | N |
|---|---|---|---|---|---|---|---|
| SC | 0.962 | 19.19*** | 0.947*** | 0.000341 | 6.334 | 0.0964 | 18,586 |
| | | (6.948) | (0.248) | | | | |
| ST | 0.967 | 9.251*** | 0.892*** | 0.000277 | 4.383 | 0.223 | 15,820 |
| | | (2.935) | (0.181) | | | | |
| OBC | 0.962 | 8.532*** | 0.882*** | 0.000100 | 4.664 | 0.198 | 46,560 |
| | | (1.99) | (0.0968) | | | | |
| GEN | 0.971 | 7.91*** | 0.873*** | 0.00000510 | 0.171 | 0.982 | 33,615 |
| | | (0.83) | (0.0194) | | | | |

The table reports the estimated parameters of the utility function for each caste group.

Table 8: Marginal Propensity of Consumption

| Sample | Mean | Median | 25th %tile | 75th %tile | Min | Max |
|---|---|---|---|---|---|---|
| Overall | 0.683 | 0.775 | 0.5 | 0.971 | 0.000 | 1 |
| ST | 0.683 | 0.739 | 0.515 | 0.962 | 0.004 | 0.928 |
| SC | 0.795 | 0.972 | 0.999 | 0.730 | 0.000 | 1 |
| OBC | 0.751 | 0.865 | 0.637 | 0.976 | 0.002 | 0.999 |
| General | 0.529 | 0.5 | 0.380 | 0.737 | 0.000 | 0.998 |
| Rural | 0.724 | 0.816 | 0.529 | 0.978 | 0.000 | 1 |
| Urban | 0.622 | 0.693 | 0.424 | 0.953 | 0.000 | 1 |

Table 9: Imputed MPC for SC households

| | Mean |
|---|---|
| Actual SC MPC | 0.795 |
| | (0.323) |
| SC MPC with General R | 0.744 |
| | (0.323) |
| SC MPC with General's $\alpha$ and $\delta$ | 0.583 |
| | (0.296) |
| General MPC | 0.529 |
| | (0.285) |

Table 10: Income Transfer Policies

| Policy | Transfer Amount | Tax | Funding Source | Information Required |
|---|---|---|---|---|
| UBI | Rs. 1122 | NA | External | None |
| Progressive Transfers | Equation 8 | NA | External | Consumption level |
| Redistribution | Equation 9 | Equation 9 | Self-Financed | Consumption level |
| Social Group based Redistribution | Rs. 1122 for SC, ST, OBC | Rs. 2681 on General Group | Self-Financed | Caste Identity |
| Socio-economic Redistribution | Rs. 1122 for SC, ST, OBC with below median consumption | Rs. 636.14 on General Group above median consumption level | Self-Financed | Caste Identity and Consumption bracket* |
| Gender-based Redistribution | Rs. 1122 for female-headed households | Rs. 170.83 on male-headed households | Self-Financed | Gender of the household head |

The table describes the key features of various income transfer policies. Consumption bracket refers to the household belonging above or below the median of consumption level.

Table 11: Change in Consumption across Income Transfer Policies

| | Mean | SD | Median | 25th Percentile | 75th Percentile |
|---|---|---|---|---|---|
| UBI | 766.204 | 354.66 | 868.70 | 560.22 | 1088.84 |
| Progressive | 837.41 | 745.29 | 679.90 | 364 | 1105.88 |
| Redistribution | 35.22 | 641.753 | -92.91 | -319.01 | 183.58 |
| Social Group based Redistribution | 173.46 | 1149.67 | 749.12 | -650.47 | 1072.92 |
| Socio-economic Redistribution | 97.76 | 611.35 | 0 | 0 | 560.22 |
| Gender-based Redistribution | 0.371 | 188.53 | -23.68 | -83.064 | -0.411 |

Table 12: Aggregate Welfare Change across Income Transfer Policies

| Income Transfer Schemes | Welfare Change |
|---|---|
| UBI | 0.656% |
| Progressive | 0.676% |
| Redistribution | 0.022% |
| Social Group based Redistribution | 0.031% |
| Socio-economic Redistribution | 0.072% |
| Gender-based Redistribution | -0.008% |

Table 13: Ex-Post Instrument Validation

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Jeevan Bima Yojana | -0.036 | | | -0.042 |
| | [0.041] | | | [0.044] |
| Suraksha Bima Yojana | | 0.022 | | 0.046 |
| | | [0.041] | | [0.044] |
| Atal Pension Yojana | | | -0.205* | -0.208* |
| | | | [0.089] | [0.087] |
| Observations | 109462 | 109462 | 109462 | 109462 |
| $R^2$ | 0.126 | 0.126 | 0.126 | 0.126 |