Targeted interventions: Consumption dynamics and distributional effects *

Anindya S. Chakrabarti† Abinash Mishra‡ Mohsen Mohaghegh§

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Abstract

Targeted interventions focus only on a fraction of the population, usually based on their income level. To study the distributional effects of such policies in India, we develop a heterogeneous agent production economy where agents face uninsurable income risks. We rely on a novel panel dataset on Indian households to model income risks across the distribution. We find that standard interventions that frequently identify and target a specific group -say, the first decile in the income distribution- have muted impacts on the consumption share of targeted groups. However, a more sophisticated identification scheme generates noticeably larger distributional effects for the same amount of cash transfers. We study a case where individuals' participation in the program is guaranteed for two consecutive years regardless of their future income status. In the spirit of the current institutions and policies in India, we show that an intervention in the order of 0.6 percent of the output increases the consumption share of targeted groups by nearly 2.5 percent, which is five times larger than the effect of a standard intervention. Additionally, the gap between the impact of both policies persists as either the size of the intervention or the size of the targeted group rises.

Keywords: Consumption Inequality, Targeted Interventions, Incomplete Markets.

JEL Codes: E21, D51, E26.

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†(corresponding author) anindyac@iima.ac.in. Economics area and Misra Centre for Financial Markets and Economy, Indian Institute of Management, Vastrapur, Ahmedabad, Gujarat-380015, India.

‡Email: phd18abinashm@iima.ac.in. Economics area, Indian Institute of Management, Vastrapur, Ahmedabad, Gujarat-380015, India.

§Email: mohsenm@iima.ac.in. Economics area, Indian Institute of Management, Vastrapur, Ahmedabad, Gujarat-380015, India.

1 Introduction

Large-scale targeted interventions, which are common in both developed and developing countries, are often designed to provide financial security to the poor (Drèze and Khera (2017)). A large body of literature studies the impacts of such policies on the recipients at individual level(Dreze and Sen (1990), Afridi (2010), Dutta et al. (2014), Imbert and Papp (2015), and Banerjee et al. (2020)).[1] However, despite the fact that inequality measures are at the heart of such programs, their distributional effects are surprisingly less studied. This is our main objective.

A reason for this lack of attention is scarcity of data. Tax records as the standard source for income and consumption data, are proven to be more reliable for the rich(Atkinson and Piketty (2010)). This is while targeted transfers typically target the left tail of income distribution. In addition, the poor in many countries including India are, to a large degree, exempt from paying income taxes. Therefore, tax records are not the best source of information for the poor. In developing countries, the lower quality of data collection, specially in urban areas, adds to this lack of sufficiency.

To overcome this issue, we use a novel dataset published by the Centre for Monitoring Indian Economy Pvt. Ltd. (CMIE), which tracks a panel of more than two hundred thousand Indian households across various demographic compositions.[2] The CMIE dataset, by design, focuses on the poor, which makes in more suitable for our study.[3] We use this dataset to calibrate a stochastic process that determines individuals' labour income.

This is different from the standard approach in the literature as this stochastic process determines the workers' income rather than their idiosyncratic labour productivity. The panel nature of the CMIE dataset allows us to measure income dynamics directly. We simulate a large sample of workers outside of our model structure, and use the SMM to parametrize this stochastic income process such that the distribution of labour income matches the cross-sectional distribution of labour earnings in the data.

The randomness of labour income governs precautionary savings in our model. This is why our diversion from the common approach to simulating income risks is a key to our analysis as it allows us to make a connection between various policy alternatives and their impact on income risks of recipients and non-recipients. We develop a general equilibrium

[1]Such effects have been studied in many dimensions including, but not limited to, education, nutrition, health and gender.

[2]Source: https://consumerpyramidsdx.cmie.com.

[3]Although the bottom-end is represented more accurately in CMIE than any other Indian survey, a shortcoming of this data set is that it does not cover the entire distribution. In particular, top-earners of the Indian economy are absent in the data set. Therefore, true inequality may still be underestimated.

production economy with heterogeneous workers who face uninsured idiosyncratic shocks to study the distributional effects of different targeting policies.

We first show that our model replicates the consumption and savings behaviour of Indian households fairly well buy comparing respective moments of each distribution in the model with the data. Then, we analyse the effects of several targeting scenarios in the spirit of the Employment Guarantee Act in India.[4] The quantum of transfers in most cases is quite substantial for the recipients. Thus, targeted interventions can change the precautionary savings motive (and consumption behaviour) of households. To quantify the impacts, each scenario is translated to a perturbation in the transition matrix. To do so, we identify eligible households in our sample, and augment their income with the amount (and frequency) that is promised under each scenario. To stay consistent with the existing policies in India, we simulate the effect of intervention packages that are worth 0.6 percent of aggregate output in the benchmark.[5] The total size of intervention remains constant in most of our exercises. This is to make sure that our proposed identification scheme imposes no additional fiscal burden on the government.

In the most basic approach, which is also what the institutions in India imply, to determine individuals' eligibility certain criteria are set; for instance, those whose income is below a given threshold, or those in the first or second decile. Since eligibility criterion does not vary over time, any current recipient of benefits would only be eligible in the future, if they qualify for participation in any given period. In that sense, government policy resemble a positive but temporary income shock because individuals will be automatically disqualified as soon as their income reaches a pre-determined level. We find that when in this framework, a policy targets the first decile (or the first two deciles) of the income distribution, it has a very small impact on the consumption share of both targeted and non-targeted groups.

On the other hand, we consider an alternative policy where current recipients are promised to be eligible in the next period regardless of their future income status. This could potentially affect the saving (and consumption) behaviour of targeted and non-targeted groups as it has a stronger impact on the distribution of risk in the economy. Our findings suggest that when targeting does not solely depend on current income, its impact on the consumption share of targeted groups would be noticeably larger. This increase is associated with a small and evenly distributed reduction in the share of non-targeted groups. The impacts, if any, on macro aggregates and prices are minimal.

To check the robustness of our results, we run complementary exercises in two dimensions; (1) by increasing the amount of payments, which inevitably increases the size of the

[4]A brief description of institutional details are provided in section 2.2.

[5]We target the size of currently running Employment Guarantee Act programs.

intervention, and (2) by considering an environment where the number of recipients rises as over time new recipients are allowed to apply for qualification. We find that in both dimensions, the impact of any intervention of a given size on the consumption share of targeted groups is larger, if eligibility is not conditional only on current income.

To better justify the relevance of our study, we should mention that as figure 1 depicts, the total size of government transfers in India are about 1.1 percent of India's GDP. This is considerably lower than many other developing countries such as Russia (9.7%), Brazil (17.3%) and Mexico (2.7%). Our results suggest that increasing total transfers to levels seen in other developing countries, if done through more sophisticated identification methods, could have significant distributional effects on targeted groups.

It is important to note that in our quantitative exercises we do not simulate large-scale interventions comparable to other countries. Firstly, because large transfers would have drastic impacts on the distribution of income risk in the model such that comparing the results with the baseline model would not be very justified. Secondly, such massive interventions induce noticeable changes in prices, and have non-negligible implications for the tax schedule as the fiscal burden substantially grows. Both of these issues are beyond the scope of our study. That said, taken together, our estimates provide a lower bound of the total distributional effect that would be seen if the interventions in India were of the magnitude found in its economically peer group of countries.

Background literature: Our work contributes to the growing body of literature that studies distributional, or more generally welfare-related, effects of public programs in developing countries (e.g., Loayza et al. (2007), Baird et al. (2011), Liu and Barrett (2013), Dutta et al. (2014), Berg et al. (2018), Deininger and Liu (2019)). We build on these mostly empirical studies, and build a general equilibrium framework for examining the distributional effects of targeted interventions in India.

Our work is also related to several studies that explore the impacts of public cash transfers. In Latin America, conditional cash transfer programs have attracted much attention, though mainly from a microeconomic perspective. Parker and Todd (2017) review a range of studies on the impact of Oportunidades (formerly PROGRESA) program in Mexico. These studies show that direct and targeted cash transfers have positive impacts on education, health and nutrition among recipients. It has also been documented that this program, in longer-horizons, leads to small but significant increases in consumption, income and agricultural investment. Similarly, Soares et al. (2010) show that Bolsa Familia program in Brazil has reduced inequality and extreme poverty while improving education outcomes. On the other hand, some have argued that such programs have adverse spillover effects, particularly on non-recipients, mainly through their impact on prices of certain goods and services.[6] This literature has been mostly focused on individuals or individual items. We take a different approach by conducting a macroeconomic analysis of the distributional effects of targeted interventions.

We use a canonical heterogeneous-agent incomplete-market model[7] to compare various intervention schemes. It has been theoretically argued that government transfers provide insurance to individuals who face uninsured risks and may face borrowing limits. However, their impact on macroeconomic aggregates remains uncertain. While some argue that rising transfers ease liquidity constraints, which in turn increase investment and output (Woodford, 1990), others claim that increasing transfers, by weakening precautionary motives for savings, lowers aggregate capital and output (Aiyagari and McGrattan, 1998). Additionally, Targeted transfer are believed to be expansionary due to their positive wealth effect on labour supply and the aggregate demand; despite the fact that they have different impacts on different households(Oh and Reis, 2012). In essence, government transfers are supposed to reduce inequality by redistributing resources. However, even if this objective is achieved, it is a costly one. Additional tax collections that are needed to finance the transfers may distort labour supply and savings. Thus, they negatively affect employment and capital, which, in turn, possibly hinders economic growth (Alesina and Rodrik, 1994; Persson and Tabellini, 1994). Although, this need not be the case as public transfers may offset capital market imperfections by generating a sizeable positive effect among the poor (Aghion and Bolton, 1997; Benabou, 2000; Floden, 2001).

Our study provides a quantitative examination of (some of) these mostly theoretical views in the context of a large developing economy with relatively small public transfers, India. We study both the distributional and aggregate impacts of government interventions in a general equilibrium model. Interventions directly affect the income risk distribution in the model. Hence, they potentially act as an insurance policy. However, we find that, at least at current levels in India, existing public interventions do not have a significant impact on neither the consumption distribution nor the macro aggregates. Our proposed change in the identification scheme amplifies the distributional effects. It, however, has virtually no impact on the aggregate labour, capital, or output. To avoid any distortions due to additional taxations, we study fiscally-neutral schemes. Furthermore, we find that prices

[6] Cunha et al. (2019) show that cash transfers can cause prices of non-tradable or perishable goods to increase in remote areas with weak links to markets, while in-kind transfers can have the opposite effect of reducing food prices. Similarly, Filmer et al. (2018) show that cash transfers have non-negligible effects in the increase in price of protein-rich perishable food items, which negatively affects non-beneficiary children.

[7] For detailed surveys, see Heathcote et al. (2009), Guvenen (2011), Quadrini and Ríos-Rull (2015); De Nardi and Fella (2017), and Kaplan and Violante (2018).

-thus, capital and output- are unaffected by our proposed change. These resolve many of the growth-related concerns. Essentially, we propose a change in the policy that makes government interventions more effective, while does not have an impact on other aspects of the economy.

2 Data and Institutional Background

2.1 Consumer Pyramids Household Survey (CPHS)

We obtain data on monthly income and expenditure of households in India from the Consumer Pyramids Households Survey database developed by the Centre for Monitoring the Indian Economy (CMIE). CMIE conducts nationwide surveys throughout India. SBy design, CPHS is a continuous panel as households are retained across the years, unless for unsystematic reasons. This is a very helpful feature for our study.

The CMIE has started reporting their data since 2014. This survey covers over 160,000 households in all the 640 districts in the 2011 Census. Surveyed households are selected through a multi-stage stratification process that ensures geographical diversity. Households who are in the survey are paid a visit every four months, and their expenditures and income are recorded via a detailed list for each item. An important feature of the CPHS for our study is that it, by design, focuses on the left tail of the income distribution.[8]

2.1.1 Our Sample

Each household in the CPHS is interviewed once every four months. However, for a variety of reasons, there are many cases of households not continuing their participation in the survey, or failing to report their information in some waves. Our sample consists of a balanced panel of households who have participated in all five years of sampling, and for whom at least ten observations are available between 2014 to 2019. This allows us to verify that these households are not outliers since we can check track their economic decisions over time.[9]

Each households consumption is its total expenditure while its labour income is the sum of earnings from wages and 80 percent of business profits in a given period. The fact that every household is interviewed once every four months implies that the collected responses may have a recency bias. The CPHS contains adjusted observations to account for such biases. However, since one period in our model is one year, we construct annual measures

[8]For details, see https://consumerpyramidsdx.cmie.com/kommon/bin/sr.php?kall=wkb.
[9]For robustness check, we run exercises using the entire 2018-19 survey in section 6.1.

of consumption and income based on the estimated monthly responses. This reduces the effects of recency biases.

Tables 11 and 12 show the summary statistics of our sample from 2014 to 2019. The CPHS does not fully cover the right tail of the income distribution. This is best seen in table 11 where the maximum income in our sample for 2018 is around INR 3.5 million (around 47000 US dollars). With that caveat, the income Gini fluctuates between 0.36 and 0.39 during the 2014-19 period.

2.2 Institutional Background

Targeted intervention is a growing topic in both academic and policy circles in India. In the 2018-19 fiscal year, India spent around INR 2140 billion under cash-based schemes under Direct Benefit Transfer (DBT), which amounts to nearly 1.1 percent of the country's GDP.[10] This is a significant increase from 0.49 percent of GDP in FY 2016-17. In addition to that, the number of schemes under the DBT also increased from 142 in FY 2016-17 to 369 in FY 2018-19. Many of newly introduced programs target a particular group of the population, though not all of them involve direct cash transfers. For instance, one of the schemes under the DBT, the Pradhanmantri Kisan Samman Nidhi Yojana (PM-KISAN) scheme, targets small and marginal farmer families who own less than two hectares of land.[11] In contrast, the Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS) promises at least 100 days of employment every year to all Indian citizens above 18 years of age who are residing in rural areas.

Considering the large number of programs and the fact that they have inclusion criteria, identification is an important issue. "Ration cards" that are usually issued by state governments are one of the primary identification methods in India.[12] One example of such cards are 'Below–Poverty–Line (BPL) cards' that were issued based on the public censuses conducted by the government. Given many examples of data inaccuracy or inadequacy, operational complications, and fraud, there is a growing call for a comprehensive revision of these programs.[13] Our analysis sets the stage for further exploring how changes in implementation of policies can improve the outcome.

[10] Source: https://dbtbharat.gov.in/

[11] According to the Agricultural Census conducted by the Government of India in 2015-16, small and marginal holdings (below two hectares) constituted 86.21 percent of the total landholdings.

[12] Source: https://dfpd.gov.in/faq.htm

[13] Just as an example, the Nobel laureate Abhijit Banerjee, in 2016, proposed replacing all the existing subsidies and welfare programs with one universal annual transfer: Source: https://www.ideasforindia.in/topics/poverty-inequality/universal-basic-income-the-best-way-to-welfare.html.

3 Model Environment

3.1 Households

The economy is populated by a unit mass of ex-ante identical households who maximize their expected discounted lifetime utility. Every household's period utility over consumption is given by a CRRA period utility, $u(c_t) = \frac{c_t^{1-\sigma}}{1-\sigma}$, where σ determines intertemporal elasticity of substitution. Households discount utility at a constant rate, β. They own both factors of production, labour and capital, which they supply in competitive markets.

Households face an uninsurable income risk. At the beginning of each period, they draw an idiosyncratic shock, e_t, which determines their period labour earnings. Given that it follows a Markov process, this income shock drives precautionary savings in our model. As will be discussed later, this is not an idiosyncratic labour productivity shock, rather e_t determines the entire earnings of each household. Households may transfer consumption across time and state by investing in a risk-free asset which is available to everyone in the economy. Household savings are productive, and there is no aggregate risk in the economy. Therefore, the rate of return on savings, r, is constant.

$$
\begin{aligned}
V(e,a) &= \max_{\{c,\,a'\}} u(c) + \beta \mathbb{E} V(e',a') \\
\text{subject to} & \\
c + a' &\leq y - \tau(y) + a \\
y &= e + ra + b_p \\
a &\geq \underline{\mathbf{a}}
\end{aligned}
\tag{1}
$$

Therefore, each household's state is given by its current labour income, e, and its asset holdings a. All households face a common natural borrowing limit $\underline{\mathbf{a}}$. A household's income, y, consists of three sources: labour income, capital income, and public transfers, b_p. All three sources are taxable according to an economy-wide tax schedule $\tau(y)$. Therefore, households' programming problem is given by equation 1.

3.2 Income Process

Each households' labour income in period t is the sum of two independent random draws, e_t^1 and e_t^2; i.e. $e_t = e_t^1 + e_t^2$. Each of these two draws follows a modified autoregressive process with ρ being the autocorrelation coefficient, and ε_t being the i.i.d innovation in period t.

$$e_t^i = \rho^i e_{t-1}^i + \eta_{1,t}^i \eta_{2,t}^i \varepsilon_t^i \quad \text{where} \quad \varepsilon_t^i \sim \left| N\left(0, \sigma^{i^2}\left(\eta_{2,t}^i, \eta_{3,t}^i\right)\right) \right| \quad \text{for} \quad i = \{1, 2\} \tag{2}$$

There are three main differences between this stochastic process and a standard AR(1) process. First, unlike an AR(1), in equation 2, innovations are occasional. In other words, ε_t shocks are not drawn in every period. Their random and occasional occurrence, which is captured by η_1^i, follows a Poisson process the rate θ^i.

$$\eta_{j,t}^i = \begin{cases} 1 & \text{with probability} \quad \theta_j^i \\ 0 & \text{with probability} \quad 1 - \theta_j^i \end{cases} \qquad \text{for} \quad j = \{1, 3\} \tag{3}$$

The second difference is ε shocks are drawn from a folded normal distribution. A random variable, $\eta_{2,t}^i$, determines the sign of each shock at any given period. η_2^i takes two possible values $\{-1, 1\}$ with the probability of negative draws being equal to a constant parameter θ_2^i. Lastly, the variance of the underlying normal distribution from which ε shocks are drawn can vary over time. Two random variables, η_2^i and η_3^i, jointly determine the variance of the underlying normal distribution, where η_3^i is another Poisson process with the rate θ_3^i.

Effectively, we assume that households' labour income is subject to an i.i.d. shock. However, these shocks only arrive some of times, and even when they do, the underlying distribution from which they are drawn changes from time to time. Mohaghegh (2020) shows that this approach is effective in generating some important features of the data including the high kurtosis and negative skewness in the distribution of earnings growth rates.

To identify the income process e_t, in a large sample of households whose labour income follow the above stochastic process, we use the method of simulated moments (SMM) to estimate all the parameters. In the simulation process, we target the share of each decile as well as the Gini coefficient of the (labour) income distribution in our CPHS sample. Then, we approximate our calibrated stochastic earnings process by a ten-state Markov process, which we use in our quantitative exercises. We rely on our data to directly measure the transition probability matrix for our Markov process.[14]

3.3 Production Sector

A representative firm hires labour and capital in perfectly competitive markets, and uses a standard CRS technology to produce a homogeneous consumption good. The capital share

[14] To fully identify equation 2, 12 parameters are needed. We assume that the likelihood of negative and unusual shocks are common across both components of income' i.e., $\eta_2^1 = \eta_2^2$ and $\eta_3^1 = \eta_3^2$. We use 11 empirical moments to estimate 10 distinct parameters.

in the production technology is γ. Therefore, the aggregate output is given by

$$Y = AK^{\gamma}N^{1-\gamma} \tag{4}$$

where N and K are the aggregate labour and capital demanded by the firm, respectively.

The main difference between our approach and what is standard in the literature comes from the households' income process and computing the labour supply. In the standard approach, at the beginning of each period, households draw a random productivity shock - say, z. Knowing their idiosyncratic labour productivity and the wage rate, households choose their hours worked -say, n- to maximize their utility, which determines their effective supply of labour, zn. Thus, each household's labour income is an endogenous object and equal to $e = wzn$. Then, it would be straightforward to compute the time-invariant distribution of households, μ, and the aggregate supply of labour. In a general equilibrium setting, the equilibrium wage rate sets the labour demand equal to the aggregate labour supply.

In our model, however, labour income, e is exogenous and given directly by the households' random draw. This approach not only improves our ability to capture income risks more accurately, allows us to compare various targeted intervention schemes. Within the framework of standard models, identifying targeted groups, if our identification is solely based on current income, are only possible after the steady state distribution is computed. This itself adds to the computational cost. Moreover, as we will further discuss later, we are interested in schemes that consider households' history -i.e. their previous income- as well. In a standard heterogeneous-agent model, this would only be possible by expanding the state space, which substantially adds to the computational cost.

$$N = \int_{e\otimes a} \mu(e,a)\,\frac{e}{w}\,d(e\otimes a). \tag{5}$$

In our approach, on the other hand, we are able to analyse the impacts of any intervention policy outside of our model, and translate it to a change in the transition probability matrix. This allows us to compare a variety of alternative targeting schemes with basically no additional computational cost. This, however, requires a modification of the standard computational algorithm.

To compute the aggregate labour supply, we use the fact that, in equilibrium, there is a one-to-one mapping between the distribution of households over the labour income grid and their distribution over a hypothetical grid that determines their effective labour supply, zn. In other words, as far as the distribution is concerned, the wage rate w, is a scale parameter that maps e to effective labour, $\frac{e}{w}$.[15] Therefore, the aggregate supply of labour, which is the

[15] Mohaghegh (2020) has an analytical argument for this mapping.

sum of effective supply of labour by all households, which is given by equation 5 where w is the market-clearing wage rate, and μ is the steady state distribution.

3.4 Government

The government levies progressive income taxes, $\tau(y)$, and pays a constant benefit, b_p, to households. The government budget, which is balanced in every period, is given by $T_t = TR_t + G_t$ where T, TR and G are government's tax income, transfer payments and expenditure, respectively. The tax income is defined as follows:

$$T = \int_{e \otimes a} \mu(e, a)\, \tau(y)\, d(e \otimes a). \tag{6}$$

The tax schedule is such that the after-tax income follows an exponential form: $D(y) = y - \tau(y) = \beta_1 y^{\beta_2}$. This is proven effective in capturing the progressive nature of income tax schedules.[16] The total transfer is given by:

$$TR = \int_{e \otimes a} b_p\, \mu(e, a)\, d(e \otimes a). \tag{7}$$

3.5 Competitive Equilibrium

A Recursive Competitive Equilibrium (RCE) in this economy is a set of functions for values $V(e, a)$, individual policies $a'(e, a)$, government policies $\{\tau(y), b_p, G\}$, factor prices $\{r, w\}$, and a stationary probability measure of households over the state space $\mu(e, a)$ such that

1. value functions and policies solve household's optimization problems.
2. prices are determined competitively.
3. the government budget is balanced.
4. the steady state distribution of households evolves according to:

$$\mu = \int_e \Big(\int_a \mu(e', a') \pi_{ee'} da \Big) de \tag{8}$$

   where $\pi_{ee'}$ is the transition probability matrix of household's idiosyncratic labour income shock.

[16] See Violante et al. (2014) and Heathcote et al. (2017).

4 Parametrization

4.1 Household Income

Each period, households draw an exogenous random variable that determines the labour portion of their income.We translate households' income to a ten-state Markov process of order one as is common in the literature for our quantitative exercises. Therefore, the stochastic *income* process of households consists of a vector of ten shock values and a transition probability matrix.

Since our sample is a panel of Indian households, we are able to directly measure our transition probability matrix in the data. This is an advantage for our study as it allows us to capture income risks in our model accurately. Since, we use a vector of size ten to model income shocks, we divide income data to ten bins and empirically measure the likelihood of transitioning across these ten states. Here we motivate our choice of ten states in the income-generating process. We use data from 2018 and 2019 to measure these transition.

$$\pi_{ee'} = \begin{bmatrix} 0.687 & 0.175 & 0.047 & 0.029 & 0.015 & 0.014 & 0.011 & 0.009 & 0.006 & 0.002 \\ 0.094 & 0.406 & 0.247 & 0.116 & 0.068 & 0.030 & 0.022 & 0.005 & 0.007 & 0.001 \\ 0.048 & 0.184 & 0.273 & 0.200 & 0.142 & 0.079 & 0.042 & 0.017 & 0.006 & 0.004 \\ 0.045 & 0.093 & 0.182 & 0.228 & 0.185 & 0.138 & 0.071 & 0.030 & 0.015 & 0.008 \\ 0.026 & 0.050 & 0.116 & 0.191 & 0.213 & 0.179 & 0.129 & 0.059 & 0.021 & 0.0105 \\ 0.028 & 0.038 & 0.066 & 0.107 & 0.166 & 0.219 & 0.200 & 0.131 & 0.034 & 0.005 \\ 0.016 & 0.025 & 0.034 & 0.066 & 0.099 & 0.174 & 0.241 & 0.217 & 0.103 & 0.020 \\ 0.023 & 0.014 & 0.016 & 0.039 & 0.068 & 0.095 & 0.174 & 0.289 & 0.221 & 0.057 \\ 0.018 & 0.007 & 0.012 & 0.014 & 0.032 & 0.054 & 0.087 & 0.183 & 0.381 & 0.207 \\ 0.011 & 0.003 & 0.002 & 0.005 & 0.006 & 0.014 & 0.017 & 0.055 & 0.202 & 0.680 \end{bmatrix}. \tag{9}$$

In principle, the number of states can be larger or smaller than ten. A larger number, (1) increases the computational cost of numerical simulation, and (2) increases the number of parameters to be determined, which requires more data moments to keep the income process identified. In the opposite side, n could have been smaller as well. However, it seems natural to use a ten-state Markov process as in the model, we target various deciles of the income distribution. Therefore, a ten-state Markov process, we believe, is a useful case such that the model remains tractable, while we can model policy interventions in a more empirically sensible way.[17]

[17]We have also simulated the model with transition matrices with $n = 9$ and 11 states. The resulting

Thus, the process will be fully identified upon determination of the values for ten states. We use the Simulated Method of Moments (SMM) to find shocks values that would replicate measures of income concentration in the data. In particular, we target shares of all the deciles and the Gini coefficient of the labour income distribution in the data. The resulting vector of income states, after normalization, is given by:

$$\ln(e) = \begin{bmatrix} 0 & 1.18 & 1.33 & 1.51 & 1.65 & 1.82 & 1.965 & 2.19 & 2.49 & 3.05 \end{bmatrix}. \tag{10}$$

Table 3 reports respective moments in the data and the simulated sample.

4.2 Structural Parameters

The households' discount rate, β, is determined such that the interest rate remains close to the targeted value of three percent. The only parameter to identify households' utility, σ, is assumed to be 1.2, following the literature. Also, following what is standard in the literature, capital share of income, γ, equals 0.2 while its depreciation is set to $\delta = 0.1$. A period in the model represents one year in the data.

The government levies income taxes and pays public benefits to households. Income tax schedule follows a parsimonious functional form, $\tau(y) = y - \beta_1 y^{\beta_2}$ where β_2 captures the progressivity of the tax system.[18] Public transfers, b_p are paid by the government whose only objective is to balance its budget every period. Therefore, the government's policy variables can be determined using three moments in the Indian data. Table 4 reports parameter values in the benchmark economy.

5 Targeted Interventions

In this section, we describe the effect of (1) targeted interventions and (2) lump-sum transfers, and their effect on consumption and accumulated savings of households in the model. We evaluate the results obtained from these simulations against empirical findings in the literature.

distributional characteristics remain qualitatively and quantitatively similar with the case with $n = 10$ states, indicating the robustness of our results with respect to the choice of number of states.

[18]See Benabou (2002) and Heathcote et al. (2017) for more details.

5.1 Alternative Targeting Plans

In this section, we study the effects of targeted intervention policies implemented through changes in the income transition matrix. We divide these policies into broadly two categories: income-based (I) and non-income-based (NI) interventions. In both categories, the income of the households is augmented by a pre-determined amount. These interventions differ in terms of their temporal permanence. Non-income-based interventions identify eligible households in the starting period and extend the augmented income into the subsequent period of the study. In income-based interventions, however, eligible households are identified every period. Then their income is augmented only in the current period with no promise about the future.

Non-income-based targeting brings a sense of persistence to households' supplementary income shock. For example, a household in the first decile of the income distribution may move to a higher decile in the next period. If households in the first decile are targeted, in the case of income-based intervention, this household would part of the program only in the first period, and not in the second one. While in non-income-based targeting, this household would receive the additional payment in both periods.

The idea of non-income-based targeting is motivated by the design of some cash transfer programs in different countries. One example is the PROGRESA in Mexico, which started in 1997 and then, was renamed to Oportunidades in 2001. An average benefit paid to eligible households was about USD 300 in the starting years and increased substantially over time. Eligible families, once identified, remain in the program for three years without any further verification (Parker and Todd (2017)). In India, the Below-Poverty-Line (BPL) cards program is a form of in-kind transfers program run by the government which grants households a card they can use to buy food rations at subsidized prices. These were distributed on the basis of surveys conducted for five years between 1992 and 2002 (Ramey (2011)). Although these cards have validity for a household as long as they meet the issue criteria, the surveys grant an implicit validity of at least five years.

We start by our benchmark model. Figure 2 and table 3 report the consumption distribution in our benchmark and compare it to the data. This is to make sure that our benchmark is a valid and empirically consistent point of reference for analysing various targeting schemes. In the benchmark model, there are no transfers. The calibrated parameters that we used in the benchmark, are used in other simulations as well.

To determine the amount of each individual payment in our quantitative exercises, we rely on estimations about the impacts of a scheme run by the Indian government under the Mahatma Gandhi National Rural Employment Guarantee Act (MNREGA), which reportedly raised income per household by INR 1400 per month in 2019.[19] We assume that households in our sample may increase their income by working under the scheme for at least ten months. Therefore, the targeted households for the intervention would receive an additional INR 14000 (around 185 US dollars), annually. The increment of INR 14000 in the case of all the policies is slightly more than 50 percent of the mean annual income of the first decile in 2018 and 2019.

We study the effects of four policy combinations as follows. Policy I_1 targets households in the first decile of the income distribution 2018 and 2019. Only households who are in the first decile in each period are eligible for this policy. In this sense, I_1 is an income-based targeting. The second policy, NI_1, is a non-income-based scheme where households in the first decile are identified only in the base year, and they continue to receive the transfer in the subsequent year, irrespective of their next-period income. The two other policy alternatives I_2 and NI_2 are similar schemes where both first and second decile are cumulatively targeted. In all these experiments, any increase in the number of recipients is offset by a proportional decrease in the amount of distributed benefits such that the total budget for the intervention remains constant.

Tables 7 and 5 report the results of these four experiments. Table 5, in particular, shows how each policy intervention changes the consumption distribution compared to the benchmark. Our results show that, non-income-based targeting is more powerful than income-based targeting in increasing the consumption share of targeted groups. For instance, under NI_1, the consumption share of the first decile increases by 2.46 percent compared to the benchmark model, while I_1, though effective in rising their share, has a much smaller impact. The difference between income-based and non-income-based targeting is true in case of cumulatively targeting both the first and second deciles as well. This is while prices and aggregate variables that are reported in table 6 are almost unchanged. This is why we argue that a modification of identification scheme could improve the effectiveness of targeted policies with almost no significant aggregate cost.

The negative share of the first two deciles under accumulated savings, in table 5, suggest that these households are in debt. However, interventions slightly improve their negative accumulated savings. This can be explained by the change in the precautionary motives of the targeted households as interventions act as an insurance policy. The overall impact on the average welfare of each decile, also reported in table 5, shows that there is a marginal improvement in welfare for the targeted groups under non-income-based targeting schemes, which is the mirror-image of the documented increase in their consumption shares.

[19]Source: https://economictimes.indiatimes.com/news/economy/policy/mnregs-income-per-household-nearly-doubles-to-1400-a-month/printarticle/78113574.cms

5.2 Targeting an Expanding Base

In this experiment, we implement a policy along the lines of non-income based targeting schemes; i.e., targeted households in the first period continue to receive the benefits in the second period. However, the households which were not eligible in the first period but became eligible in the second period get the benefits in the second period as well. This expands the base of the program. This, could potentially, increase the fiscal burden as more households become eligible.

To maintain parity and comparability across all the policies, we have fixed the fiscal burden of the program across all periods. Therefore, the amount of transfers is reduced. We label these policies ENI_1 and ENI_2. Table 10 shows that under ENI_1, consumption shares of the targeted first decile have increased by 1.8 percent from the benchmark. Consumption shares increase in the same direction even in case of targeting the first and second deciles together. Given that the quantum of each payment has reduced, the impacts of this policy should be compared with income-based targeting schemes that distribute the same amount. This is done in section 5.1.

5.3 Lump-sum Transfers

The preceding discussion showed that the effects of an augmented income could be captured in the income transition matrix when households perceive an increased income. By matching this income process from the data into our model, we find a comparatively positive impact on relative consumption levels for the targeted households under certain policies. In this section, we describe the results obtained by including public transfers as a model parameter. To simplify our analysis, we have considered the government's expenditure as a free parameter to balance the budget in every period. This simplification covers the case when the government may run deficits for financing these transfers. In addition, the transfers apply to the whole continuum of households in the model and no particular group of households is targeted in the model. Finally, we set the public transfer parameter as a percentage of the corresponding simulated output.

Transfer parameter set to zero is the benchmark model for comparison. This benchmark is the same as the one compared with different targeting policies in section 5.1. We set the parameters for public transfers in terms of the percentage of the equilibrium output and increase it incrementally. These percentage values of transfers are comparable with data shown in figure 1. Figure 1 shows that, in 2018, the Indian government rolled out transfers to the tune of 1.1 percent of GDP in cash and 0.6 percent of GDP in kind. If we ignore the absolute amounts involved and looked at the average percentage of transfers, the

Scandinavian nations have rolled out cash transfers of 15.25 percent and in-kind transfers of 16.75 percent of their GDP in 2018. We would exercise caution in directly comparing our results based on the transfer parameter with the impact of cash transfer programs in various nations since; (1) these nations are different economies altogether, and our model is tuned to the moments of income distribution on a sample of Indian households; (2) the parameters used for simulating the Indian economy may not be adequate for other nations given the current living standards and stages of growth these economies are in. Nevertheless, our results can be seen in perspective with successful transfer programs like Oportunidades in Mexico.

Table 13 shows a very consistent picture of consumption shares of households in each decile. First, there is a consistent increase in consumption for the poorer households grouped in the lower deciles. A similar trend appears for the higher deciles, but there is a consistent decrease in consumption. This divide in the direction of change in consumption from the benchmark appears from the sixth decile as shown in table 15. The change in consumption compared to the benchmark is highest in the poorest decile. Although the transfers are welfare improving based on the increase in overall consumption of the households, table 15 shows a significant decrease in the accumulated savings for the first decile. The following contains an explanation.

It is well recognized in the literature that liquidity constraints usually caused by market imperfections, may become one of the obstacles in consumption smoothing for certain groups of households.[20] Deaton and Paxson (1994) argue that in case of imperfect consumption insurance as found in the empirical literature, the process by which a group of individuals save or dissave to smooth their consumption would lead to a wide disparity in consumption within the group. Even in the case of the same random draw for the group, their consumption and wealth would eventually depend on their accumulated draws.

Among many approaches, the most cited evidence for the operation of liquidity constraints is excessive sensitivity of consumption to income. Deaton (1991) simulates the inter-temporal consumer problem under uncertainty and argues that under borrowing constraints, it is optimal for the impatient consumer to consume their income when labour income follows a random walk. Carroll et al. (1992), in their buffer-stock model also argue that impatient consumers subject to persistent and temporary shocks to their labour income set their consumption close to their income. Similar arguments are applicable in the case of households in the first decile of our model.

In our model, households are subject to a positive income shock. Borrowing is allowed in our model and is restricted within a specified limit. The households in the first decile

[20] See, for example, Zeldes (1989), and Hayashi (1985).

increase their consumption as transfers augment their labour income. As transfers increase, their consumption exceeds income, which is seen in their wealth levels decreasing compared to the benchmark model. They resort to borrowing to the limits. As shown in table **??**, the data also indicates that the mean income is less than the mean expenditure for the first decile. In contrast, comparatively rich households like the tenth decile group display a higher propensity to save and thus increase their wealth while reducing their consumption levels. Since our model maps the income process from moments in the data, such consumption profiles have emerged from the simulation as shown in table 13.

So far, in this section, we have implemented lump-sum transfers in the model by varying the parameter b_p in the model. In addition, we conduct another simulation exercise. We implement a targeted transfer scheme by adding transfers to the labour-income of the bottom ten percent of the income distribution in the model. For comparability with earlier simulations, we set the total amount of transfers distributed to the target group at 0.6 percent of the GDP in the model. We find a similar consumption response as in Policy I_1 (see section 5.1), consistent with the proposed channel via perturbed empirical transition matrix.

6 Robustness

6.1 Population and Income Dispersion

We have used a balanced panel for a sample of 26411 households to cover some possible inconsistencies in the dataset as explained in section 2.1.1. The panel contains responses from these 26411 households for a period between 2014 and 2019. These households were selected based on at least ten months of registered responses every year. We have a larger sample if we focus on households that have responded for all the months between 2018 and 2019. The number of such households increases to 62468. In this section, we study the results obtained from simulating our model based on the parameters described in section 4.2, with the income process extracted from a larger sample of households. Table 16 in the appendix shows that the larger dataset(62468 households) had a range of INR 3.9 million (around 52000 US dollars) in 2018, which is larger than the reported figure for the smaller dataset (26411 households). In the case of 2019, ranges are the same for both datasets, which could be explained by households earning more than INR 3.4 million in 2018 were earning less in 2019. The income distribution for the larger sample is slightly more peaked, as shown by a higher kurtosis figure. There is also a minor variation in the income shares of various deciles as shown in the comparison of tables 17 and 2.

The reason behind using the responses of these households for 2018 and 2019 are twofold.

First, our model involves a static general equilibrium state space. We extract the stochastic process determining the labour income in the model from the data in the form of a transition matrix. Now, the formulation of this matrix needs two points in time. We translated the income responses of households from 2018 to 2019 into the transition matrix. We avoided distant time points to circumvent any systematic non-random component causing changes in incomes of these households. Second, we could take advantage of a development in India reported in an article stating that there has been a doubling of income per household under a popular government-run scheme under the Mahatma Gandhi National Rural Employment Guarantee Act in 2019.[21] This development has provided a basis for our analysis of income-based and non-income-based intervention policies studied in section 5.1.

Table 16 shows the percentage increase(or decrease) in shares of consumption and wealth for all the income groups. The reference for the shares of consumption and wealth is the benchmark model. The transition matrix is extracted from the income of households reported without any augmentation to income due to any intervention policy. The policies are the same as described in section 5.1.

For the non-income-based policy targeting the first decile, the increase of 2.464 percent in consumption share of the targeted group compared to the benchmark model reported in table 20 is close to 2.46 percent reported for the smaller sample (26411 households), as shown in table 7. The general equilibrium state space also has a similar structure as shown in a comparison of tables 6 and 19, which suggests that our model is agnostic of sample size and limited variations in income distribution.

6.2 Degree of Intervention

In this section, we study the distributional outcome when the transition matrices are extracted from the targeted interventions with varying amounts of increments. In section 5.1, we based our results on the annual increment of INR 14000 (around 185 US dollars) under various policies of targeted interventions. The targeted households were the poorest groups represented in the first and second deciles. A a household in the first decile had a mean income of INR 29897 in 2018. On average, an increment of INR 14000 would mean an increase of about 60 percent. In this section, we study the cases with various increments.

Table 21 shows the percentage increase (decrease) in shares of consumption from the benchmark model of no intervention. As the increment amounts are increased, the consumption share of the targeted group increases. An increment of INR 10000 under the non-income-based policy, NI_1, targeting the first decile leads to an increase in the share of

[21] Source: https://economictimes.indiatimes.com/news/economy/policy/mnregs-income-per-household-nearly-doubles-to-1400-a-month/printarticle/78113574.cms

consumption of the targeted group by 1.91% that is higher than an increment of INR 38000 in case of the income-based targeting. This effect is even more pronounced in case of policies targeting the first and second cumulatively.

7 Summary and Conclusion

Many governments around the world have adopted large-scale programs with the goals of targeted economic interventions. Typically, the aim is to reduce inequality by increasing the targeted groups' income. In this paper, we investigate such distributional effects on consumption in an incomplete market model with heterogeneous agents.

Heterogeneous agent models have been predominantly used to explain the observed concentration of income and wealth. In contrast, our focus is on the left tail of the distribution. We take advantage of a novel dataset which systematically collects income and consumption at the household-year level in India. For people in the left tail of income distribution, a monetary intervention which may be modest with respect to the population average, can be relatively large. Therefore, such interventions can change the precautionary motives for savings, which we capture through the transition probability matrix for an idiosyncratic and stochastic process that exogenously determined households' labour income. By comparing alternative targeting schemes, we find that non-income-based plans, where eligible households to continue to be a part of the intervention program regardless of their future income status, have larger distributional impacts compared to income-based schemes where only eligible households in each period receive the benefits. This is true even after accounting for a proportional reduction in payments that reflect an increase in the number of recipients.

Our work leads to two new questions for further research. The first question is about the impact of running significantly larger programs in India. As we discuss in the paper, India, in total spends nearly 1.1 percent of its GDP in such targeted interventions. This is considerably lower than several other developing economies including Brazil and Mexico. Considering the relative effectiveness of non-income-based targeting plans that we propose, it is important to study potential impacts of running larger intervention schemes by the government of India on consumption inequality. Additionally, this brings up two other issues: the financing of these interventions, and their potential impact on the macro aggregates; both of which we abstracted from in our analysis. However, experiences across developing countries suggest that government may run deficits or increase taxes on the rich to finance such interventions. Though, these may have counter-productive longer-term effects, they might have positive general equilibrium effects that could justify those costs. Thus there can be a trade-off between short- and long-term benefits leading to the question of optimal design of such interventions.

The second question is about the potential impacts of more sophisticated identification schemes. There is an ongoing debate in India -though, mainly from political and social perspectives- about which demographic characteristics should and could be considered while the government designs intervention policies. Since some demographic characteristics do not strongly correlate with incomes, the resulting effects of different targeting schemes could be quite different. It is not easy to gauge a priori the directions of such effects, and future research may address this question.

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Appendix

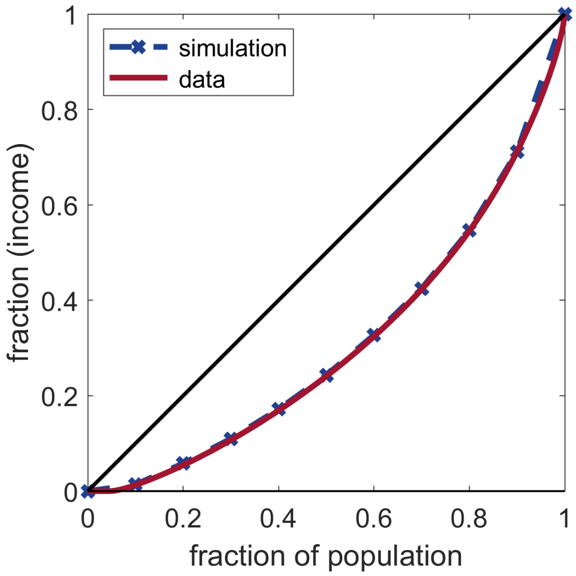
Appendix A: Figures and Tables

Location	In-cash	In-kind	GDP
Asia			
New Zealand	9.1	11.3	0.2
Indonesia	0.2		1.0
Australia	6.6	12.0	1.4
Russia	9.7	7.4	1.7
Korea	5.1	8.8	1.7
India	1.1	0.6	2.7
Japan	12.5	12.1	5.0
Scandinavian Nations			
Finland	18.4	15.1	0.3
Denmark	15.8	17.3	0.4
Norway	14.2	15.7	0.4
Sweden	12.6	18.9	0.6
Latin America			
Colombia	10.3	5.3	0.3
Mexico	2.7	5.7	1.2
Brazil	17.5	8.6	1.9

Location	In-cash	In-kind	GDP
Europe			
Hungary	11.3	9.9	0.2
Greece	19.2	8.8	0.2
Portugal	16.3	9.3	0.2
Austria	17.9	12.2	0.5
Belgium	16.9	15.0	0.5
Poland	14.9	9.7	0.6
Switzerland	9.7	6.3	0.7
Netherlands	10.5	16.5	0.9
Spain	15.4	11.0	1.4
Italy	19.7	10.9	2.1
France	19.5	15.2	2.8
United Kingdom	12.7	12.1	2.9
Germany	15.5	12.9	4.0
North America			
Canada	9.9		1.7
United States	14.3	6.0	20.6

Source: *OECD (2021), Social benefits to households (indicator)and World Bank*
Data on India is extracted from https://dbtbharat.gov.in/page/frontcontentview/?id=NjU=
Transfers are in % of GDP
GDP is in Trillion USD (Current exchange) PPP unadjusted

Figure 1: Comparison of cash and in-kind transfers rolled out in nations across the world for the year 2018. The data was compiled according to the 2008 System of National Accounts (SNA). In national accounts, social benefits to households occur in two categories: in-kind and the rest. In-kind transfers are related to the provision of certain goods and services (for example, health–care and education). Transfers other than in-kind are typically in cash which can be further divided into pension and non-pension benefits. These cash transfers are made by the government or by non-profit institutions serving households to meet their financial needs in unexpected events such as health issues, unemployment, housing or education. All the indicators are measured in percentage of GDP.



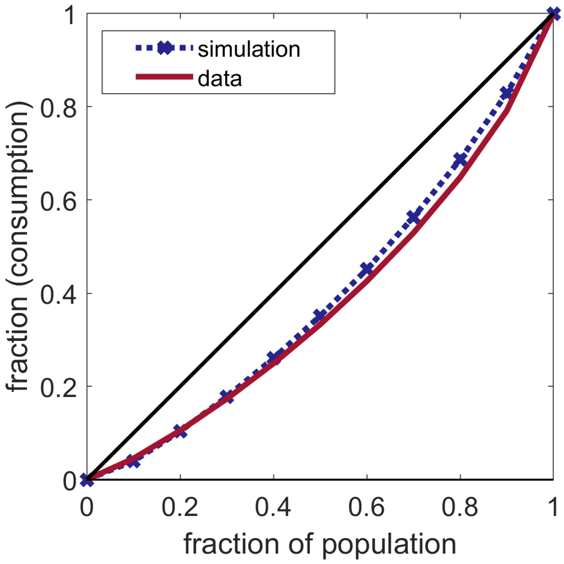


Figure 2: Plots of Lorenz curves from data and simulation using the parameters given table 4. Panel (a): Income. Panel (b): Consumption.

Table 1: Summary statistics of a balanced panel of household-level data extracted from the Consumer Pyramids Household Survey conducted by Centre for Monitoring Indian Economy (CMIE), India. All values are in Indian Rupees. Sample size **N** is given in count. Summary of household-level income and expenditure are provided for years 2018 and 2019.

Year	N	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis
Labour income									
2018	26411	233318	192830	180000	0	3338600	3338600	2.93	17.33
2019	26411	242987	194067	189240	0	3483600	3483600	2.58	13.49
Expenditure									
2018	26411	156200	77113	137795	25217	1294713	1269496	2.47	13.55
2019	26411	160142	71918	142304	14415	1281792	1267377	2.01	9.06

Table 2: Income and expenditure share of households in the data. Share of income and expenditure reported under each decile is in percentage.

	Deciles										
Year	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	Gini
Labour income											
2018	1.28	4.17	5.26	6.20	7.19	8.34	9.89	12.26	16.65	28.76	0.39
2019	1.09	4.32	5.44	6.36	7.28	8.44	9.95	12.28	16.59	28.25	0.38
Expenditure											
2018	4.54	5.99	6.82	7.57	8.38	9.28	10.36	11.90	14.31	20.84	0.24
2019	4.72	6.24	7.04	7.79	8.51	9.36	10.48	11.93	14.05	19.87	0.23

Table 3: Income and expenditure share of households in the data and the approximated stochastic process (reported under 'Simulation'). Share of income and expenditure reported under each decile is in percentage.

	Deciles										
Year	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**	**Gini**
Labour income											
2018	1.28	4.17	5.26	6.20	7.19	8.34	9.89	12.26	16.65	28.76	0.39
2019	1.09	4.32	5.44	6.36	7.28	8.44	9.95	12.28	16.59	28.25	0.38
Simulation	1.37	4.44	5.17	6.19	7.12	8.43	9.75	12.21	16.49	28.84	0.38
Expenditure											
2018	4.54	5.99	6.82	7.57	8.38	9.28	10.36	11.90	14.31	20.84	0.24
2019	4.72	6.24	7.04	7.79	8.51	9.36	10.48	11.93	14.05	19.87	0.23
Simulation	4.03	6.36	7.39	8.26	9.12	10.04	11.09	12.44	14.17	17.10	0.21

Table 4: Parameter Values

Parameter	Description	Value	Source / Target
β	Time discount factor	0.96	r = 3 %
σ	Elasticity of substitution	1.2	between 1.00 and 2.00
δ	Capital depreciation rate	0.1	between 5 and 10 percent
γ	Capital share of output	0.2	Chakrabarti (2016)
β_1	Income tax function parameter	1.081	Curve-fitting on Indian tax schedule
β_2	Income tax function parameter	0.845	

Table 5: Decile-wise shares of consumption, accumulated savings and welfare under various policies. The models are calibrated to 2018-19 data as per section 4. Income-based targeting policy, I_1, targets the first decile in order of income: targeted households in the first and second period (not necessarily the same set of households) are subjected to an increment in annual income of INR 14000 (around 185 US dollars) per household. Non-income-based targeting policy, NI_1, targets first decile in order of income: targeted households identified in the first period are subjected to an increment in annual income of INR 14000 per household for both periods. Income-based targeting policy, I_2, targets both first and second decile: targeted households are subjected to similar increments in annual income as in Policy I_1. Non-income-based targeting policy, NI_2, targets both first and second decile: targeted households are subjected to similar increments in annual income as in Policy NI_1. Share reported under each decile is in percentage.

	Deciles									
	1st	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Consumption										
Benchmark model	4.027	6.363	7.390	8.263	9.115	10.039	11.093	12.443	14.165	17.100
Policy I_1	4.049	6.357	7.388	8.260	9.114	10.040	11.094	12.444	14.162	17.093
Policy NI_1	4.126	6.350	7.373	8.244	9.101	10.029	11.086	12.438	14.161	17.093
Policy I_2	4.030	6.365	7.390	8.262	9.115	10.039	11.092	12.442	14.165	17.100
Policy NI_2	4.121	6.382	7.384	8.249	9.100	10.024	11.079	12.429	14.149	17.084
Accumulated Savings										
Benchmark model	-2.973	-1.597	-0.091	1.704	3.964	6.932	10.913	16.301	24.104	40.743
Policy I_1	-2.907	-1.530	-0.031	1.754	4.004	6.957	10.918	16.269	24.021	40.545
Policy NI_1	-2.896	-1.516	-0.036	1.733	3.967	6.912	10.874	16.248	24.040	40.674
Policy I_2	-2.972	-1.596	-0.090	1.705	3.964	6.932	10.912	16.300	24.103	40.743
Policy NI_2	-2.932	-1.539	-0.040	1.741	3.983	6.933	10.892	16.260	24.043	40.659
Welfare										
Benchmark model	-0.428	-0.384	-0.374	-0.364	-0.357	-0.350	-0.345	-0.336	-0.326	-0.317
Policy I_1	-0.428	-0.383	-0.372	-0.365	-0.358	-0.350	-0.344	-0.335	-0.327	-0.316
Policy NI_1	-0.426	-0.384	-0.373	-0.364	-0.358	-0.351	-0.344	-0.335	-0.326	-0.317
Policy I_2	-0.428	-0.384	-0.373	-0.365	-0.357	-0.350	-0.345	-0.336	-0.326	-0.317
Policy NI_2	-0.426	-0.383	-0.374	-0.364	-0.357	-0.351	-0.343	-0.336	-0.327	-0.316

Table 6: Equilibrium results under various policies. The models are calibrated to 2018-19 data as per section 4. Income-based targeting policy, I_1, targets the first decile in order of income: targeted households in the first and second period (not necessarily the same set of households) are subjected to an increment in annual income of INR 14000 (around 185 US dollars) per household. Non-income-based targeting policy, NI_1, targets first decile in order of income: targeted households identified in the first period are subjected to an increment in annual income of INR 14000 per household for both periods. Income-based targeting policy, I_2, targets both first and second decile: targeted households are subjected to similar increments in annual income as in Policy I_1. Non-income-based targeting policy, NI_2, targets both first and second decile: targeted households are subjected to similar increments in annual income as in Policy NI_1.

Economy						**Gini**	
	r	**w**	**Labour**	**Capital**	**GDP**	**(Wealth)**	**(Consumption)**
Benchmark model	0.028	0.895	8.173	14.220	9.131	0.676	0.210
Policy I_1	0.028	0.894	8.178	14.372	9.155	0.673	0.210
Policy NI_1	0.028	0.894	8.178	14.263	9.141	0.674	0.209
Policy I_2	0.028	0.895	8.173	14.219	9.130	0.676	0.210
Policy NI_2	0.028	0.894	8.178	14.292	9.144	0.674	0.209

r - Equilibrium interest rate
w - Equilibrium wage rate

Table 7: Decile-wise percentage increase (decrease) in share of consumption under policies I_1, NI_1, I_2 and NI_2 with respect to benchmark model. The models are calibrated to 2018-19 data as per section 4.

Consumption	**Decile**									
	1st	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Policy I_1	0.55	-0.09	-0.04	-0.04	-0.01	0.00	0.01	0.00	-0.02	-0.04
Policy NI_1	2.46	-0.20	-0.24	-0.22	-0.16	-0.10	-0.07	-0.04	-0.03	-0.04
Policy I_2	0.08	0.03	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00
Policy NI_2	2.33	0.30	-0.09	-0.17	-0.17	-0.15	-0.13	-0.12	-0.11	-0.10

Table 8: Decile-wise shares of consumption, accumulated savings and welfare under policies ENI_1 and ENI_2 with respect to the benchmark model. The models are calibrated to 2018-19 data (section 4). Non-income-based targeting policy with extended base, ENI_1 targets first decile in order of income. Targeted households in the first period continue receiving the benefits in the second period, although the per-capita transfer amount is less in the second period. Households who were not targeted in the first period but are eligible in the second period are added to the program in the second period. The total budget for the intervention in each period is fixed to cover a per-capita annual transfer amount of INR 14000 (around 185 US dollars), leading to a lower value of per-capita transfer in the second period. Policy ENI_2 is similar to Policy ENI_1 except that both first and second deciles are targeted. Share reported under each decile is in percentage.

	Deciles									
	1st	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Consumption										
Benchmark model	4.027	6.363	7.390	8.263	9.115	10.039	11.093	12.443	14.165	17.100
Policy ENI_1	4.099	6.357	7.379	8.249	9.106	10.032	11.088	12.439	14.160	17.091
Policy ENI_2	4.058	6.384	7.396	8.263	9.113	10.035	11.086	12.433	14.149	17.082
Accumulated Savings										
Benchmark model	-2.973	-1.597	-0.091	1.704	3.964	6.932	10.913	16.301	24.104	40.743
Policy ENI_1	-2.896	-1.514	-0.026	1.749	3.987	6.934	10.890	16.252	24.021	40.602
Policy ENI_2	-2.917	-1.527	-0.024	1.765	4.014	6.965	10.919	16.263	24.009	40.532
Welfare										
Benchmark model	-0.428	-0.384	-0.374	-0.364	-0.357	-0.350	-0.345	-0.336	-0.326	-0.317
Policy ENI_1	-0.426	-0.384	-0.373	-0.363	-0.358	-0.351	-0.343	-0.336	-0.327	-0.316
Policy ENI_2	-0.427	-0.383	-0.373	-0.363	-0.359	-0.350	-0.344	-0.335	-0.327	-0.316

Table 9: Equilibrium results under various policies under policies ENI_1 and ENI_2 with respect to the benchmark model. The models are calibrated to 2018-19 data (section 4). Non-income-based targeting policy with extended base, ENI_1 targets first decile in order of income. Targeted households in the first period continue receiving the benefits in the second period, although the per-capita transfer amount is less in the second period. Households who were not targeted in the first period but are eligible in the second period are added to the program in the second period. The total budget for the intervention in each period is fixed to cover a per-capita annual transfer amount of INR 14000 (around 185 US dollars), leading to a lower value of per-capita income shock in the second period. Policy ENI_2 is similar to Policy ENI_1 except that both first and second deciles are targeted.

Economy						**Gini**	
	r	**w**	**Labour**	**Capital**	**GDP**	**(Wealth)**	**(Consumption)**
Benchmark model	0.028	0.895	8.173	14.220	9.131	0.676	0.210
Policy ENI_1	0.028	0.894	8.178	14.312	9.147	0.673	0.209
Policy ENI_2	0.028	0.894	8.178	14.378	9.155	0.672	0.209

r - Equilibrium interest rate
w - Equilibrium wage rate

Table 10: Decile-wise percentage increase (decrease) in share of consumption under policies ENI_1 and ENI_2 with respect to benchmark model.

Consumption	**Decile**									
	1st	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Policy ENI_1	1.80	-0.11	-0.15	-0.16	-0.11	-0.07	-0.05	-0.04	-0.04	-0.05
Policy ENI_2	0.78	0.33	0.08	0.00	-0.03	-0.05	-0.06	-0.08	-0.11	-0.11

Appendix B: Additional Tables

Table 11: Summary statistics of a balanced panel of household-level data extracted from the Consumer Pyramids Household Survey conducted by Centre for Monitoring Indian Economy (CMIE), India. All values are in Indian Rupees. Sample size **N** is given in count. Summary of household-level income and expenditure are provided for years from 2014 till 2019.

Year	N	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis
Labour Income									
2014	26411	162502	140103	120320	0	2536000	2536000	3.43	22.76
2015	26411	159551	125053	123600	0	2715000	2715000	3.20	23.16
2016	26411	165534	125520	131000	0	2072000	2072000	2.83	15.46
2017	26411	194383	154757	154000	0	2151040	2151040	3.01	17.86
2018	26411	233318	192830	180000	0	3338600	3338600	2.93	17.33
2019	26411	242987	194067	189240	0	3483600	3483600	2.58	13.49
Expenditure									
2014	26411	104103	48866	93838	19202	1192033	1172831	3.46	37.84
2015	26411	113420	48771	103260	12608	1047883	1035275	3.11	25.69
2016	26411	120077	55551	108382	16476	986477	970001	3.08	22.55
2017	26411	133164	62262	121019	18933	1014750	995817	2.59	15.65
2018	26411	156200	77113	137795	25217	1294713	1269496	2.47	13.55
2019	26411	160142	71918	142304	14415	1281792	1267377	2.01	9.06

Table 12: Income and expenditure share of households in the data. Share of income and expenditure reported under each decile is in percentage.

	Deciles										
Year	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	Gini
Labour Income											
2014	2.08	4.15	5.10	5.95	6.88	8.09	9.71	12.08	16.30	29.66	0.39
2015	2.08	4.56	5.56	6.37	7.24	8.38	9.88	12.06	15.97	27.88	0.36
2016	2.06	4.70	5.64	6.47	7.39	8.54	9.99	12.07	15.79	27.36	0.36
2017	1.47	4.47	5.51	6.45	7.42	8.53	9.96	12.09	16.03	28.08	0.37
2018	1.28	4.17	5.26	6.20	7.19	8.34	9.89	12.26	16.65	28.76	0.39
2019	1.09	4.32	5.44	6.36	7.28	8.44	9.95	12.28	16.59	28.25	0.38
Expenditure											
2014	4.83	6.18	7.02	7.78	8.60	9.47	10.47	11.79	13.81	20.06	0.23
2015	5.16	6.51	7.30	8.02	8.74	9.52	10.44	11.66	13.49	19.16	0.21
2016	4.85	6.31	7.13	7.86	8.63	9.47	10.45	11.71	13.63	19.95	0.22
2017	4.52	6.08	7.02	7.83	8.65	9.57	10.60	11.92	13.82	19.98	0.23
2018	4.54	5.99	6.82	7.57	8.38	9.28	10.36	11.90	14.31	20.84	0.24
2019	4.72	6.24	7.04	7.79	8.51	9.36	10.48	11.93	14.05	19.87	0.23

Table 13: Decile-wise shares of consumption, wealth and welfare under variations in the transfer parameter b_p. The model is calibrated to 2018-19 data as per section 4. The benchmark model described in sections 5.1 and 5.3 has the transfer parameter set to zero. The transfer parameter is shown as a percentage of output. To put a perspective on the magnitude of the transfer parameter in the model, the Indian government had allocated 1.1 percent of GDP as in-cash transfers in 2018, as shown in figure 1. Mexico's 2.7 percent transfer which includes the Oportunidades program and Brazil's 17.5 percent which includes the Bolsa Familia program, can also be considered.

		Transfer/	**Deciles**									
	Transfer	**Output (%)**	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Consumption												
	0	0.0	4.027	6.363	7.390	8.263	9.115	10.039	11.093	12.443	14.165	17.100
	0.06	0.7	4.069	6.391	7.410	8.277	9.124	10.042	11.088	12.427	14.131	17.041
	0.1	1.1	4.095	6.407	7.424	8.285	9.129	10.044	11.085	12.417	14.110	17.005
	0.2	2.2	4.163	6.450	7.456	8.307	9.142	10.048	11.076	12.391	14.055	16.911
	0.5	5.5	4.346	6.568	7.542	8.369	9.177	10.056	11.050	12.318	13.912	16.663
	1	10.9	4.626	6.743	7.672	8.459	9.230	10.066	11.007	12.206	13.698	16.293
	1.5	16.4	4.881	6.901	7.790	8.541	9.273	10.074	10.968	12.104	13.505	15.963
	2	21.9	5.105	7.040	7.893	8.612	9.312	10.078	10.930	12.013	13.339	15.677
Accumulated Savings												
	0	0.0	-2.973	-1.597	-0.091	1.704	3.964	6.932	10.913	16.301	24.104	40.743
	0.06	0.7	-3.009	-1.660	-0.156	1.647	3.921	6.910	10.918	16.336	24.179	40.913
	0.1	1.1	-3.044	-1.712	-0.211	1.597	3.881	6.884	10.917	16.363	24.248	41.078
	0.2	2.2	-3.101	-1.810	-0.313	1.505	3.810	6.847	10.921	16.417	24.368	41.356
	0.5	5.5	-3.294	-2.123	-0.645	1.194	3.557	6.695	10.908	16.581	24.779	42.349
	1	10.9	-3.525	-2.525	-1.087	0.769	3.203	6.477	10.877	16.789	25.322	43.699
	1.5	16.4	-3.643	-2.782	-1.392	0.469	2.956	6.321	10.851	16.925	25.681	44.613
	2	21.9	-3.764	-3.030	-1.692	0.163	2.687	6.139	10.799	17.045	26.056	45.597
Welfare												
	0	0.0	-0.428	-0.384	-0.374	-0.364	-0.357	-0.350	-0.345	-0.336	-0.326	-0.317
	0.06	0.7	-0.426	-0.383	-0.371	-0.364	-0.356	-0.351	-0.343	-0.336	-0.327	-0.315
	0.1	1.1	-0.425	-0.382	-0.372	-0.363	-0.355	-0.351	-0.343	-0.335	-0.327	-0.315
	0.2	2.2	-0.422	-0.382	-0.370	-0.362	-0.355	-0.349	-0.341	-0.334	-0.327	-0.315
	0.5	5.5	-0.415	-0.377	-0.366	-0.359	-0.352	-0.347	-0.339	-0.333	-0.325	-0.313
	1	10.9	-0.403	-0.371	-0.361	-0.355	-0.349	-0.342	-0.336	-0.329	-0.322	-0.311
	1.5	16.4	-0.394	-0.365	-0.356	-0.351	-0.343	-0.339	-0.332	-0.327	-0.319	-0.310
	2	21.9	-0.386	-0.360	-0.352	-0.346	-0.341	-0.335	-0.330	-0.324	-0.317	-0.308

Table 14: Equilibrium results under variations in the transfer parameter b_p. The model is calibrated to 2018-19 data as per section 4. The benchmark model described in sections 5.1 and 5.3 has the transfer parameter set to zero. The transfer parameter is shown as a percentage of output. To put a perspective on the magnitude of the transfer parameter in the model, the Indian government had allocated 1.1 percent of GDP as in-cash transfers in 2018, as shown in figure 1. Mexico's 2.7 percent transfer which includes the Oportunidades program and Brazil's 17.5 percent which includes the Bolsa Familia program, can also be considered.

	Transfer/						Gini	
Transfer	**Output (%)**	**r**	**w**	**Labour**	**Capital**	**GDP**	**(Wealth)**	**(Consumption)**
0	0.0	0.028	0.895	8.173	14.220	9.131	0.676	0.210
0.06	0.7	0.028	0.894	8.183	14.212	9.139	0.678	0.209
0.1	1.1	0.029	0.893	8.188	14.158	9.136	0.681	0.208
0.2	2.2	0.030	0.892	8.203	14.129	9.146	0.685	0.205
0.5	5.5	0.032	0.888	8.238	13.852	9.140	0.699	0.198
1	10.9	0.035	0.883	8.286	13.504	9.136	0.717	0.188
1.5	16.4	0.038	0.878	8.328	13.355	9.153	0.728	0.178
2	21.9	0.040	0.875	8.360	13.079	9.143	0.739	0.170

r - Equilibrium interest rate
w - Equilibrium wage rate

Table 15: Decile-wise percentage increase (decrease) in share of consumption under variation of the transfer parameter with respect to benchmark model. The model is calibrated to 2018-19 data as per section 4.

	Transfer/	Deciles									
Transfer	**Output (%)**	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
0.06	0.7	1.057	0.430	0.274	0.171	0.094	0.028	-0.045	-0.128	-0.246	-0.350
0.1	1.1	1.701	0.688	0.450	0.271	0.147	0.043	-0.075	-0.210	-0.391	-0.559
0.2	2.2	3.382	1.364	0.893	0.539	0.288	0.083	-0.154	-0.417	-0.776	-1.106
0.5	5.5	7.920	3.218	2.053	1.286	0.674	0.166	-0.394	-1.007	-1.789	-2.558
1	10.9	14.878	5.975	3.814	2.375	1.255	0.263	-0.779	-1.906	-3.297	-4.723
1.5	16.4	21.200	8.454	5.410	3.371	1.732	0.345	-1.132	-2.721	-4.662	-6.654
2	21.9	26.776	10.635	6.800	4.231	2.160	0.385	-1.471	-3.453	-5.834	-8.324

Table 16: Robustness check: Summary statistics of a panel of household-level data extracted from the Consumer Pyramids Household Survey conducted by Centre for Monitoring Indian Economy (CMIE), India. All values are in Indian Rupees. Sample size **N** is given in count. Summary of household-level income and expenditure are provided for years 2018 and 2019. This dataset includes only those households that have responded for all the months for years 2018-19.

	Year	N	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis
Income										
	2018	62468	239397	203895	183200	0	3975000	3975000	3.24	20.85
	2019	62468	250881	205315	193975	0	3483600	3483600	2.87	15.99
Expenditure										
	2018	62468	155232	76940	136462	15182	1447300	1432118	2.54	14.70
	2019	62468	161299	73687	143040	14415	1281792	1267377	2.14	10.08

Table 17: Income and expenditure share of households in the data. Share of income and expenditure reported under each decile is in percentage.

	Deciles										
	1st	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**	**Gini**
Income											
	1.38	4.15	5.20	6.15	7.13	8.28	9.85	12.18	16.37	29.32	0.39
	1.22	4.34	5.40	6.28	7.20	8.36	9.88	12.24	16.44	28.63	0.39
Expenditure											
	4.60	6.00	6.83	7.59	8.37	9.25	10.30	11.80	14.20	21.06	0.24
	4.75	6.23	7.04	7.78	8.49	9.31	10.38	11.83	14.00	20.18	0.23

Table 18: Robustness check: Decile-wise shares of consumption, accumulated savings and welfare under various policies with respect to benchmark model based on a larger sample of households (62468 in number) as per section 6.1. The models are calibrated as per section 4. Income-based targeting policy, I_1, targets the first decile in order of income: targeted households in the first and second period (not necessarily the same set of households) are subjected to an increment in annual income of INR 14000 (around 185 US dollars) per household. Non-income-based targeting policy, NI_1, targets first decile in order of income: targeted households identified in the first period are subjected to an increment in annual income of INR 14000 per household for both periods. Income-based targeting policy, I_2, targets both first and second decile: targeted households are subjected to similar increments in annual income as in Policy I_1. Non-income-based targeting policy, NI_2, targets both first and second decile: targeted households are subjected to similar increments in annual income as in Policy NI_1. Shares reported under each decile are in percentage.

	Deciles									
	1st	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Consumption										
Benchmark model	4.026	6.335	7.378	8.253	9.106	10.039	11.099	12.454	14.186	17.122
Policy I_1	4.038	6.322	7.372	8.250	9.106	10.039	11.100	12.457	14.190	17.125
Policy NI_1	4.125	6.326	7.361	8.239	9.095	10.029	11.091	12.447	14.177	17.109
Policy I_2	4.035	6.333	7.377	8.252	9.105	10.038	11.098	12.454	14.186	17.122
Policy NI_2	4.122	6.355	7.371	8.239	9.092	10.024	11.085	12.440	14.169	17.104
Accumulated Savings										
Benchmark model	-2.892	-1.503	-0.010	1.774	4.015	6.961	10.914	16.262	23.999	40.479
Policy I_1	-2.877	-1.492	-0.010	1.766	4.000	6.944	10.899	16.254	24.003	40.512
Policy NI_1	-2.827	-1.435	0.034	1.793	4.009	6.937	10.875	16.216	23.951	40.448
Policy I_2	-2.891	-1.499	-0.005	1.776	4.015	6.960	10.911	16.259	23.996	40.478
Policy NI_2	-2.849	-1.442	0.041	1.809	4.031	6.958	10.892	16.218	23.939	40.403
Welfare										
Benchmark model	-0.427	-0.385	-0.371	-0.366	-0.357	-0.350	-0.343	-0.336	-0.326	-0.317
Policy I_1	-0.427	-0.385	-0.373	-0.364	-0.358	-0.350	-0.343	-0.337	-0.327	-0.316
Policy NI_1	-0.425	-0.385	-0.373	-0.364	-0.357	-0.350	-0.344	-0.336	-0.327	-0.316
Policy I_2	-0.428	-0.384	-0.372	-0.366	-0.356	-0.350	-0.344	-0.336	-0.326	-0.317
Policy NI_2	-0.426	-0.384	-0.373	-0.365	-0.357	-0.350	-0.343	-0.335	-0.327	-0.317

Table 19: Robustness check: Equilibrium results under various policies based on a larger sample of households (62468 in number) as per section 6.1. The models are calibrated as per section 4. Income-based targeting policy, I_1, targets the first decile in order of income: targeted households in the first and second period (not necessarily the same set of households) are subjected to an increment in annual income of INR 14000 (around 185 US dollars) per household. Non-income-based targeting policy, NI_1, targets first decile in order of income: targeted households identified in the first period are subjected to an increment in annual income of INR 14000 per household for both periods. Income-based targeting policy, I_2, targets both first and second decile: targeted households are subjected to similar increments in annual income as in Policy I_1. Non-income-based targeting policy, NI_2, targets both first and second decile: targeted households are subjected to similar increments in annual income as in Policy NI_1.

Economy						**Gini**	
	r	**w**	**Labour**	**Capital**	**GDP**	**(Wealth)**	**(Consumption)**
Benchmark model	0.028	0.895	8.178	14.320	9.148	0.672	0.211
Policy I_1	0.028	0.895	8.178	14.289	9.144	0.672	0.211
Policy NI_1	0.028	0.894	8.183	14.344	9.155	0.670	0.210
Policy I_2	0.028	0.895	8.178	14.318	9.147	0.672	0.211
Policy NI_2	0.028	0.894	8.183	14.389	9.161	0.670	0.210

r - Equilibrium interest rate
w - Equilibrium wage rate

Table 20: Robustness check: Decile-wise percentage increase (decrease) in share of consumption under various policies with respect to benchmark model based on a larger sample of households (62468 in number) as per section 6.1. The models are calibrated to 2018-19 data as per section 4.

Consumption	**Deciles**									
	1st	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Policy I_1	0.296	-0.204	-0.083	-0.037	-0.005	0.004	0.013	0.018	0.026	0.017
Policy NI_1	2.464	-0.141	-0.231	-0.178	-0.127	-0.097	-0.069	-0.056	-0.064	-0.079
Policy I_2	0.228	-0.029	-0.022	-0.018	-0.012	-0.011	-0.007	-0.005	-0.003	-0.002
Policy NI_2	2.381	0.308	-0.105	-0.174	-0.157	-0.149	-0.126	-0.116	-0.119	-0.109

Table 21: Robustness check: Decile-wise percentage increase (decrease) in share of consumption under various policies with respect to benchmark model as per section 6.2. Income-based targeting policy, I_1, targets the first decile in order of income: targeted households in the first and second period (not necessarily the same set of households) are subjected to an increment in annual income. Non-income-based targeting policy, NI_1, targets first decile in order of income: targeted households identified in the first period are subjected to an increment in annual income for both periods. Income-based targeting policy, I_2, targets both first and second decile: targeted households are subjected to similar increments in annual income as in Policy I_1. Non-income-based targeting policy, NI_2, targets both first and second decile: targeted households are subjected to similar increments in annual income as in Policy NI_1. Here, the annual increment in income, *Amount*, is varied from INR 7000 (around 95 USD) to INR 38000 (around 510 USD) per household.

Consumption											
% of total		**Deciles**									
income	**Amount**	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Policy I_1											
0.30	7000	0.14	-0.08	-0.04	-0.02	0.00	0.00	0.00	0.01	0.01	0.01
0.43	10000	0.57	-0.07	-0.04	-0.03	-0.01	0.00	0.01	0.00	-0.03	-0.05
0.60	14000	0.55	-0.09	-0.04	-0.04	-0.01	0.00	0.01	0.00	-0.02	-0.04
0.77	18000	0.64	-0.16	-0.08	-0.07	-0.03	0.01	0.02	0.02	-0.01	-0.03
1.20	28000	0.81	-0.45	-0.14	-0.11	-0.04	0.02	0.05	0.05	0.03	0.00
1.63	38000	1.88	-0.90	-0.40	-0.22	-0.08	0.01	0.07	0.08	0.08	0.04
Policy NI_1											
0.30	7000	1.45	-0.13	-0.11	-0.10	-0.07	-0.05	-0.03	-0.03	-0.04	-0.05
0.43	10000	1.91	-0.17	-0.17	-0.16	-0.11	-0.07	-0.05	-0.03	-0.04	-0.05
0.60	14000	2.46	-0.20	-0.24	-0.22	-0.16	-0.10	-0.07	-0.04	-0.03	-0.04
0.77	18000	3.08	-0.25	-0.30	-0.29	-0.21	-0.14	-0.09	-0.06	-0.03	-0.04
1.20	28000	4.38	-0.20	-0.37	-0.36	-0.27	-0.18	-0.14	-0.10	-0.10	-0.12
1.63	38000	5.37	-0.23	-0.45	-0.43	-0.32	-0.23	-0.18	-0.15	-0.13	-0.14
Policy I_2											
0.30	7000	-0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.43	10000	-0.01	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.60	14000	0.08	0.03	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00
0.77	18000	0.18	0.04	-0.01	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	0.00
1.20	28000	0.27	0.06	-0.03	-0.03	-0.02	-0.02	-0.02	-0.01	-0.01	0.00
1.63	38000	0.57	0.03	-0.04	-0.06	-0.05	-0.04	-0.03	-0.02	-0.01	0.00
Policy NI_2											
0.30	7000	1.29	0.15	-0.03	-0.07	-0.07	-0.06	-0.06	-0.06	-0.09	-0.09
0.43	10000	1.64	0.21	-0.05	-0.10	-0.10	-0.09	-0.08	-0.08	-0.10	-0.09
0.60	14000	2.33	0.30	-0.09	-0.17	-0.17	-0.15	-0.13	-0.12	-0.11	-0.10
0.77	18000	2.85	0.37	-0.12	-0.23	-0.22	-0.19	-0.16	-0.14	-0.12	-0.10
1.20	28000	3.99	0.53	-0.19	-0.34	-0.33	-0.28	-0.24	-0.20	-0.15	-0.12
1.63	38000	5.23	0.72	-0.18	-0.41	-0.39	-0.34	-0.29	-0.27	-0.25	-0.22