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Anindya S. Chakrabarti
Abinash Mishra
Mohsen Mohaghegh

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Targeted interventions: Consumption dynamics and distributional effects *

Anindya S. Chakrabarti† Abinash Mishra‡ Mohsen Mohaghegh§

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Abstract

Income distribution-based targeted interventions are quite common in developing economies. However, often due to institutional frictions, identification of the recipients happens at a lower frequency than the frequency of movement across income groups, leading to mis-identification of true and false recipients. What are the general equilibrium effects of such interventions? To measure the effects, we develop a heterogeneous agent production economy where agents face uninsurable income risks and we calibrate it to a novel panel dataset on monthly household income and consumption in India. We study the effects of persistent (identity-based) shocks as opposed to the usual temporary (income-based) income shocks, the difference being that in persistent payments individuals are guaranteed a payment across periods, regardless of their income status in future. We find that temporary interventions have muted distributional effects, while identity-based stimulus of the same size give rise to more prominent effects. In particular, a persistent income shock to the poorest decile equivalent to 0.6% of GDP leads to a 0.543% increase in consumption.

Keywords: Consumption heterogeneity, targeted interventions, right-to-work act, inequality.

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: fpm18abinashm@iima.ac.in. Economics area, Indian Institute of Management, Vastrapur, Ahmedabad, Gujarat-380015, India.

§Email: mohagheghm12@gmail.com. Economics area, Indian Institute of Management, Vastrapur, Ahmedabad, Gujarat-380015, India.

1 Introduction

Large–scale programs with low–intensity economic interventions are common in both developed and developing countries. Often the goal is to provide economic and financial security to those in the poorest sections of the economy (Drèze and Khera (2017)). There is a large literature that is devoted to understanding the impacts of such policies on recipients.[1] A complementary literature has evolved which tries to identify the effects of such programs on non-participants as well (see e.g. Imbert and Papp (2015) and Dutta et al. (2014)). Banerjee et al. (2020) extended this literature in a new direction by studying the effects of targeted interventions in the long run. Most of the attention in both strands has been given to the micro-level effects of such policies. However, overall impacts on measures of inequality, which are at the heart of these transfers, somewhat surprisingly are less studied. In this paper, we address this gap and study the indirect general equilibrium effects of targeted interventions.

A major reason why such general equilibrium effects of targeted interventions have not been well studied is the scarcity of data. A natural way to estimate general equilibrium effects would be via structural models and not directly from empirical data. However, the model first needs to be calibrated well to empirical data before characterizing the effects and this is where lies the problem. To empirically estimate income and consumption distribution, a standard source of information is tax records. However, tax records are far more reliable for the rich while targeted transfers typically target the left tail of income distribution (Atkinson and Piketty (2010)).[2] The scarcity of data becomes a more severe problem in developing countries where collecting consumption, income and wealth data are likely to be less organized as it is in their developed counterparts.

In this paper, we study distributional impacts of targeted interventions in a general equilibrium setup. To guide our structural model, we utilize a novel data set published by the Centre for Monitoring Indian Economy Pvt. Ltd. (CMIE).[3] This data set tracks more than two hundred thousand Indian households across various demographic compositions and reports their income and consumption. A very useful feature of CMIE data for our present purpose is that it, by design, tracks poor households. Therefore, this data set provides a credible picture of the left tail of the distribution (as opposed to Banerjee and Piketty (2005) which studies the right tail of the distribution).[4]

[1] Such effects have been studied in many dimensions including, but not limited to, education, nutrition, health and gender. See for example, Dreze and Sen (1990) and Afridi (2010) among others.

[2] The macroeconomics of top income earners are well documented and studied. For example, see a review by Jones (2015).

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

[4] 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

We develop a general equilibrium production economy where workers face uninsured idiosyncratic shocks that set the labor portion of their income. We calibrate a stochastic earning process, independent from our model structure, that matches the cross-sectional distribution of labor earnings in 2018. The panel nature of our data allows us to directly measure income dynamics. These dynamics determine precautionary savings in the model. We further verify our simulated economy by comparing wealth and consumption distributions in our model with we observe in the CMIE.

Then we introduce targeted interventions in the spirit of the Employment Guarantee Act.[5] We are primarily interested in the distributional impacts of such interventions via their impact on individuals' consumption and savings decisions. Therefore, we map transfers promised by this act -as well as other forms of interventions we propose- to a change in the income transition matrix. The quantum of transfers in most targeted policies are quite substantial for the recipients. Thus, translated to a Markov process, receiving a sizable transfer may change the probability of transitioning to higher states in the stochastic process; and, hence, may have on savings and consumption of individuals.

Again we rely on our data set to quantify the magnitude of these perturbations in the transition matrix. The *right-to-work* act provides income to those who participate in the labor force and whose income is below a certain threshold. We call such interventions, which are the most common form in India and other countries, *temporary* as households will be automatically disqualified as soon as their income reaches a pre-determined level. As opposed to that, we also run experiments with *persistent* interventions where recipients are promised an equivalent transfer for the next period regardless of their future income. Currently, for those who pass the threshold, such persistent transfers are only possible if the list of registered recipients is not updated whether due to institutional inefficiencies or fraud. However, we explore the possibility of persistent targeted transfers as an alternative policy proposal.

We show that temporary targeted income shocks do not generate substantial distributional impacts while persistent targeting has the potential to lead to significant changes in all measures of inequality. In other words, when income shocks are temporary, they increase consumption and wealth share of targeted households only marginally. However, more persistent shocks schedules have more pronounced impacts not only on consumption and wealth distribution but also on macroeconomic aggregates.

Quantitatively, we measure the size of these transfers to be consistent with currently running Employment Guarantee Act programs in India. We show that when these transfers

the Indian economy are absent in the data set. Therefore, the true inequality may still be underestimated.

[5] A brief description of institutional details are provided in section 2.4.

persistently target the poorest decile, they a 0.543% increase in their consumption share, which leads to a significant reduction in inequality. This, however, comes at a price. In some of these simulations, non-targeted deciles see, an albeit negligible, a fall in their relative share of consumption.

The relevance of these exercises would be clear if we refer to figure 1. India provides a total transfer of 1.1 % of its GDP to its citizens. This is considerably lower than many other developing countries. For example, this ratio is much larger in Russia (9.7%) and Brazil (17.3%); although, it is comparable to Mexico (2.7%) and larger than Indonesia (0.2%).

Therefore, we argue that increasing total transfers to levels seen in other developing countries, especially if they are *persistent* -in the sense we discuss in this paper- would have significant distributional and aggregate impacts in the Indian economy. We, for two reasons, do not simulate such large scale interventions. Firstly, because very large transfers change the nature of income risk so drastically that a comparison with the baseline model would not be very informative. Secondly, such massive interventions also induce noticeable changes in the market structure through prices and the government's budget, which lies beyond the scope of our study.

Background literature: Our work contributes to the growing body of literature that studies the macroeconomic dynamics in developing countries (e.g. Loayza et al. (2007) and Ghate et al. (2013)). A distinct strand of this literature has emerged around distributive, or more generally welfare-related, effects of public programs in developing countries (see for example, Liu and Barrett (2013), Dutta et al. (2014), Deininger and Liu (2019), Berg et al. (2018), Baird et al. (2011)). We build on these studies to build a general equilibrium framework to examine distributional effects of alternative transfer schemes.

In Latin America, conditional cash transfer programs have attracted much attention, though mainly from a micro 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 clear positive impacts on education, health and nutrition indicators among recipients. Also, it's 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 helped reduce inequality and extreme poverty, and has improved education outcomes. However, some studies suggest negative spillover effects of these programs, particularly on non-recipients; mainly through their impact on prices of certain goods and services[6]. We

[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. Filmer et al. (2018) show that cash transfers have real effects such as price increases

contribute to this literature by providing a macroeconomic analysis of the effects of targeted distributions in a general equilibrium setting where we explore these impacts on various deciles across the distribution of income, wealth and consumption.

We use a canonical heterogeneous-agent incomplete-market model to compare the effects of persistent transfers with temporary interventions.[7] Aiyagari and McGrattan (1998) and Woodford (1990) theoretically show that government transfers provide insurance to individuals facing uninsured risks and borrowing constraints. In terms of their impact on aggregates, however, they differ substantially. Woodford (1990) argues that rising transfers ease liquidity constraints, which in turn increase investment and output. In contrast, Aiyagari and McGrattan (1998) show that increasing transfers reduce the need for precautionary savings; thus, reduce capital and output. Oh and Reis (2012) explore a different mechanism, where they show that lump-sum transfers have aggregate effects by targeting. Such lump-sum transfers have different impacts on different households. For some households, it increases consumption or labour supply while for others, it lowers them; leaving the aggregate impacts ambiguous. We contribute to this literature by providing an analysis that examines both distributional and aggregate impacts in a general equilibrium model.

Oh and Reis (2012) show that lump-sum targeted transfers can be expansionary because of a positive wealth effect on labour supply, and an increase in the aggregate demand. In a similar setup, Floden (2001) showed that government transfers reduce inequality by redistributing resources between rich and poor households. But this comes at a cost. The taxes needed to finance the transfers distort labour supply and savings; thus negatively affecting employment and capital, which, in turn, possibly hinders economic growth[8]. Other studies show that redistributive transfers need not inherently deter growth when government transfers benefit the poor and help offset the capital market imperfections (e.g., Aghion and Bolton (1997) and Benabou (2000)). We belong to this literature as we, too, study the aggregate effects of a specific form of redistributive transfers. However, we use our data set to our advantage to inch towards a fiscally-neutral transfer scheme that has significant distributional impacts. This would resolve, to a large degree, taxation and growth-related concerns, and make government interventions more effective in reducing inequality.

In terms of modeling risk, we simulate a stochastic earnings process that determines labour income directly from data. This is in contrast with the standard practice where the data is used to calibrate an idiosyncratic productivity shock process, which would be the main source of income risk in the model. Our approach, though causes some computational

in protein-rich perishable food items negatively affecting 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).

[8]See Alesina and Rodrik (1994) and Persson and Tabellini (1994).

difficulties, improves the modeling of risk, which is critical for studying distributional effects. What we do to construct an income transition matrix is similar to the quantile transition matrix method discussed by Formby et al. (2004). We further explain this approach, the computational difficulties it introduces, and our solution method in the paper.

The environment consists of ex-ante identical households who face uninsurable income risks due to their draws. To this setup we introduce a progressive income tax system as consistent with the data. We build on Bakış et al. (2015), Conesa and Krueger (2006) and Heathcote et al. (2017) in modeling the progressivity of income taxation. We use our data set to directly estimate an exponential tax schedule to reproduce historical trends in the Indian tax system.

2 Data Description and Institutional Background

2.1 Source: CMIE Consumer Pyramids Household Survey

We obtain data on monthly income and expenditure of households from Consumer Pyramids Households Survey (CPHS henceforth) database starting from January 2014 to December 2019. The Centre for Monitoring the Indian Economy (CMIE), a privately run organization based in India, maintains this database. This database is the result of a nation-wide survey conducted by CMIE. This is similar to the Survey of Income and Program Participation (SIPP), a longitudinal survey conducted by the United States Census Bureau since its inception in 1983. Unlike SIPP, which is a series of panels, each lasting from 2.4 to 4 years, the CPHS is a continuos panel. Like the Consumer Expenditure Survey (CE) conducted by US Census Bureau for the Bureau of Labor Statistics (BLS), CPHS follows a similar rotational schedule and unlike the CE survey, a sample household unit is not dropped from the survey after the fourth round and replaced by a new one. Since the household units are retained across the years, unless dropped for any unsystematic reason, CPHS is a balanced panel.

2.2 Sample Selection

The survey covers over 160,000 households. The sample set of households in the CPHS are based on the Census 2011 conducted by the Government of India. Details of expenditure are recorded for 82 household items and income of the household is recorded under several streams like wages, rent from business among others. The database is a result of a systematic survey conducted across the nation. The survey is designed in such a way that each household that is part of the panel gets visited in every 4 month's interval which is thrice a year for their responses. One remarkable thing about the survey is that the execution schedule is created in a way that the survey is conducted everyday and geographical diversity is ensured through careful selection of the households marked for interviews on a particular day. In a nutshell, the CPHS follows a multi-stage stratified survey design where the first level of stratification covers villages and towns identified under the Census 2011 and households are identified from the first strata as a second level of stratification. This survey covers all the 640 districts in Census 2011 list spanning across most of the states of the nation.[9]

Our sample consists of 26411 households for whom we have a balanced panel. Below we explain the sample selection method. As a proxy for consumption, we use the data given under total expenditure in CPHS and for a measure of labour income by including income from wages and 80% of business profits earned by a household given in the database. We cover for four complications. First, the execution schedule of the survey is planned such that responses from households are collected on a daily basis. The set of households that are scheduled for an interview on a given day are selected such that a nation-wide representation is ensured. This enables CMIE to generate pan-India weighted estimates of income and expenditure on a daily frequency. But there could be non-responses and other failures in the execution leading to inadequacies in a truly national representation and could limit the inferences drawn from such fast-frequency of data. Second, pertaining to ensuring national representation, the database does not actually cover every district every month. The execution schedule uses a rotation for each primary sampling unit (a town or village) with households in a given unit gets interviewed once every four months in a given year. This pattern of execution means that although most of the listed districts would be covered once every four months, it is more likely that larger ones would be visited more frequently than others. Thus, a typical month may not contain responses drawn from the complete list of districts. Third, over the course of five years of the survey, over 65000 households were added to the original sample and around 58000 households were dropped for various reasons. There are cases of households for whom observations are present intermittently across years. For example, for a household, observations would be missing from May to June in 2015 and from March to July in 2017. For another household, participation would have happened in 2016 and they would have dropped in 2018. We have retained only those households for whom at least 10 observations are available for all the years from 2014 to 2019. A final caveat about the data. Since every household is interviewed once every four months, the responses recorded for each month may have a recency bias for the current month's expenditure than for the previous months. Although the database contains adjusted

[9]For details on survey design and execution, downloadable content is provided in https://consumerpyramidsdx.cmie.com/kommon/bin/sr.php?kall=wkb,accessedon24thJan2021.

observations, we construct aggregates of measures of consumption and income over a year based on the estimated monthly responses. By aggregating over years, the effects of recency bias in consumption is minimized.

Finally, there are other datasets which provide partial information for household income and expenditure in the Indian context, e.g. the Consumer Expenditure Survey conducted by the National Sample Survey Office (NSSO) for the Ministry of Statistics & Programme Implementation, India Human Development Survey (IHDS) and the Inter University Consortium for Applied Political and Social Sciences Research (ICPSR). However, they suffer from one or more than one among the following drawbacks: lower frequency, lack of consistency among households across time and lack of coverage of variables. Therefore, we use the CHPS dataset in the present context.

2.3 Heterogeneity in Income and Consumption

Tables 1 and 2 show the summary statistics of the dataset from 2014 to 2019. We note that the income gini has been around 0.36 to 0.39 through 2014-19. While comprehending the gini data, it should be kept in mind that this survey data does not include the top-most end of the income distribution. For example, table 1 shows the maximum income in our sample for 2018 is around INR 3 million (around 45000 US dollars). The minimum value of income for all the years is shown to be zero. The reason for zero income lies in the exclusion of some sources of income that are not attributable to labour or rent income. These sources of income could be pensions, private transfers and even income from gambling. Table 11 in the appendix shows an overall decrease in mean income for the first decile. Years 2016-17 and 2017-18 are noticeable years for the 10th decile, whose mean income increased by 20% and 23% respectively, while the 1st decile was worst hit by a decrease of 16% and 5% respectively.

2.4 Institutional Background: Targeted Interventions

In a report on status of implementations of human rights recommendations released on June 5th 2020, the National Human Rights Commission (NHRC) apprised the United Nations Human Rights Council (UNHRC) of the Government of India's active consideration of implementation of a Universal Basic Income (UBI). This report was the outcome of the third round of the Universal Periodic Review process. The Government of India's consideration of implementing UBI was one of the 152 accepted recommendations of the UPR working group of the UN agency that the Government of India accepted in September 2017.[10] This surfaced

[10]Source: https://www.thehindu.com/news/national/govt-actively-considering-universal-basic-income-nhrc-tells-un/article31805107.ece

at a time when the pandemic had already started to hurt employment and household income.

More than just consideration of implementing the UBI, there have been instances of such policies brought out by the Government of India. Operational in December 2018, the Pradhanmantri Kisan Samman Nidhi Yojana, (PM-KISAN) scheme presents as a limited version of a UBI. PM-KISAN targets small and marginal farmer families who own less than two hectares of land.[11] It promises INR 6000 (Roughly 80 US dollars) per annum cash transfers in three equal installments. On December 25th 2020, the government transferred around INR 180 Billion to over 90 million registered families. This was the third installment of INR 2000 per family.[12]

The Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA henceforth) has also been proclaimed as something very close to a one-size-fits-all basic income policy that on-paper guarantees 100 days of employment for the eligible. In 2015, Prime Minister Modi termed the program as one of the failures of the previous regime but the ruling government has not only continued the program but also announced an increase in its budgetary allocation by INR 400 Billion in May 2020 over an allocation of INR 615 Billion.[13] In a report by CRISIL in August 2020, a credit rating research agency in India, reported that the average income per person per month doubled to INR 1000 in the first four months of 2020 fiscal than in the previous.[14]

There has been several recommendations in the academic discourse over the course of recent years. To cite a few, Bardhan recommends an annual transfer of INR 10,000 to every Indian citizen at an expense of 10% of GDP.[15] Maitreesh Ghatak proposes an annual transfer of INR 13,432 rupees at 11% of GDP.[16] Vijay Joshi recommends an annual UBI of INR 3500 at 3.5% of GDP.[17] There are economists who recommend a more targeted (instead

[11] One hectare of land around 2.47 acres, visually equivalent to the size of around two European football fields kept side by side. According to the Agricultural Census conducted by the Government of India in 2015-16, small and marginal holdings (below two hectares) constituted 86.21% of the total land holdings. https://www.thehindu.com/sci-tech/agriculture/indian-farms-getting-smaller/article25113177.ece.

[12] Source: https://economictimes.indiatimes.com/news/economy/agriculture/pm-modi-releases-over-rs-18000-crore-to-more-than-nine-crore-farmers-under-pm-kisan-scheme/articleshow/79952497.cms?from=mdr.

[13] Source: https://www.moneycontrol.com/news/business/economy/budget-2021-mnrega-is-vital-but-needs-more-govt-attention-6370221.html

[14] Source: https://www.livemint.com/news/india/average-income-per-person-per-month-under-mgnrega-doubled-yoy-in-april-july-11598349066912.html

[15] Source: https://www.ideasforindia.in/topics/poverty-inequality/basic-income-in-a-poor-country.html

[16] Source: https://indianexpress.com/article/opinion/columns/basic-income-in-india-brexit-referendum-switzerland-basic-income-jan-dhan-yojana-guarantee-employment-programme-mgnrega-2879930/

[17] Source: https://www.ideasforindia.in/topics/poverty-inequality/universal-basic-income-for-india.html

of a universal) approach. Abhijit Banerjee proposes an annual transfer of INR 13,000 by replacing the existing subsidies and welfare programs targeted at the poor.[18] As an action plan for the Government of India to tackle the crisis due to the pandemic, an article by C Rangarajan, former Central Bank of India governor, and S Mahendra Dev, recommends a combination of cash transfers and expanded MGNREGA policy scheme for implementation of UBI. They stress on the expansion of the MGNREGA policy to urban areas on top of the existing rural areas and an increase in employment guarantee days to 150 from existing 100. He estimates that the additional fiscal expenditure to be 1% to 1.22% of the GDP.[19]

2.5 Institutional Background: Frequency of Identification

Ration card has been one of the primary channels of public distribution systems in India.[20] It is issued by the state governments in India to eligible households. Before the National Food Security Act (2013) was passed, the state governments issued these cards under the Targeted Public Distribution System (TPDS). Below–Poverty–Line (BPL) cards are one type of ration cards under the TPDS. Before the NFSA, three BPL censuses have been conducted in 1992, 1997 and 2002, along with the Socio-Economic Caste Census of 2011 to identify eligible households for the program Alkire and Seth (2013). Pradhan and Roy (2019) find that in some states, there are irregularities in ration card distribution under the NFSA. They also find that in their sample, either the cards were issued with a lag of at least three years after the NFSA or were not issued at all, some even before the NFSA. In some cases, after the NFSA, households who had received BPL cards were dropped out of the new beneficiary list.

In summary, we see that the number of policies on targeted interventions are quite large and the demand has grown stronger. However, it is not clear what would be the distributional effect of such policies. Below, we analyze a heterogeneous agent model to analyze the effects.

[18]Source: https://www.ideasforindia.in/topics/poverty-inequality/universal-basic-income-the-best-way-to-welfare.html

[19]Source: https://indianexpress.com/article/opinion/columns/corona-crisis-india-healthcare-system-universal-basic-income-mgnrega-migrant-workers-6487481/

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

3 A Heterogeneous Agent Model

3.1 Model Environment

3.1.1 Households

The economy is populated by a unit mass of ex-ante identical households. They maximize their expected discounted life time utility. Every household's period utility over consumption is given by $u(c)$ denote, and future utility is discounted at a constant rate β. Households have a CRRA period utility, $u(c_t) = \frac{c_t^{1-\sigma}}{1-\sigma}$, where σ determines intertemporal elasticity of substitution.

Each period, households' draw an idiosyncratic shock, e, which determines their period earnings. It is possible to transfer consumption across time and state by investing in a risk-free asset that is available to everyone in the economy. Household savings, as we will explain shortly, are productive. However, there is no aggregate risk in the economy. Therefore, rate of return on savings, r, is constant.

In addition to that, households may receive a direct public transfer, b_p. Household income, y, therefore, consists of three potential sources; earnings, capital income, and public transfers. All three sources are taxable according to an economy-wide tax schedule $\tau(y)$.

Therefore, a household whose state is (e, a), solves the following programming problem:

$$V(e,a) = \max_{\{c,\, a'\}} u(c) + \beta \mathbb{E} V(e', a') \tag{1}$$

subject to

$$\begin{aligned} c + a' &\leq y - \tau(y) + a \qquad (2) \\ y &= e + ra + b_p. \qquad (3) \end{aligned}$$

3.1.2 Production Sector

A representative firm hires labor and capital in perfectly competitive markets, and uses a standard CRS technology to produce a homogeneous consumption good. The capital share in the production technology is γ. The aggregate supply of labor is defined by Eq. 4 where N is the effective total hours supplied by workers, and K is the stock of capital demanded by the firm.

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

The aggregate supply of labor is the sum of effective supply of labor by households, which is given by:

$$N = \int_e \int_a \mu(e, a)\, \frac{e}{w}\, dade \tag{5}$$

with w being the market-clearing wage rate. This is slightly different from the standard approach in the literature. In the standard approach, households draw a random productivity shock z, and supply their effective hours zn in the labor market. Then each household's earnings is equal to $e = wzn$, which will be determined after solving for the equilibrium wage rate. Here, we directly calibrate an exogenous stochastic process for earnings (Mohaghegh (2020)), and solve for the equilibrium wage rate. The aggregate supply of labor can be computed from Eq. 5.

3.1.3 Government

The government levies progressive income taxes, $\tau(y)$, and pays a constant benefit, b_p, to households. The government budget in period t 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 and public transfers are defined as follows:

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

where tax schedule is such that the after-tax income is $D(y) = y - \tau(y) = \beta_1 y^{\beta_2}$.[21] Also, $\mu(e, a)$ is the steady state distribution of households in the economy.

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

The budget is balanced every period.

3.1.4 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.

[21] See Benabou (2002) and Violante et al. (2014) for more details.

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 earnings.

3.2 Calibration

3.2.1 Household Income

Each period, households draw an exogenous random variable which determines the labor portion of their income. This stochastic process, in effect, shapes households' precautionary saving motive. The standard approach in the literature uses data to identify idiosyncratic labor productivity shocks as the risky component of income. In this paper, we use a stochastic process that determines labor income altogether. This improves our ability to model risks as it allows us to calibrate a stochastic process outside of our model environment that matches several moments of the data.

For our quantitative exercises we translate households' income to a Markov process of order one as is common in the literature. Therefore, the stochastic income process of households consists of a vector of shock values (n parameters), and a transition probability matrix (n^2 parameters). Therefore, to fully identify households' income we need $n + n^2$ parameters.

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. We use a vector of order ten to model income shocks. We divide income data in each year in our panel in 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. In principle, the number of states can be larger or smaller than ten. However, if it is larger, then two problems appear. One, the problem of dimensionality leads to possible during numerical simulation of the model. Two, the number of parameters grow as n^2 where n is the number of states. Therefore, the number of average data points per parameter shrinks quadratically with respect to n, leading to non-robust estimate of the transition matrix for large n. In the opposite side, n could have been smaller as well. However, given that the model maps intervention into $1/n$-th fraction of the population, the magnitude of the intervention would be comparatively large for small n. For example, if $n = 4$, the intervention would cover a quartile of the population. However, in the present context, we are not modeling such a large-scale interventions for two reasons. One, empirical data indicates that the scope of interventions are typically smaller. Two, the main phenomena we want to model is the general equilibrium effects of targeted interventions. If the degree of intervention is wide-spread, it will lead to direct effect on the income and consumption behavior which will mask the general equilibrium effect. To summarize the discussion, $n = 10$ represents a useful case such that the model remains solvable and tractable, while it also captures the policy interventions such that general equilibrium effects are visible.

We construct the transition matrix in the following way. Let's consider a base year y_1 and a final year y_2. The matrix is constructed by estimating the decile–to–decile flow of agents given the interventions added to the empirical distributions in the years y_1 and y_2. All of our benchmark results are based on the transition matrix obtained from the years 2018 and 2019 with zero interventions:

$$\pi_{ee'} = \begin{bmatrix} 0.687358 & 0.175625 & 0.047691 & 0.029145 & 0.015897 & 0.014383 & 0.011355 & 0.009841 & 0.006056 & 0.00265 \\ 0.094247 & 0.40651 & 0.24754 & 0.1162 & 0.06813 & 0.03028 & 0.02271 & 0.005678 & 0.007192 & 0.001514 \\ 0.04807 & 0.18433 & 0.273278 & 0.200606 & 0.142695 & 0.079485 & 0.042771 & 0.017411 & 0.006813 & 0.004542 \\ 0.045042 & 0.093868 & 0.182438 & 0.228615 & 0.185844 & 0.13891 & 0.071158 & 0.03028 & 0.015519 & 0.008327 \\ 0.026874 & 0.050341 & 0.116957 & 0.191522 & 0.213853 & 0.179031 & 0.129826 & 0.059803 & 0.021196 & 0.010598 \\ 0.028388 & 0.038229 & 0.066238 & 0.107873 & 0.16654 & 0.219909 & 0.200606 & 0.131718 & 0.034822 & 0.005678 \\ 0.016654 & 0.025738 & 0.034822 & 0.066995 & 0.099546 & 0.174111 & 0.241484 & 0.21726 & 0.103331 & 0.020061 \\ 0.023089 & 0.014383 & 0.016276 & 0.039743 & 0.068887 & 0.095382 & 0.174868 & 0.289175 & 0.221045 & 0.057154 \\ 0.018925 & 0.007949 & 0.012491 & 0.014005 & 0.032173 & 0.054504 & 0.087434 & 0.183195 & 0.381908 & 0.207419 \\ 0.011394 & 0.003038 & 0.002279 & 0.005317 & 0.006457 & 0.014052 & 0.01785 & 0.05583 & 0.20281 & 0.680972 \end{bmatrix}. \tag{9}$$

Thus, the process will be fully identified upon determination of the values for ten states. To construct the vector with the values of the states, we simulate a large sample of households whose income evolves according to Eq. 9. We use the Generalized Method of Moments (GMM) to find shocks values that would replicate measures of income concentration in the data. In particular, we target shares of all quantiles as well as the Gini coefficient of the labor income distribution in the data. Table 3 reports respective moments in the data and the simulated sample. The resulting vector of income states is given by:

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

3.2.2 Structural Parameters

The only parameter to identify households' utility, σ, is determined in the calibration process. Following what is standard in the literature, capital share of income, γ, is equal to 0.21 while its depreciation is set to $\delta = 0.1$. A period in 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.[22] Public transfers, b_p are paid by the government whose only objective is to balance its budget every period. Therefore, government's policy variables can be determined using three moments in the Indian data. Table 4 reports parameter values in the benchmark economy.

4 Targeted Intervention and Quantitative Effect on Consumption Inequality

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

4.1 Targeted Intervention through Income Process

In this section we study the effects of targeted intervention policies implemented through changes in the income transition matrix, which in turn is an input to our model. We divide these policies in broadly two categories: income-based intervention and identity-based intervention. In both of these categories the income of the households are augmented by a predetermined amount. These interventions differ in terms of temporal permanence. Identity-based intervention identifies the eligible households in the starting period and extends the augmented income into the subsequent period of the study whereas the income-based intervention identifies eligible households in every period for augmenting their incomes. The identity-based intervention brings a sense of permanence in the income shock for the households. For example, a household in the first decile of the income distribution may move to the second decile in the subsequent period. If the eligibility criteria pertains to the first decile then this household would be subjected to an augmented income in both periods in case of the identity-based intervention. In case of income-based intervention, this household would be subjected to an augmented income in the first period only and not in the second period. The immediate pertinent query would be regarding the amount by which the households would perceive their income as augmented.

We refer to an article that reports doubling of income per household under a scheme run by the Indian government under the Mahatma Gandhi National Rural Employment

[22] See Benabou (2002) for more details.

Guarantee Act (MNREGA) to INR 1400 per month in 2019.[23] We assume that a potential household in our sample may augment their income by working under the scheme for at least 10 months. Therefore, we the eligible households for the intervention would perceive their income augmented annually by INR 14000 (around 185 US dollars). In the temporary-identification policy, eligible households identified in every period perceive an augmented income, based on an income-based intervention. In the permanent-identification policy, the eligible households receive an augmented income in the first and the subsequent period, based on an identity-based intervention. The increment of INR 14000 in case of all the policies is more than 50% of the mean annual income of the first decile in 2018 and 2019 as shown in table 11.

The permanent-identification policy is motivated by the design and practices followed in current and legacy conditional cash transfer programs administered in various nations.[24] In case of Oportunidades program in Mexico, beneficiary families remain in the program for three years without verification of their economic status (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 ration at subsidized prices. These were distributed on the basis of surveys conducted for a span of 5 years between 1992 and 2002 (Ramey (2011)). Although these cards have a validity for a household as long as they meet the criteria of issue, the span of the surveys grant an implicit validity of at least 5 years.

On similar lines, unlike the temporary-identification policy, the permanent-identification policy emphasizes on the continuity of benefits to the same household for an extended period. Table 5 shows the absolute figures of distribution of consumption, wealth and welfare for all the income groups of households obtained from the simulation. The benchmark model is characterized by no transfers exogenous or endogenous to the model. The calibrated parameters of the benchmark model have been used in simulations for all the policy experiments.

To summarize, we study the effects of four policy combinations as follows. *Policy* T_1: Temporary income shock targeted at the 1st decile in both the years. *Policy* P_1: Income shock targeted at the 1st decile in the base year and the same set of agents get the income

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

[24]In Mexico, the PROGRESA program began in 1997 and was renamed Oportunidades in 2001. Average monetary benefits received by beneficiary households in the starting years of the program were about USD 300 per year and have increased substantially over time (ref). In Brazil, the Bolsa Familia program started in 2003 with the merger of four existing conditional and unconditional cash transfer programs. As of march 2020, the program has reached 13.8 million families paying an average of USD 34 per month. This makes an average transfer of around USD 400 per annum or equivalent INR 29000 per annum (Source: https://www.npr.org/2020/08/31/906215778/coronavirus-hit-brazil-considers-major-public-funds-for-poor-and-unemployed).

shock in the next year as well irrespective of their incomes. *Policy* T_2 and *Policy* P_2 replicate the same interventions except that the the 2nd decile is targeted.

The following sections elaborate on the results further.

4.1.1 Consumption

As shown in table 7 consumption share of the first decile increases by 0.543% above the benchmark model in case of the permanent-identification policy. While in the temporary-identification policy, the increment of 0.056% is insignificant compared to the permanent-identification policy. These cash transfers are income shocks to the households. In case of the temporary-identification policy, by continuing the transfer for the same households increases the likelihood of these households to transition to higher living standards marked by higher consumption. The permanent-identification policy adds permanence to the income shocks, significantly easing the liquidity constraints which are usually caused by market imperfections. There are documented positive effects on consumption of conditional and unconditional cash transfers. From a randomized experiment conducted in Mexico on households enrolled in the Oportunidades program, Gertler et al. (2012) estimate that for every peso transferred, households consumed 74 cents and permanently increased long-term consumption by 1.6 cents, a growth of 2.16%. The consonance of our results with this study could be traced to the enrolment duration of the Oportunidades program, which is three years. This is apparent from the difference in results for the temporary-identification and the permanent-identification policy, which target the first decile or the second decile. This suggests that not just targeting but also continuing the benefits for an extended period of time also has significant general equilibrium impacts.

4.1.2 Wealth

In case of the permanent-identification policy that targets the first decile, wealth of households in the first decile in the model decreases by 15.346% over the benchmark, as shown in table 7. In case of the permanent-identification policy that targets the second decile, the share of wealth increases by 1.681%. Precautionary savings motive can explain the constrast in wealth share of the first decile under the policies that target the first and second decile. On a cautionary note about our results on wealth, the dataset does not have explicit information on wealth of the households for comparison. Larger marginal-propensity-to-consume (MPC) of poorer households can possibly explain the decrease in wealth of the targeted households in the first decile for the temporary-identification and permanent-identification policies.

4.1.3 Welfare

As shown in table 7, all policies are welfare-improving for the targeted group. For example, in the temporary-identification policy, welfare improves for the first decile by 0.031% and in permanent-identification it improves by 0.349% with respect to the benchmark model. This suggests that cash transfers in general have positive welfare-improving and re-distributive effects and targeted transfers made for an extended period of time for the targeted decile fares better.

4.2 Intervention Covering Expanding Base

In the previous section we report the results from simulations on two types of policies that differ in a sense of perceived permanence of benefits. We observe that under the permanent-identification policy, the targeted households increase their consumption share noticeably larger than that of the temporary-identification policy. Eligible households under the permanent-identification policy are assured of continuation of benefits in the subsequent period. In contrast, under the temporary-identification policy, eligible households in the first period are not certain about receiving benefits in the second period since some of these households may not be eligible in the second period because they would have moved to a higher income group. Also, there could be households which are not eligible in the first period may become poor in the second period and would be eligible for the program. Such households are effectively ignored in the permanent-identification policy.

In this section, we implement a policy on the lines of the permanent-identification policy such that eligible households in the first period continue to receive the benefits in the second period. Unlike the permanent-identification policy, the households which were not eligible in the first period but become eligible in the second period get the benefits in the second period. In order to implement such a policy, the fiscal burden increases in the second period as more households become eligible. In all the previous policies, the total benefits disbursed is same for every period, which is, per-capita annual transfer of INR 14000 times the number of eligible households. In case of the policy with an extended base of participants, the number of households in the second period increases. In order to maintain parity and comparability across all the policies, we have fixed the fiscal burden of the program for every period. Since the total amount of transfers is fixed and the number of participants increase in the second period, the amount of per-capita transfer decreases. For 2018-19, the per-capita transfer amount is around INR 10600 for permanent-identification policy with extended base targeting first decile in the second period with 3468 participants. While, in the first period, 2642 participants receive INR 14000. Also, these 2642 participants are a subset of the 3468 participants in the second period.

We label the policies as *Policy* EP_1 and *Policy* EP_2 indicating the expanded base. Simulation results are shown in table 8 and 9. Table 9 shows that consumption shares have increased by 0.409% from the benchmark shares in case of the permanent-identification policy with extended base targeting first decile and by 0.103% in case of policy targeting second decile. In comparison, for the permanent-identification policy with a fixed base targeting first decile, the change was 0.543% and for the policy targeting the second decile, 0.201% as shown in table 7. This noticeable rise in consumption share for the targeted group is present even in case of restricting the fiscal burden of the intervention in each period.

4.3 Lump-sum Transfers

In the preceding discussion, we have shown that households perceive an augmented income and its effects can be captured in the income transition matrix. By matching this income process from the data into our model, we find comparatively positive effects on relative levels of consumption 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 in our model as a free parameter to allow for balancing of the budget in every period. This simplification covers for the case when the government may run deficits for financing these transfers. In addition, the transfers are applicable to the whole continuum of households in the model. To avoid complications, no particular group of households is targeted in the model. Finally, the amount of public transfer as a model parameter is interpreted as a ratio to the corresponding simulated output.

Transfer parameter set to zero is the benchmark model for comparison. This benchmark is same as the one compared with different targeting policies in section 4.1. The parameters set for public transfers is increased incrementally and each of these values is interpreted in terms of percentage of the equilibrium output. These percentage values of transfers are comparable with data shown in figure 1. Figure 1 shows that, in 2018, the Indian government has rolled out transfers to the tune of 1.1% of GDP in cash and 0.6% of GDP in kind. If we ignore the absolute amounts involved and simply looked at the average percentage of transfers, the scandinavian nations have rolled out cash transfers of 15.25% and in-kind transfers of 16.75% 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 pertaining to 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 some of the successful transfer programs like Oportunidades in Mexico.

Table 12 shows a very consistent picture of consumption shares of households in each decile. First, for the poorer households which are grouped in the lower deciles there is a consistent increase in consumption. A similar trend appears for the higher deciles but there is a consistent decrease in consumption. This divide in direction of change in consumption from the benchmark appears from the 5th decile as shown in table 14. The change in consumption with respect 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 14 shows a significant decrease in wealth of the households in the first decile. The explanation can be found in the following.

It is well recognized in literature that liquidity constraints usually caused by market imperfections, may become one of the obstacles in consumption smoothing for certain groups of households.[25] Deaton and Paxson (1994) argue that in case of imperfect consumption insurance as found in 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 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 widely cited evidence for 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 labor income follows a random walk. Carroll et al. (1992), in their buffer-stock model also argue that impatient consumers subject to permanent and temporary shocks to their labor income, set their consumption close to their income. Similar arguments are applicable in 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 increase their consumption as their labor income is augmented by transfers. As transfers are increased, their consumption exceeds that of income which is seen in their negative wealth levels. They resort to borrowing to the limits. As shown in table 11, 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

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

the simulation as shown in table 12.

5 Robustness

5.1 Population and Income Dispersion

We have used a balanced panel for a sample of 26411 households in order to cover for some possible inconsistencies in the dataset as explained in section **??**. The panel contains responses from these 26411 households for a period between 2014 and 2019. These households were selected such that each of them have registered repsonses for atleast ten months every year between 2014 and 2019. If we focus on the households that have responded for all the months between 2018 and 2019, we have a larger sample. The number of such households increase to 62468. In this section, we study the results obtained from simulating our model based on the parameters described in section 3.2.2, with the income process extracted from a larger sample of households. Table 15 in the appendix shows that the larger dataset(62468 households) has a range of INR 3.9 million(around 52000 US dollars) in 2018. This is larger than the reproted figure for the smaller dataset(26411 households). In case of 2019, the ranges are same for both the datasets which could be explained by the fact that the households earning more than INR 3.4 million in 2018 are 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 16 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. The stochastic process that determines the labour income in the model is extracted from the data in the form of a transition matrix. Now, 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 in order to circumvent any systematic non-random component causing changes in incomes of these households. Second, we could take the 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.[26] This development has provided a basis for our analysis of identity-based and income-based intervention policies studied in section 4.1.

Table 15 shows the percentage increase(or decrease) in shares of consumption and wealth

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

for all the income groups. The reference for the shares of consumption and wealth is the benchmark model in which the transition matrix is extracted from the income of households reported without any augmentation due to any intervention policy. The policies are same as described in section 4.1.

The increase of 0.555% in consumption share for the targeted decile (the first decile) with the respect to the benchmark model in case of the permanent-identification policy, is close to 0.543% reported in case of the smaller sample (26411 households) as shown in table 7. Similarly, the decrease in wealth share of the targeted (first) decile in the permanent-identification policy is 15.416%, which is also comparatively close to the figure of 15.346% as reported for the case of smaller sample in table 7. Besides, comparing figure by figure in tables 15 and 7, the direction of changes are also similar. The general equilibrium state space also has a similar structure as shown in comparison of tables 6 and 16. This suggests that our model is agnostic of sample size and limited variations in income distribution.

5.2 Degree of Intervention

In this section, we study the behavior of the model when the transition matrices are extracted from the targeted interventions with varying amounts of increment in income. In section 4.1 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. Table 11 shows that a household in the first decile had a mean income of INR 29897 in 2018. On an average, a household in the first decile would be subjected an increment of around 50% of their income with an amount of INR 14000. In this section, we study the cases when the increments are around 25% and 100% of average income of a household in the first decile.

Tables 19 and 20 show the percentage increase (decrease) in shares of consumption and wealth from the benchmark model of no intervention. Table 19 shows comparisons for the temporary-identification policy and table 20 for the permanent-identification policy under various increment amounts in income. Under these policies, households in the first decile are targeted. As the increment amounts are increased, the consumption shares of the targeted households increase. Two observations in tables 19 and 20: (1) 0.0234% increase in the consumption share in case of an increment of 7000 under the temporary-identification policy, which is around 25% of the average income of an household belonging to the first decile and (2) 0.3057% increase in consumption share in case of an increment of 7000 under the permanent-identification policy suggest strongly that a certain level of performance (based on the permanent-identification policy's design) in the income shock brought about by the intervention has a significant impact on the consumption shares of the poorest decile. Even an increment of around 25% of the average income for a household in the first decile brings about an increase in consumption when the increment is extended to the next period for the same household, which is captured under the permanent-identification policy.

Two interesting observations in tables 19 and 20: (1) For the permanent-identification policy, increasing the amount from INR 14000 to INR 28000 leads to an effective increase in wealth share for the first decile suggested by a significant difference between -15.346% in case of INR 14000 and 22.435% in case of INR 28000; (2) For the temporary-identification policy, a similar noticeable difference between -4.005% and -11.474% [27] in case of INR 14000 and INR 28000 respectively; suggest that this could be attributed to a larger marginal propensity to consume (MPC) in case of poorer households.

6 Summary and Conclusion

There has been a growing interest in large-scale targeted economic interventions. Hence, it is important to pay attention to the general equilibrium effects of these large-scale programs. In this paper we set out to investigate the general equilibrium impact of large scale public conditional cash transfer programs. We study the impact on consumption, wealth and welfare in a heterogeneous agent incomplete markets setup.

These models have been extensively used in explaining observed distributions of income and wealth in developed economies (De Nardi (2015)). Although these models have focused to match the right tail of the income distributions due to ready availability of data from tax records, our application focuses on the left-tail of the distribution. We take advantage of a novel data set that includes a sample of households that could be target candidates for such large-scale public transfer programs. We follow a novel approach in calibrating our model with the labor income data. We translate the household's income from data into a Markov process in the form of an income transition matrix. This is used as a stochastic process that determines labor income in our model. This stochastic process shapes household's precautionary savings motive. To study the impact of cash transfers we follow two channels; (1) by allocating transfer amounts to the target group in the data and formulate the income transition matrix after allocation; (2) by variations in the transfer parameter in the model. The first channel is exogenous to the model and the transfers are targeted and the second is endogenous to the model with lump-sum transfers without targeting.

[27] Note: Negative percentage values mean a decrease in consumption/wealth share for a particular decile. This doesnot mean that the consumption share itself is negative, which is absurd or the wealth share is negative suggesting that the households in the decile resort to borrowing.

We observe a rise in consumption for the targeted households through both the channels. In addition, we observe spillover rise in consumption in households adjacent to the targeted group. This could be explained from the perspective of risk-sharing within the community. Table 2 indicates the proximity of mean incomes of the households in various deciles. We also observe that targeting the poorest group has relatively best of results in terms of increase in consumption and welfare. Finally, the reduction in wealth for the poorest households indicates that the group resorts to borrowing to cover for the rise in consumption. This indicates that the poorest group is most sensitive to the income shock from the transfer and this is validated by the second channel.

Our attempt in this paper has room for several directions of further research. One question pertains to the financing of these transfers. In our model, we have kept the government expenditure as free parameter such that government's budget is always balanced. In reality, government may run deficits to finance such transfer programs which may have counter-productive longer-term effects. Second, transfers could also be studied in the light of tax rebates to certain income groups or age groups. We hope future research will address such questions.

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Appendix: 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

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

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

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 provision of certain goods and services (for example, health–care and education). Transfers that are 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 case of unexpected events such as health issues, unemployment, housing or education. All the indicators are measured in percentage of GDP.

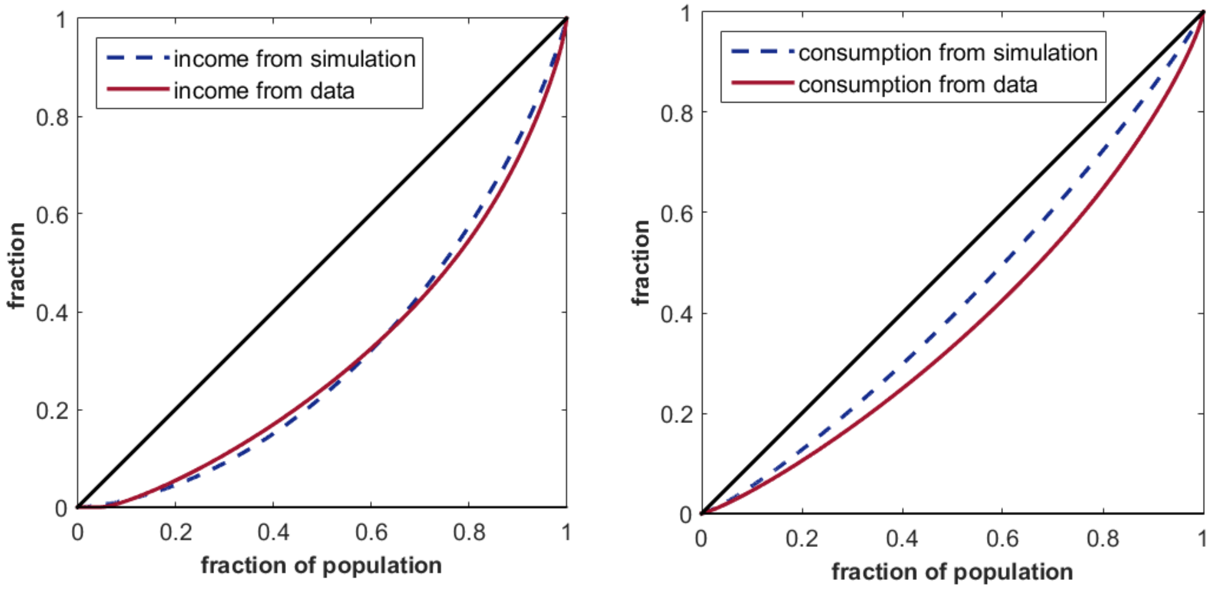

Figure 2: Plots of Lorenz curves from data and simulation using the parameters given table 4. Panel (a): Income. Panel (b): Consumption.

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.

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

Table 2: Income and expenditure share of households in the data grouped in order of income.

	Deciles										
	1st	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**	**Gini**
2018											
Income	1.3%	4.2%	5.3%	6.2%	7.2%	8.3%	9.9%	12.3%	16.6%	28.8%	0.39
Expenditure	7.3%	6.5%	7.4%	8.1%	8.8%	9.5%	10.5%	11.3%	13.0%	17.5%	0.24
2019											
Income	1.1%	4.3%	5.4%	6.4%	7.3%	8.4%	10.0%	12.3%	16.6%	28.2%	0.38
Expenditure	7.4%	6.6%	7.5%	8.0%	8.8%	9.6%	10.5%	11.4%	13.1%	17.1%	0.23

Table 3: Share of Income groups in the Data and the Approximated Stochastic Process. All values are in percentage

	Deciles	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**	**Gini**
Income	Data(2018)	1.28	4.17	5.26	6.20	7.19	8.34	9.89	12.26	16.65	28.76	0.39
	Data(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	Data(2018)	7.29	6.48	7.38	8.12	8.81	9.55	10.50	11.33	12.99	17.55	0.24
	Data(2019)	7.44	6.59	7.46	8.04	8.76	9.57	10.54	11.36	13.10	17.14	0.23
	Simulation	5.48	7.25	8.15	8.90	9.59	10.28	10.98	11.78	12.79	14.80	0.15

Table 4: Parameter Values

Parameter	Description	Value
β	time discount factor	0.98
σ	elasticity of substitution	1.50
δ	capital depreciation rate	0.06
γ	capital share of output	0.4
β_1	income tax function parameter	1.081
β_2	income tax function parameter	0.845
b_p	public transfer (baseline model)	0.0

Table 5: Decile-wise shares of consumption, wealth and welfare under various policies. The models are calibrated to 2018-19 data as per section 3.2. Temporary-identification policy targeting first decile (Policy T_1): Eligible 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 per household. Permanent-identification policy targeting first decile (Policy P_1): Eligible households are subjected to an increment in annual income of INR 14000 (around 185 US dollars) per household for both periods. Temporary-identification policy targeting second decile (Policy T_2): Similar to Policy T_1, households in the second decile are targeted. Permanent-identification policy targeting the second decile (Policy P_2): Similar to Policy P_1, households in the second decile are targeted.

Consumption										
decile	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Benchmark model	5.4815	7.2490	8.1481	8.8991	9.5939	10.2755	10.9838	11.7803	12.7931	14.7958
Policy T_1	5.4845	7.2466	8.1471	8.8989	9.5939	10.2764	10.9843	11.7809	12.7930	14.7943
Policy P_1	5.5112	7.2437	8.1441	8.8959	9.5908	10.2744	10.9813	11.7783	12.7886	14.7917
Policy T_2	5.4878	7.2506	8.1490	8.8993	9.5938	10.2751	10.9830	11.7791	12.7910	14.7913
Policy P_2	5.5170	7.2636	8.1533	8.8993	9.5914	10.2700	10.9764	11.7708	12.7801	14.7781
Wealth										
decile	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Benchmark model	0.2604	1.9725	3.5990	5.3205	7.1839	9.2478	11.6277	14.5537	18.6212	27.6133
Policy T_1	0.2500	1.9524	3.5782	5.3017	7.1711	9.2417	11.6274	14.5655	18.6466	27.6653
Policy P_1	0.2205	1.8941	3.5125	5.2401	7.1204	9.2104	11.6204	14.5926	18.7241	27.8650
Policy T_2	0.2607	1.9713	3.5969	5.3180	7.1821	9.2470	11.6268	14.5555	18.6240	27.6176
Policy P_2	0.2648	1.9780	3.5993	5.3153	7.1765	9.2401	11.6194	14.5475	18.6245	27.6346
Welfare										
decile	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Benchmark model	-0.1086	-0.0923	-0.0868	-0.0830	-0.0803	-0.0771	-0.0752	-0.0721	-0.0697	-0.0646
Policy T_1	-0.1086	-0.0923	-0.0868	-0.0830	-0.0802	-0.0774	-0.0750	-0.0723	-0.0695	-0.0647
Policy P_1	-0.1082	-0.0923	-0.0870	-0.0831	-0.0801	-0.0775	-0.0751	-0.0724	-0.0691	-0.0651
Policy T_2	-0.1087	-0.0919	-0.0870	-0.0833	-0.0801	-0.0776	-0.0746	-0.0724	-0.0694	-0.0648
Policy P_2	-0.1085	-0.0921	-0.0869	-0.0829	-0.0801	-0.0776	-0.0748	-0.0725	-0.0695	-0.0647

Table 6: Equilibrium results under various policies. The models are calibrated to 2018-19 data as per section 3.2. Temporary-identification policy targeting first decile (Policy T_1): Eligible 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 per household. Permanent-identification policy targeting first decile (Policy P_1): Eligible households are subjected to an increment in annual income of INR 14000 (around 185 US dollars) per household for both periods. Temporary-identification policy targeting second decile (Policy T_2): Similar to Policy T_1, households in the second decile are targeted. Permanent-identification policy targeting the second decile (Policy P_2): Similar to Policy P_1, households in the second decile are targeted.

Economy	**r**	**w**	**Labour**	**Capital**	**GDP**	**Gini**	
						(Wealth)	**(Consumption)**
Benchmark model	0.0207	1.7446	4.19	57.88	11.98	0.4451	0.1501
Policy T_1	0.0207	1.7446	4.19	57.59	11.96	0.4462	0.1500
Policy P_1	0.0207	1.7446	4.19	56.80	11.89	0.4499	0.1498
Policy T_2	0.0207	1.7446	4.19	57.73	11.97	0.4451	0.1499
Policy P_2	0.0207	1.7446	4.19	57.47	11.95	0.4452	0.1493

r - Equilibrium interest rate
w - Equilibrium wage rate

Table 7: Decile-wise percentage increase (decrease) under various policies with respect to benchmark model. The models are calibrated to 2018-19 data as per section 3.2. Temporary-identification policy targeting first decile (Policy T_1): Eligible 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 per household. Permanent-identification policy targeting first decile (Policy P_1): Eligible households are subjected to an increment in annual income of INR 14000 (around 185 US dollars) per household for both periods. Temporary-identification policy targeting second decile (Policy T_2): Similar to Policy T_1, households in the second decile are targeted. Permanent-identification policy targeting the second decile (Policy P_2): Similar to Policy P_1, households in the second decile are targeted.

Consumption										
decile	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Policy T_1	0.056%	-0.033%	-0.012%	-0.002%	0.001%	0.009%	0.005%	0.005%	-0.001%	-0.010%
Policy P_1	0.543%	-0.073%	-0.050%	-0.035%	-0.032%	-0.010%	-0.023%	-0.017%	-0.036%	-0.028%
Policy T_2	0.116%	0.022%	0.011%	0.002%	0.000%	-0.003%	-0.007%	-0.010%	-0.017%	-0.031%
Policy P_2	0.649%	0.201%	0.063%	0.003%	-0.025%	-0.053%	-0.068%	-0.080%	-0.102%	-0.120%
Wealth										
decile	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Policy T_1	-4.005%	-1.018%	-0.576%	-0.354%	-0.179%	-0.066%	-0.002%	0.081%	0.136%	0.188%
Policy P_1	-15.346%	-3.978%	-2.401%	-1.511%	-0.885%	-0.405%	-0.062%	0.267%	0.552%	0.912%
Policy T_2	0.121%	-0.060%	-0.057%	-0.047%	-0.026%	-0.009%	-0.007%	0.012%	0.015%	0.016%
Policy P_2	1.681%	0.279%	0.009%	-0.098%	-0.104%	-0.083%	-0.071%	-0.043%	0.018%	0.077%
Welfare										
decile	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Policy T_1	0.031%	-0.002%	0.048%	-0.025%	0.123%	-0.430%	0.161%	-0.339%	0.261%	-0.112%
Policy P_1	0.349%	0.004%	-0.244%	-0.092%	0.154%	-0.622%	0.064%	-0.459%	0.863%	-0.790%
Policy T_2	-0.041%	0.440%	-0.168%	-0.389%	0.249%	-0.660%	0.674%	-0.374%	0.312%	-0.239%
Policy P_2	0.146%	0.223%	-0.137%	0.090%	0.224%	-0.746%	0.459%	-0.616%	0.203%	-0.134%

Table 8: Decile-wise shares of consumption, wealth and welfare under policies EP_1 and EP_2 with respect to the benchmark model. The models are calibrated to 2018-19 data (section 3.2). Permanent-identification policy with extended base targeting first decile (Policy EP_1): Eligible households in each period are targeted. Eligible 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 eligible 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 EP_2 is similar to Policy EP_1 except that the second decile is targeted.

Consumption										
decile	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Benchmark model	5.4815	7.2490	8.1481	8.8991	9.5939	10.2755	10.9838	11.7803	12.7931	14.7958
Policy EP_1	5.5039	7.2456	8.1460	8.8971	9.5918	10.2747	10.9819	11.7786	12.7892	14.7913
Policy EP_2	5.5008	7.2565	8.1515	8.8998	9.5931	10.2731	10.9801	11.7752	12.7855	14.7845
Wealth										
decile	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Benchmark model	0.2604	1.9725	3.5990	5.3205	7.1839	9.2478	11.6277	14.5537	18.6212	27.6133
Policy EP_1	0.2351	1.9199	3.5400	5.2651	7.1409	9.2216	11.6230	14.5791	18.6917	27.7835
Policy EP_2	0.2638	1.9727	3.5953	5.3137	7.1770	9.2421	11.6221	14.5521	18.6278	27.6335
Welfare										
decile	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Benchmark model	-0.1086	-0.0923	-0.0868	-0.0830	-0.0803	-0.0771	-0.0752	-0.0721	-0.0697	-0.0646
Policy EP_1	-0.1084	-0.0922	-0.0869	-0.0833	-0.0800	-0.0776	-0.0748	-0.0724	-0.0695	-0.0647
Policy EP_2	-0.1086	-0.0920	-0.0871	-0.0831	-0.0802	-0.0771	-0.0751	-0.0724	-0.0694	-0.0647

Table 9: Decile-wise percentage increase (decrease) under policies EP_1 and EP_2 with respect to the benchmark model. The models are calibrated to 2018-19 data (section 3.2). Permanent-identification policy with extended base targeting first decile (Policy EP_1): Eligible households in each period are targeted. Eligible 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 eligible 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 EP_2 is similar to Policy EP_1 except that the second decile is targeted.

Consumption										
decile	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Policy EP_1	0.409%	-0.048%	-0.026%	-0.022%	-0.021%	-0.008%	-0.017%	-0.014%	-0.031%	-0.031%
Policy EP_2	0.352%	0.103%	0.042%	0.008%	-0.008%	-0.023%	-0.034%	-0.043%	-0.059%	-0.076%
Wealth										
decile	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Policy EP_1	-9.725%	-2.669%	-1.638%	-1.041%	-0.598%	-0.283%	-0.040%	0.175%	0.378%	0.617%
Policy EP_2	1.298%	0.010%	-0.103%	-0.128%	-0.096%	-0.062%	-0.048%	-0.011%	0.035%	0.073%
Welfare										
decile	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Policy EP_1	0.211%	0.103%	-0.097%	-0.425%	0.313%	-0.719%	0.486%	-0.474%	0.213%	-0.149%
Policy EP_2	0.020%	0.375%	-0.327%	-0.125%	0.129%	-0.037%	0.090%	-0.499%	0.327%	-0.176%

Appendix: Additional Tables

Table 10: 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. Decile-wise classification of households is done on the basis of their annual income.

										Deciles										
	N	**Mean**	**SD**	**Median**	**Min**	**Max**	**Range**	**Skew**	**Kurtosis**	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**	**Gini**
2014																				
Income	26411	162502	140103	120320	0	2536000	2536000	3.43	22.76	2.1%	4.1%	5.1%	6.0%	6.9%	8.1%	9.7%	12.1%	16.3%	29.7%	0.39
Expenditure	26411	104103	48866	93838	19202	1192033	1172831	3.46	37.84	7.0%	6.8%	7.7%	8.4%	8.9%	9.5%	10.3%	11.4%	13.0%	17.1%	0.23
2015																				
Income	26411	159551	125053	123600	0	2715000	2715000	3.20	23.16	2.1%	4.6%	5.6%	6.4%	7.2%	8.4%	9.9%	12.1%	16.0%	27.9%	0.36
Expenditure	26411	113420	48771	103260	12608	1047883	1035275	3.11	25.69	7.7%	7.2%	7.9%	8.5%	9.1%	9.5%	10.3%	11.2%	12.6%	16.1%	0.21
2016																				
Income	26411	165534	125520	131000	0	2072000	2072000	2.83	15.46	2.1%	4.7%	5.6%	6.5%	7.4%	8.5%	10.0%	12.1%	15.8%	27.4%	0.36
Expenditure	26411	120077	55551	108382	16476	986477	970001	3.08	22.55	7.6%	7.0%	7.7%	8.4%	8.9%	9.6%	10.3%	11.2%	12.8%	16.5%	0.22
2017																				
Income	26411	194383	154757	154000	0	2151040	2151040	3.01	17.86	1.5%	4.5%	5.5%	6.4%	7.4%	8.5%	10.0%	12.1%	16.0%	28.1%	0.37
Expenditure	26411	133164	62262	121019	18933	1014750	995817	2.59	15.65	7.3%	6.6%	7.6%	8.3%	9.0%	9.8%	10.5%	11.3%	12.8%	16.7%	0.23
2018																				
Income	26411	233318	192830	180000	0	3338600	3338600	2.93	17.33	1.3%	4.2%	5.3%	6.2%	7.2%	8.3%	9.9%	12.3%	16.6%	28.8%	0.39
Expenditure	26411	156200	77113	137795	25217	1294713	1269496	2.47	13.55	7.3%	6.5%	7.4%	8.1%	8.8%	9.5%	10.5%	11.3%	13.0%	17.5%	0.24
2019																				
Income	26411	242987	194067	189240	0	3483600	3483600	2.58	13.49	1.1%	4.3%	5.4%	6.4%	7.3%	8.4%	10.0%	12.3%	16.6%	28.2%	0.38
Expenditure	26411	160142	71918	142304	14415	1281792	1267377	2.01	9.06	7.4%	6.6%	7.5%	8.0%	8.8%	9.6%	10.5%	11.4%	13.1%	17.1%	0.23

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. Mean and standard deviation (SD) of household-level income and expenditure within each decile of income group are provided for years from 2014 till 2019. Decile-wise classification of households is done on the basis of their annual income.

			Income		Expenditure					Income		Expenditure	
	Size	Decile	Mean	SD	Mean	SD		Size	Decile	Mean	SD	Mean	SD
2014							**2017**						
	2642	1	33773	22884	73179	37869		2642	1	28517	28300	97662	52871
	2642	2	67370	4577	70265	23132		2642	2	86845	7281	88258	27843
	2642	3	82852	4228	79700	20528		2642	3	107079	5248	100784	28952
	2642	4	96729	3913	87047	29678		2642	4	125301	5293	110710	30057
	2642	5	111703	4950	92328	23620		2642	5	144131	5528	120014	33017
	2642	6	131356	6580	99039	27133		2642	6	165724	7026	129957	34702
	2642	7	157726	9333	107549	28244		2642	7	193522	9510	139818	39678
	2642	8	196301	14121	118122	38537		2642	8	234988	14979	150730	45648
	2642	9	264825	27138	135776	42251		2642	9	311485	32282	170750	56861
	2633	10	483475	201370	178274	73577		2633	10	547439	206934	223260	97091
2015							**2018**						
	2642	1	33120	24917	86861	40149		2642	1	29897	31301	113843	65313
	2642	2	72788	5199	81512	22783		2642	2	97306	8400	101232	40242
	2642	3	88713	4087	89823	22031		2642	3	122574	6682	115191	30456
	2642	4	101615	3549	96307	22285		2642	4	144647	6310	126856	38653
	2642	5	115512	4505	102755	29031		2642	5	167676	7045	137548	35627
	2642	6	133679	6111	108261	28497		2642	6	194636	8688	149111	44379
	2642	7	157609	8220	116422	35235		2642	7	230635	12628	163989	49466
	2642	8	192429	12136	126557	44279		2642	8	286015	20412	176934	56068
	2642	9	254745	25357	142669	41945		2642	9	388237	39882	202764	72060
	2633	10	446273	168125	183268	73890		2633	10	673053	251407	274935	112714
2016							**2019**						
	2642	1	34009	26537	91396	44580		2642	1	26359	31757	119140	60036
	2642	2	77772	5205	83578	25419		2642	2	104873	9873	105538	30030
	2642	3	93326	3978	92792	26628		2642	3	132253	6798	119401	29849
	2642	4	107057	4211	100321	25794		2642	4	154551	6357	128644	29702
	2642	5	122217	4788	107262	28339		2642	5	176819	6877	140243	37184
	2642	6	141275	6242	115360	32901		2642	6	205056	9388	153153	38093
	2642	7	165314	7956	123174	36595		2642	7	241792	12399	168702	44987
	2642	8	199660	12496	134755	44023		2642	8	298258	20950	181870	51414
	2642	9	261321	25256	153385	54342		2642	9	402937	43760	209788	62322
	2633	10	454370	162260	199014	87960		2633	10	688489	233477	275329	100449

Table 12: Decile-wise shares of consumption, wealth and welfare under variations in the transfer parameter. The model is calibrated to 2018-19 data as per section 3.2. The benchmark model described in sections 4.1 and 4.3 has the transfer parameter set to zero. The transfer parameter is shown as % of output. To put a perspective on the magnitude of the transfer parameter in the model, Indian government had allocated 1.1% of GDP as in-cash transfers in 2018, as shown in figure 1. As a counterfactual, Mexico's 2.7% transfer which includes the Oportunidades program and Brazil's 17.5% which includes the Bolsa Familia program can be considered.

Consumption											
Transfer	**(% of Output)**	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
0	0%	5.481	7.249	8.148	8.899	9.594	10.275	10.984	11.780	12.793	14.796
0.08	**0.6%**	5.552	7.277	8.166	8.906	9.592	10.261	10.956	11.743	12.761	14.784
0.1	0.8%	5.559	7.282	8.170	8.909	9.593	10.260	10.955	11.741	12.756	14.776
0.2	1.6%	5.594	7.308	8.187	8.921	9.599	10.260	10.950	11.727	12.728	14.727
0.5	4.1%	5.698	7.381	8.236	8.951	9.613	10.260	10.931	11.687	12.656	14.588
1	8.2%	5.893	7.498	8.312	8.995	9.625	10.240	10.880	11.603	12.537	14.417
1.5	12.0%	6.072	7.599	8.378	9.032	9.631	10.217	10.829	11.527	12.435	14.279
2	17.1%	6.255	7.755	8.496	9.111	9.681	10.239	10.813	11.457	12.280	13.914
Wealth											
Transfer	**(% of Output)**	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
0	0%	0.260	1.973	3.599	5.320	7.184	9.248	11.628	14.554	18.621	27.613
0.08	**0.6%**	0.336	2.066	3.709	5.429	7.273	9.302	11.634	14.498	18.470	27.283
0.1	0.8%	0.322	2.049	3.693	5.416	7.262	9.297	11.635	14.507	18.488	27.330
0.2	1.6%	0.256	1.968	3.615	5.350	7.215	9.273	11.639	14.550	18.586	27.546
0.5	4.1%	0.073	1.740	3.394	5.157	7.071	9.195	11.645	14.663	18.866	28.196
1	8.2%	-0.029	1.599	3.269	5.061	7.004	9.160	11.649	14.720	19.001	28.566
1.5	12.0%	-0.071	1.529	3.212	5.018	6.974	9.141	11.642	14.734	19.061	28.760
2	17.1%	-0.343	1.207	2.900	4.767	6.814	9.095	11.732	14.979	19.487	29.362
Welfare											
Transfer	**(% of Output)**	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
0	0%	-0.109	-0.092	-0.087	-0.083	-0.080	-0.077	-0.075	-0.072	-0.070	-0.065
0.08	**0.6%**	-0.106	-0.091	-0.086	-0.082	-0.079	-0.076	-0.074	-0.071	-0.068	-0.064
0.1	0.8%	-0.106	-0.090	-0.086	-0.082	-0.079	-0.077	-0.073	-0.072	-0.069	-0.064
0.2	1.6%	-0.105	-0.090	-0.085	-0.082	-0.079	-0.076	-0.074	-0.071	-0.068	-0.064
0.5	4.1%	-0.103	-0.089	-0.084	-0.081	-0.078	-0.075	-0.073	-0.070	-0.068	-0.063
1	8.2%	-0.098	-0.085	-0.081	-0.078	-0.075	-0.073	-0.071	-0.069	-0.066	-0.062
1.5	12.0%	-0.094	-0.083	-0.079	-0.076	-0.073	-0.071	-0.069	-0.067	-0.065	-0.060
2	17.1%	-0.092	-0.081	-0.078	-0.075	-0.073	-0.071	-0.069	-0.067	-0.064	-0.061

Table 13: Equilibrium results under variations in the transfer parameter. The model is calibrated to 2018-19 data as per section 3.2. The benchmark model described in sections 4.1 and 4.3 has the transfer parameter set to zero. The transfer parameter is shown as % of output. To put a perspective on the magnitude of the transfer parameter in the model, Indian government had allocated 1.1% of GDP as in-cash transfers in 2018, as shown in figure 1. As a counterfactual, Mexico's 2.7% transfer which includes the Oportunidades program and Brazil's 17.5% which includes the Bolsa Familia program can be considered.

Transfer	**(% of Output)**	**r**	**w**	**Labour**	**Capital**	**GDP**	**Gini**	
							(Wealth)	**(Consumption)**
0	0%	0.0207	1.745	4.19	57.88	11.98	0.45	0.15
0.08	**0.6%**	0.0220	1.726	4.24	63.30	12.50	0.44	0.15
0.1	0.8%	0.0220	1.726	4.24	63.04	12.48	0.44	0.15
0.2	1.6%	0.0220	1.726	4.24	61.68	12.37	0.44	0.15
0.5	4.1%	0.0220	1.726	4.24	57.91	12.06	0.46	0.14
1	8.2%	0.0233	1.707	4.28	59.32	12.26	0.47	0.14
1.5	12.0%	0.0246	1.690	4.33	61.97	12.55	0.47	0.13
2	17.1%	0.0246	1.690	4.33	51.76	11.68	0.49	0.12

r - Equilibrium interest rate
w - Equilibrium wage rate

Table 14: Decile-wise percentage increase (decrease) under variation of the transfer parameter with respect to benchmark model. The model is calibrated to 2018-19 data as per section 3.2. The benchmark model described in sections 4.1 and 4.3 has the transfer parameter set to zero. The transfer parameter is shown as % of output. To put a perspective on the magnitude of the transfer parameter in the model, Indian government had allocated 1.1% of GDP as in-cash transfers in 2018, as shown in figure 1. As a counterfactual, Mexico's 2.7% transfer which includes the Oportunidades program and Brazil's 17.5% which includes the Bolsa Familia program can be considered.

Consumption											
Transfer	**perc**	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
0.08	**0.6%**	1.29%	0.38%	0.22%	0.08%	-0.02%	-0.14%	-0.25%	-0.31%	-0.25%	-0.08%
0.1	0.8%	1.41%	0.45%	0.26%	0.11%	-0.01%	-0.15%	-0.26%	-0.34%	-0.29%	-0.14%
0.2	1.6%	2.05%	0.81%	0.48%	0.24%	0.05%	-0.15%	-0.31%	-0.45%	-0.51%	-0.47%
0.5	4.1%	3.95%	1.82%	1.08%	0.58%	0.19%	-0.15%	-0.48%	-0.79%	-1.07%	-1.41%
1	8.2%	7.51%	3.43%	2.01%	1.08%	0.32%	-0.34%	-0.94%	-1.51%	-2.00%	-2.56%
1.5	12.0%	10.77%	4.83%	2.82%	1.49%	0.39%	-0.57%	-1.41%	-2.15%	-2.80%	-3.49%
2	17.1%	14.11%	6.98%	4.27%	2.38%	0.91%	-0.36%	-1.56%	-2.74%	-4.01%	-5.96%
Wealth											
Transfer	**perc**	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
0.08	**0.6%**	28.91%	4.76%	3.07%	2.05%	1.23%	0.58%	0.05%	-0.38%	-0.81%	-1.20%
0.1	0.8%	23.68%	3.90%	2.61%	1.80%	1.09%	0.53%	0.07%	-0.32%	-0.71%	-1.02%
0.2	1.6%	-1.64%	-0.21%	0.45%	0.56%	0.44%	0.27%	0.10%	-0.03%	-0.19%	-0.24%
0.5	4.1%	-72.03%	-11.79%	-5.71%	-3.07%	-1.57%	-0.57%	0.15%	0.75%	1.31%	2.11%
1	8.2%	-110.96%	-18.94%	-9.17%	-4.88%	-2.50%	-0.95%	0.18%	1.14%	2.04%	3.45%
1.5	12.0%	-127.42%	-22.48%	-10.76%	-5.68%	-2.93%	-1.16%	0.13%	1.24%	2.36%	4.15%
2	17.1%	-231.60%	-38.82%	-19.42%	-10.41%	-5.16%	-1.65%	0.90%	2.92%	4.65%	6.33%
Welfare											
Transfer	**perc**	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
0.08	**0.6%**	2.36%	1.48%	1.40%	1.30%	1.84%	0.84%	1.33%	0.95%	2.02%	0.91%
0.1	0.8%	2.37%	2.03%	1.14%	1.59%	1.74%	0.65%	2.25%	0.76%	1.38%	1.37%
0.2	1.6%	3.00%	2.58%	1.99%	1.74%	1.85%	1.49%	1.88%	1.28%	2.36%	1.05%
0.5	4.1%	5.17%	3.99%	3.19%	2.94%	3.32%	2.65%	2.57%	2.53%	2.55%	2.09%
1	8.2%	9.68%	7.43%	6.56%	5.88%	6.18%	5.01%	5.29%	4.93%	5.11%	3.92%
1.5	12.0%	13.79%	10.59%	9.55%	8.40%	8.70%	7.53%	7.93%	7.41%	6.90%	6.41%
2	17.1%	15.67%	11.98%	10.64%	9.93%	9.51%	7.93%	8.64%	6.99%	7.69%	5.54%

Table 15: 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.

	N	**Mean**	**SD**	**Median**	**Min**	**Max**	**Skew**	**Kurtosis**
2018								
Income	62468	239397	203895	183200	0	3975000	3.2	20.9
Expenditure	62468	155232	76940	136462	15182	1447300	2.5	14.7
2019								
Income	62468	250881	205315	193975	0	3483600	2.9	16.0
Expenditure	62468	161299	73687	143040	14415	1281792	2.1	10.1

Table 16: Income and expenditure share of households in the data grouped in order of income.

	Deciles										
	1st	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**	**gini**
2018											
Income	1.38%	4.15%	5.20%	6.15%	7.13%	8.28%	9.85%	12.18%	16.37%	29.32%	39.30%
Expenditure	7.12%	6.46%	7.44%	8.12%	8.75%	9.47%	10.31%	11.20%	13.03%	18.10%	24.42%
2019											
Income	1.22%	4.34%	5.40%	6.28%	7.20%	8.36%	9.88%	12.24%	16.44%	28.63%	38.59%
Expenditure	7.15%	6.64%	7.45%	8.08%	8.70%	9.47%	10.41%	11.25%	13.07%	17.78%	23.03%

Table 17: Robustness check: Decile-wise percentage increase (decrease) under various policies with respect to benchmark model based on a larger sample of households (62468 in number) as per section 5.1. The models are calibrated as per section 3.2. Temporary-identification policy targeting first decile (Policy T_1): Eligible 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 per household. Permanent-identification policy targeting first decile (Policy P_1): Eligible households are subjected to an increment in annual income of INR 14000 (around 185 US dollars) per household for both periods. Temporary-identification policy targeting second decile (Policy T_2): Similar to Policy T_1, households in the second decile are targeted. Permanent-identification policy targeting the second decile (Policy P_2): Similar to Policy P_1, households in the second decile are targeted.

Consumption										
decile	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Policy T_1	0.000%	-0.047%	-0.019%	-0.006%	-0.003%	0.007%	0.005%	0.010%	0.008%	0.015%
Policy P_1	0.555%	-0.022%	-0.023%	-0.020%	-0.024%	-0.012%	-0.033%	-0.031%	-0.054%	-0.051%
Policy T_2	0.124%	0.005%	0.000%	-0.008%	-0.007%	-0.009%	-0.009%	-0.009%	-0.011%	-0.009%
Policy P_2	0.704%	0.208%	0.064%	-0.001%	-0.027%	-0.057%	-0.073%	-0.084%	-0.109%	-0.124%
Wealth										
decile	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Policy T_1	-5.153%	-1.248%	-0.686%	-0.412%	-0.213%	-0.084%	-0.005%	0.088%	0.152%	0.243%
Policy P_1	-15.416%	-3.963%	-2.365%	-1.477%	-0.860%	-0.382%	-0.059%	0.263%	0.539%	0.896%
Policy T_2	-0.414%	-0.229%	-0.178%	-0.132%	-0.085%	-0.046%	-0.024%	0.013%	0.039%	0.084%
Policy P_2	2.074%	0.250%	-0.051%	-0.154%	-0.145%	-0.108%	-0.093%	-0.042%	0.028%	0.115%
Welfare										
decile	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Policy T_1	0.219%	-0.117%	-0.068%	0.185%	-0.625%	0.105%	0.442%	-0.540%	-0.150%	0.383%
Policy P_1	0.425%	-0.079%	-0.075%	-0.165%	-0.244%	-0.129%	-0.094%	-0.288%	-0.572%	0.489%
Policy T_2	0.088%	-0.203%	0.316%	-0.022%	-0.650%	0.178%	0.484%	-0.055%	-0.398%	0.227%
Policy P_2	0.314%	-0.088%	-0.084%	0.366%	-0.539%	0.133%	-0.100%	-0.270%	-0.500%	0.509%

Table 18: Robustness check: Equilibrium results under various policies based on a larger sample of households (62468 in number) as per section 5.1. The models are calibrated to 2018-19 as per section 3.2. Temporary-identification policy targeting first decile (Policy T_1): Eligible 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 per household. Permanent-identification policy targeting first decile (Policy P_1): Eligible households are subjected to an increment in annual income of INR 14000 (around 185 US dollars) per household for both periods. Temporary-identification policy targeting second decile (Policy T_2): Similar to Policy T_1, households in the second decile are targeted. Permanent-identification policy targeting the second decile (Policy P_2): Similar to Policy P_1, households in the second decile are targeted.

Economy	**r**	**w**	**Labour**	**Capital**	**GDP**	**Gini (Wealth)**	**Gini (Consumption)**
Benchmark model	0.0207	1.7446	4.19	57.98	11.99	0.4453	0.1505
Policy T_1	0.0207	1.7446	4.19	57.76	11.98	0.4466	0.1505
Policy P_1	0.0207	1.7446	4.19	56.87	11.90	0.4500	0.1501
Policy T_2	0.0207	1.7446	4.19	57.87	11.98	0.4456	0.1504
Policy P_2	0.0207	1.7446	4.19	57.52	11.96	0.4455	0.1497

r - Equilibrium interest rate
w - Equilibrium wage rate

Table 19: Robustness check: Decile-wise percentage increase (decrease) under the temporary-identification policy with respect to benchmark model based on a larger sample of households (62468 in number) as per section 5.2. The models are calibrated as per section 3.2. The households in the first decile are targeted. In this intervention, the targeted households are subjected to an increment in income in each period and they need not be the same set of households for each period. The per-capita amounts (in INR) of transfer in the intervention are compared.

Consumption										
Amount	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
7000	0.0234%	-0.0029%	0.0030%	0.0055%	0.0046%	0.0066%	0.0025%	0.0009%	-0.0050%	-0.0179%
14000	0.0562%	-0.0328%	-0.0121%	-0.0016%	0.0007%	0.0088%	0.0046%	0.0053%	-0.0010%	-0.0104%
28000	0.0131%	-0.1309%	-0.0509%	-0.0111%	-0.0004%	0.0258%	0.0210%	0.0285%	0.0198%	0.0208%
Wealth										
Amount	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
7000	-1.964%	-0.458%	-0.248%	-0.147%	-0.067%	-0.017%	0.006%	0.043%	0.058%	0.071%
14000	-4.005%	-1.018%	-0.576%	-0.354%	-0.179%	-0.066%	-0.002%	0.081%	0.136%	0.188%
28000	-11.474%	-2.897%	-1.627%	-0.966%	-0.517%	-0.216%	0.025%	0.200%	0.377%	0.550%
Welfare										
Amount	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
7000	0.172%	-0.089%	-0.232%	-0.128%	0.138%	-0.364%	0.483%	-0.314%	0.352%	-0.244%
14000	0.031%	-0.002%	0.048%	-0.025%	0.123%	-0.430%	0.161%	-0.339%	0.261%	-0.112%
28000	0.056%	0.148%	-0.370%	0.042%	-0.181%	0.076%	0.079%	-0.621%	0.422%	-0.117%

Table 20: Robustness Check: Decile-wise percentage increase (decrease) under the permanent-identification policy with respect to benchmark model based on a larger sample of households (62468 in number) as per section 5.2. The models are calibrated as per section 3.2. The households in the first decile are targeted. In this intervention, the targeted households are subjected to an increment in income for both periods. The per-capita amounts (in INR) of transfer in the intervention are compared.

Consumption										
Amount	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
7000	0.3057%	-0.0363%	-0.0187%	-0.0151%	-0.0161%	-0.0037%	-0.0123%	-0.0100%	-0.0234%	-0.0257%
14000	0.5429%	-0.0728%	-0.0498%	-0.0352%	-0.0317%	-0.0101%	-0.0229%	-0.0169%	-0.0356%	-0.0280%
28000	1.6611%	0.0733%	0.0144%	-0.0447%	-0.0999%	-0.1890%	-0.2453%	-0.2800%	-0.1659%	0.1121%
Wealth										
Amount	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
7000	-1.964%	-0.458%	-0.248%	-0.147%	-0.067%	-0.017%	0.006%	0.043%	0.058%	0.071%
14000	-15.346%	-3.978%	-2.401%	-1.511%	-0.885%	-0.405%	-0.062%	0.267%	0.552%	0.912%
28000	22.435%	1.320%	0.844%	0.649%	0.407%	0.185%	-0.020%	-0.175%	-0.334%	-0.383%
Welfare										
Amount	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
7000	0.172%	-0.089%	-0.232%	-0.128%	0.138%	-0.364%	0.483%	-0.314%	0.352%	-0.244%
14000	0.349%	0.004%	-0.244%	-0.092%	0.154%	-0.622%	0.064%	-0.459%	0.863%	-0.790%
28000	2.169%	1.059%	0.978%	0.461%	1.105%	0.538%	1.337%	0.234%	1.308%	0.732%

Table 21: Robustness Check: Gini values pertaining to consumption and wealth under various policies with respect to benchmark model based on a larger sample of households (62468 in number) as per section 5.2. The models are calibrated as per section 3.2.

		Gini	
Amount	**Policy**	**(Wealth)**	**(Consumption)**
	Benchmark model	0.445	0.150
7000	Policy T_1	0.446	0.150
14000	Policy T_1	0.446	0.150
28000	Policy T_1	0.448	0.150
7000	Policy P_1	0.448	0.150
14000	Policy P_1	0.450	0.150
28000	Policy P_1	0.443	0.149
7000	Policy T_2	0.445	0.150
14000	Policy T_2	0.445	0.150
28000	Policy T_2	0.446	0.150
7000	Policy P_2	0.445	0.150
14000	Policy P_2	0.445	0.149
28000	Policy P_2	0.446	0.149