Optimal Basic Income for India

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Abstract

In both developed and developing countries, there is a lot of interest in the idea of a universal basic income, in which the government gives a monetary transfer to all citizens rather than targetting lower-income individuals. In developing countries, it is understood that targetting may be inefficient and inaccurate, but existing literature has argued that even if the government's ability to accurately target the poorest citizens is limited, it may be better to give a larger amount of money to those people who seem to be the poorest rather than a smaller amount to everyone. However, in a developing country such as India that is characterized by corruption in the public service, we argue that targetting imposes additional social costs by empowering local semi-independent government agents who have the opportunity to seek rents while identifying the "poor" agents who should receive a transfer. Thus, if the poor have to pay a bribe to a government employee for the transfer they receive, this could generate an additional misallocation of resources, as well as redistribution in the wrong direction (from poor recipients of transfers to relatively well-off government employees). We calibrate a simple model of targetting of transfers and find that the existence of rent-seeking may be sufficient to make a universal basic income the optimal policy for India.

Keywords: basic income, redistribution, targetting, India, rent-seeking, corruption

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1 Introduction

In recent years, there has been a resurgence of interest in the idea of a universal basic income (or UBI),[1] both in developed (Hoynes and Rothstein, 2019) and developing (Banerjee et al., 2019) countries. However, as the latter paper notes, there has been relatively little experimental study of UBI in the developing world. In the specific case of India, the idea of a UBI has been the subject of considerable recent debate: the government's Economic Survey of 2016-17 (Ministry of Finance of India, 2017) presented a proposal for a quasi-UBI that would target the poorest 75% of the population, whereas Drèze (2017) is a response that advocates caution; the latter is one of numerous articles on the subject in a recent special issue of the Indian Journal of Human Development, to which an introduction is provided by Sharma (2017). Indeed, India's main opposition party, the Indian National Congress, proposed their own quasi-UBI during the 2019 Indian election campaign (BBC News, March 25, 2019).[2]

There are a variety of arguments that advocates of UBI provide in favour of universality. Some studies, as summarized in Banerjee et al. (2019), argue that a basic income, by loosening liquidity and subsistence constraints, could lead to improvements in terms of education, health, and entrepreneurship, with important social benefits.[3] It is also often argued that a universal basic income would have the beneficial effect of reducing the government expenditures required to administer the system: the government would no longer need to pay for employees and infrastructure for targetting and keeping track of who should receive a transfer, if transfers were no longer targetted.

However, even if this is true, the arguments in favour of a UBI run into the challenge of financing: if the government redistribution budget is limited (as it must be in some sense),

[1] Such policy proposal are known by a variety of names: guaranteed minimum income and negative income tax are other common names for the same concept, though the negative income tax represents an altered implementation that includes a tax-back rate.

[2] Even for a "quasi-UBI", the Congress' proposal was relatively far from a true universal transfer, as it would have targetted roughly the poorest 20% of the population.

[3] Banerjee et al. (2019) also summarize evidence that finds little or beneficial effects of cash transfers on labour supply and expenditures on "temptation goods", though for these effects and those on outcomes such as education and health, we don't know for sure what would happen if these often-conditional cash transfers were made universal. Jhabvala (2017) describes positive evidence from some small-scale UBI experiments in India.

a universal basic income involves giving smaller amounts of money to everyone rather than giving larger amounts to a subset of the population. As a result, Hanna and Olken (2018) indicate that a basic income may not be the optimal approach in developing countries: if targetting is even moderately efficient, it may be better to give a larger amount of money to those people who seem to be the poorest, rather than a smaller amount to everyone.

In this paper, we argue that targetting may be costly for another reason in many developing countries: it may encourage or enable rent-seeking. If the government is not modelled as a unitary actor, and the targetting must be performed by local semi-independent government agents, a targetted transfer may provide the latter with the opportunity to seek rents. Essentially, citizens may have to pay bribes (formal cash bribes or informal transfers of resources) in order to be selected to receive a transfer. In other words, targetting failures may not be entirely due to random failures of the targetting technology (i.e. lack of information). If this is the case, rent-seeking could generate misallocations of resources, if the households receiving the transfers are not actually lower-income households, and it could represent a form of indirect redistribution in the wrong direction, from poorer households who must pay for their transfer to the relatively well-off government agents.[4]

We present an analysis of this argument, adapting the basic approach of Hanna and Olken (2018); that is, we ignore any benefits that may come from loosening of liquidity and subsistence constraints.[5] We only consider the tradeoff between targetting failures (due to rent-seeking as well as lack of information, and thus including the flow of resources through bribes) and administrative savings from universality.

We start with a simple two-type model of rich and poor households, to explore both the theory and a simple numerical simulation. We find that, in the absence of rent-seeking and with a plausible calibration of the targetting technology, it is very hard to generate a scenario in which a universal basic income is optimal; this result corresponds to the findings in Hanna and Olken (2018). We then show that adding a form of rent-seeking as an additional inefficiency of targetting means that universality removes the opportunity for rent-seeking,

[4]Suggestive evidence of such corruption in targetting for social benefits is provided by Camacho and Conover (2011) for the case of Colombia.

[5]We also abstract from the question of cash versus in-kind transfers, to focus only the universality of eligibility.

and as a result, a UBI is optimal in many plausible scenarios.

We then apply our model to the specific context of India, a country in which there is significant evidence of poor targetting of social programs, as shown by Asri (2019) for social pensions and Mane (2006) for the Targeted Public Distribution System. We first present a continuous-type version of our model, and then calibrate the model to Indian data, including the 2nd round of the India Human Development Survey (IHDS-II) from 2011-12 (Desai and Vanneman, 2018) as well as – for some applications – the original survey data on targetting in Karnataka from Niehaus et al. (2013). First, we assume away rent-seeking, and calibrate the targetting technology to the reported receipt of Below Poverty Line (BPL) cards in the IHDS-II; we find that we cannot accurately match the data on BPL card receipt without rent-seeking, as there is far too little receipt at low incomes in the data. With this imperfectly-calibrated model in the absence of rent-seeking, we find that transfers should be far from universal.

When we next calibrate our model in the presence of rent-seeking, we are able to fit the data much better: we first use the Niehaus et al. (2013) data to calibrate our targetting technology to eligibility for a BPL card, and then we calibrate the rent-seeking specification to match the reported receipt of BPL cards in the IHDS-II. We find that, in this calibrated model, the optimal policy is a universal basic income, and we find that even if bribes were 91.5% smaller than implied by our model, a UBI would still be optimal.

Several papers have mentioned the idea of rent-seeking in connection with targetted vs universal transfers in developing countries, but such a discussion has never been accompanied by a formal analysis. Section 4.3 of Banerjee et al. (2019) discusses the basic idea, and Ghatak and Maniquet (2019) mention the concept of a "third-best world" of corrupt local agencies, concluding that "UBI might be more appropriate in poor countries, especially those in which UBI could help circumvent the imperfections of government institutions in charge of helping the poor."[6] Bardhan (2017) also identify the fact that "Targeting the poor is too complicated, corrupt and controversial" in India specifically, and our argument that reduced targetting would reduce rent-seeking is supported by the finding in Kishore and

[6]Ghatak and Maniquet (2019) also argue that "both normative and practical considerations make UBI easier to defend as a tool of poverty alleviation in developing countries than a tool to achieve social justice in developed ones."

Chakrabarti (2015) that reduced targetting in India's Targeted Public Distribution System – as well as tightened administration and lower prices – reduced grain diversion as well as raising participation.

Our paper is also importantly related to Niehaus et al. (2013), who consider the problem of designing a proxy means test when the implementing agent is corruptible, and who discuss the possibility of bribery by both eligible and ineligible agents to improve their chances of receiving transfers; we will make use of their data on BPL card receipt in Karnataka. Their main focus is complementary to ours, as they concentrate on the complexity of targetting rules, and how the use of a larger number of poverty indicators may worsen targetting because more complex rules increases the scope for a local government agent to lie and take bribes. Our paper instead considers the universality of eligibility as a factor influencing rent-seeking by local government agents, though Niehaus et al. (2013) do briefly consider the potential for welfare gains from universal eligibility though not univeral receipt.

On a related note, Drèze and Khera (2010) suggest that simpler and more universal targetting schemes would be better for India, as they would reduce incentives for recipients to cheat; they acknowledge that "some of our findings can be read as reinforcing the case for universal as opposed to targeted social support." Banerjee et al. (2018) find that transparency and provision of better information increases the probability that Indonesian households receive the subsidies for which they are eligible, and presumably a universal transfer would be more transparent than targetting.

Additionally, our paper contributes to a small literature that performs numerical analysis of targetting vs universal transfers: Besley (1990) is a simple early analysis concentrating on poverty-reduction, whereas Hanna and Olken (2018) perform an analysis that is very similar to our own – except without rent-seeking – for Indonesia and Peru. Brown et al. (2018), meanwhile, find that even the most efficient targetting methods available to many developing countries are ineffective at reducing poverty substantially, and they propose that a basic income ("or transfers using a simple demographic scorecard") would likely be at least as effecting in reducing poverty. On a similar note, Klasen and Lange (2016) find that minimizing targetting errors may not lead to minimized poverty, highlighting the importance of modelling welfare directly as we do in this paper.

The rest of the paper proceeds as follows. Section 2 presents a simple discrete-type model of targetted redistribution, to illustrate the tradeoffs between imperfect targetting and rent-seeking by government agents. Section 3 then evaluates a continuous-type model that is calibrated to Indian data, to calculate the optimal redistribution targetting approach, and section 4 concludes the paper.

2 Basic Model of Targetted Redistribution

We begin our analysis with a simple two-type model of redistribution between rich and poor agents, in the presence of imperfect targetting. This setting is intentionally as simple as possible, to highlight the choices to be made and the intuition for our results.

2.1 Imperfect Targetting & No Rent-Seeking

In this subsection, we assume that there is no rent-seeking by government agents, so that we are in the same context as Hanna and Olken (2018) (though with discrete types). We assume that there is a mass of measure 1 of population, of two types: a fraction p of the population is poor with after-tax income y_0, and the other $1-p$ percent is rich with after-tax income y_1. Rather than explicitly modelling decreasing marginal utility from income, we assume simple linear marginal utility weights $u_0 > 1 \equiv u_1$.

We assume that the tax system is exogenously fixed and gives rise to a fixed available budget for redistribution of R; we further assume that there are no income effects, and we assume that pre-tax income does not respond to any implicit tax rates that are created by targetting. These assumptions imply that after-tax (but pre-transfer) income is exogenously fixed, as in Hanna and Olken (2018), which weakens the case for a universal basic income: targetting would typically create a positive implicit tax rate for most individuals – a higher incomes means a lower probability of receiving a transfer – which would distort labour supply downwards, but we abstract from this effect.[7]

The government will choose a targetting rule t, where t conceptually represents the maximum level of income that is "supposed" to receive a transfer. We assume that there

[7] We also abstract from arguments about political feasibility: for example, Banerjee et al. (2019) argue that broader transfers may have more political support from the population, enabling greater outlays of funds. We hope to study this idea in future extensions of our model.

exists a targetting technology such that $q_0(t)$ and $q_1(t)$ are the percentages of poor and rich who are selected to receive a transfer for a given targetting rule t, where $q_0(t) > q_1(t)\ \forall t$ and $q_i'(t) > 0$ for $i \in \{0,1\}$. The government then gives a transfer d to all targetted individuals, which implies a government budget constraint of:

$$(pq_0(t) + (1-p)q_1(t))d = R$$

which can be simply rearranged to obtain:

$$d = \frac{R}{pq_0(t) + (1-p)q_1(t)}.$$

Thus, if $q_i'(t) > 0$, the feasible transfer will decline as t increases and more individuals are targetted.

The social welfare function of a utilitarian planner is given by:

$$W = pu_0(y_0 + q_0(t)d) + (1-p)(y_1 + q_1(t)d)$$

and this can be rewritten as:

$$W = pu_0y_0 + (1-p)y_1 + \frac{pu_0q_0(t) + (1-p)q_1(t)}{pq_0(t) + (1-p)q_1(t)}R = pu_0y_0 + (1-p)y_1 + R + \frac{pR(u_0-1)q_0(t)}{pq_0(t) + (1-p)q_1(t)}.$$

We then take the derivative with respect to t to look for the optimal targetting rule:

$$\begin{aligned}\frac{dW}{dt} &= \frac{pR(u_0-1)}{(pq_0(t) + (1-p)q_1(t))^2}\left[q_0'(t)(pq_0(t) + (1-p)q_1(t)) - (pq_0'(t) + (1-p)q_1'(t))q_0(t)\right] \\ &= \frac{p(1-p)R(u_0-1)}{(pq_0(t) + (1-p)q_1(t))^2}\left[q_0'(t)q_1(t) - q_1'(t)q_0(t)\right]\end{aligned}$$

and clearly the first term is positive, whereas the sign of the terms in the square brackets is ambiguous. However, we can observe that the welfare derivative will tend to be positive if $q_0'(t)$ is relatively large and $q_1'(t)$ is relatively small, which is intuitive: if raising the targetted income provides transfers to a lot of poor people but few rich people, the social planner will tend to prefer a higher t.

It is also natural to assume that $q_0'(t)q_1(t) - q_1'(t)q_0(t)$ will be decreasing with t, because $q_0'(t)$ should be large for low t and small for higher t, and vice-versa for $q_1'(t)$: poor individuals tend to enter the program at low values of t, whereas rich people enter the program more at higher values of t. This assumption will be true in the functional form presented below, and it gives rise to an optimum at $q_0'(t)q_1(t) = q_1'(t)q_0(t)$.

We will present results assuming a specific functional form: let $q_i(t) = \exp(\beta(t^{\alpha_i} - 1))$, with $\alpha_0 < \alpha_1$.[8] Such a functional form has the desirable properties that $q_i'(t) > 0$, $q_i(1) = 1$ (representing a universal basic income), and $q_i(0) = \exp(-\beta) > 0$; the latter result essentially comes from the fact that the government must distribute R to someone, and $\exp(-\beta)$ represents the small fraction of the population that receives a transfer when targetting is extremely restrictive.

With this functional form, we find:

$$\begin{aligned} q_0'(t)q_1(t) - q_1'(t)q_0(t) &= \beta q_0(t)q_1(t)\left[\alpha_0 t^{\alpha_0 - 1} - \alpha_1 t^{\alpha_1 - 1}\right] \\ &= \beta q_0(t)q_1(t)\alpha_1 t^{\alpha_1 - 1}\left[\frac{\alpha_0}{\alpha_1}t^{\alpha_0 - \alpha_1} - 1\right] \end{aligned}$$

and this expression is equal to zero if and only if $t = \left(\frac{\alpha_0}{\alpha_1}\right)^{\frac{1}{\alpha_1 - \alpha_0}}$, which must be a value in between 0 and 1. For larger values of t, the expression – and thus $\frac{dW}{dt}$ – is negative, and for smaller values of t, it is positive; this means that the solution for t will be interior and unique, and the optimal value of t is given by $t^* = \left(\frac{\alpha_0}{\alpha_1}\right)^{\frac{1}{\alpha_1 - \alpha_0}}$.

It can then be shown that $\frac{dt^*}{d\alpha_0} > 0$ and $\frac{dt^*}{d\alpha_1} > 0$: if α_0 goes up – implying worse targetting of the poor – t^* goes up because it is no longer worth trying to keep t to target only the poor, whereas if α_1 goes up – implying better non-targetting of the rich – t^* goes up because there is no longer as much need to keep t low to keep out the rich and a larger t allows the government to better spread resources among the poor.

Of course, if α_i changes, then the percentage of people who receive a transfer changes for two reasons: the indirect effect on t^*, and the direct effect of the change in targetting efficiency. It is possible to show that $\frac{dq_0}{d\alpha_0}$ is negative if α_0 is very low, because the direct effect of lowering a very high precision of targetting of the poor dominates any indirect effect through higher t; meanwhile, $\frac{dq_0}{d\alpha_0}$ is positive if α_0 is sufficiently large, as the indirect effect of the increase in t dominates. It is also possible to show that $\frac{dt^*}{d\alpha_0} - \frac{dt^*}{d\alpha_1}$ is of ambiguous sign.

We can illustrate the conclusions of this model with a series of simulations, in which

[8] A natural alternative would be $q_i(t) = t^{\alpha_i}$ for $t \in [0, 1]$, but it turns out that the solution is degenerate in that case, with $t = 0$ as long as $\alpha_0 < \alpha_1$.

we choose $R = 1$, $u_0 = 2$, and $\beta = 4$; the latter implies that $t = 0$ means that 1.8% of both types randomly receive a transfer. Hanna and Olken (2018) find that administrative costs that could be eliminated by switching to a univeral transfer amount to 0.8% of the transfer budget in Indonesia and 1.7% in Peru,[9] so we assume that 1.7% of R is wasted on administration unless $t = 1$.

We present results in three figures depending on the values of our other parameters. Figure 1 presents the values of $q_0(t)$ and $q_1(t)$ as functions of t, as well as welfare as a function of t, for $p = 0.5$, $\alpha_0 = 0.1$, and $\alpha_1 = 0.3$. In this scenario, the optimal value of t is 0.0041, which implies $q_0(t) = 0.1844$ and $q_1(t) = 0.0395$, so the optimal policy is very far from a universal transfer. While it has no effect on the conclusion in this case, note the small spike in welfare at $t = 1$, representing the resource savings from universality.

Figure 1: Results with $p = 0.5$, $\alpha_0 = 0.1$, and $\alpha_1 = 0.3$

(a) Functions for $q_0(t)$ and $q_1(t)$ (b) Welfare as Function of t

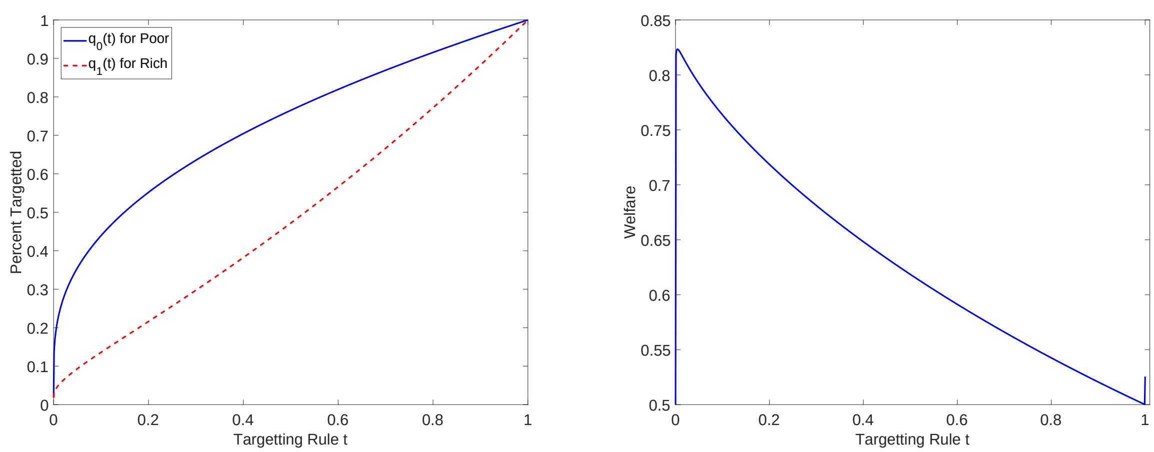


Figure 2 presents the same functions as Figure 1 for the case in which $p = 0.5$, $\alpha_0 = 0.2$, and $\alpha_1 = 0.6$, and we can notice that the precision of targetting is significantly lower now; the optimal value of t is 0.0642, at which level $q_0(t) = 0.1844$ and $q_1(t) = 0.0395$, which is actually the same as in Figure 1. Finally, Figure 3 considers a scenario in which the overwhelming majority of the population is poor, with $p = 0.9$ (and with $\alpha_0 = 0.2$ and

[9]These percentages seem rather low; a policy report (Macdonald, 2016) for Canada finds that social assistance programs spend an average of 7.5% of the transfer budget on administration, and developing countries seem likely to be even more inefficient. However, perhaps some of these administrative costs would still exist even if the transfer was made universal.

$\alpha_1 = 0.6$ as in Figure 2). The results in this final case are identical to those from Figure 2 – including the optimal policy – except that the welfare function looks a bit different: the value of welfare varies much less with t, and the universal basic income ($t = 1$) comes closer to being the optimal policy. The logic of this finding is that targetting the poor is not so important when almost everyone is poor, and wasting resources on targetting hurts the poor almost as much as having to share those resources with richer individuals.

Figure 2: Results with $p = 0.5$, $\alpha_0 = 0.2$, and $\alpha_1 = 0.6$

(a) Functions for $q_0(t)$ and $q_1(t)$ (b) Welfare as Function of t

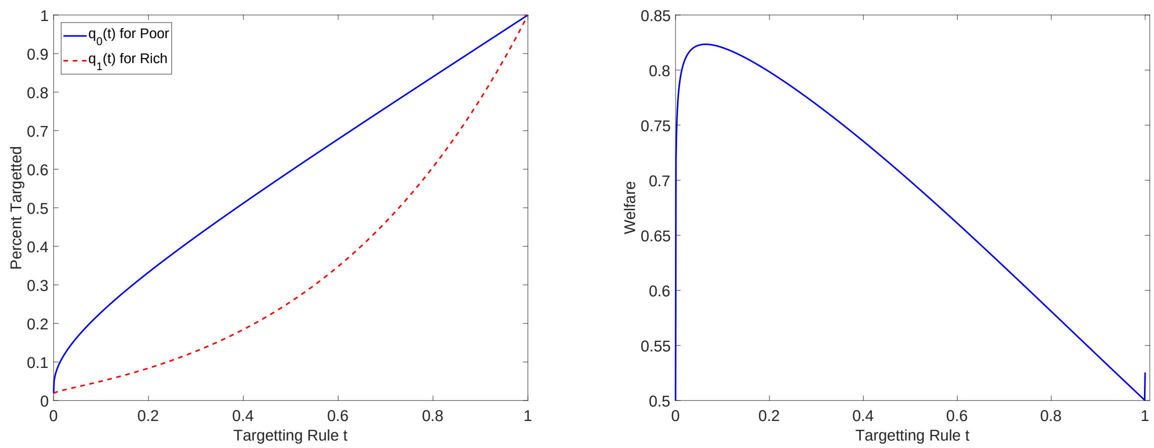
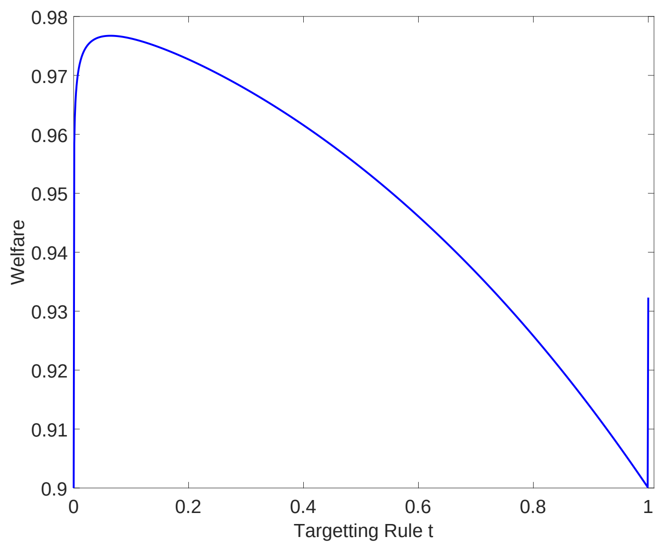


Figure 3: Welfare as Function of t with $p = 0.9$, $\alpha_0 = 0.2$, and $\alpha_1 = 0.6$



Finally, with $p = 0.5$ as in the first 2 examples, we present optimal policy results for all possible values of α_0 and α_1. Figure 4 presents the optimal value of t, ignoring the cost savings from the universal basic income ($t = 1$) for the moment, and Figure 5 shows the values of $q_0(t)$ and $q_1(t)$ for these optimal values of t. The optimal policy is particularly sensitive to α_0, with a higher optimal t and lower percentage of the poor receiving transfers when targetting the poor is less efficient.

Figure 4: Optimal Targetting Rule t with $p = 0.5$

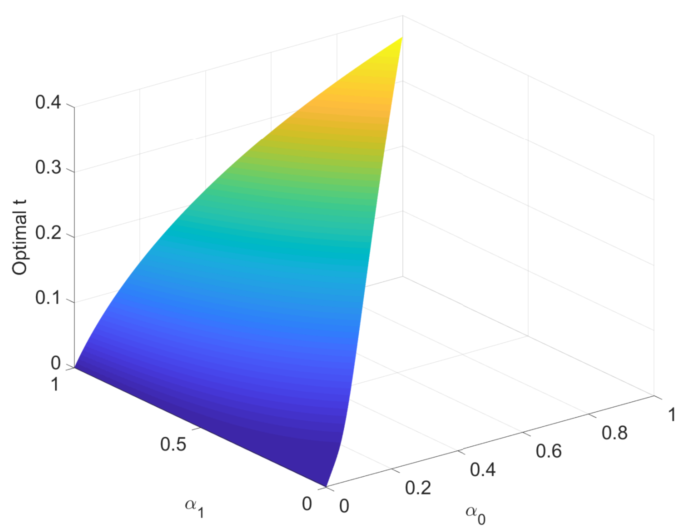
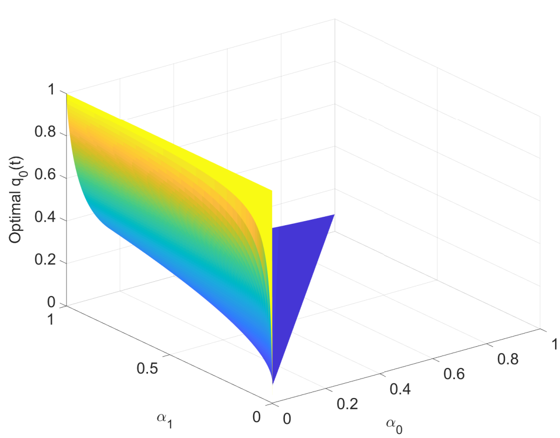


Figure 5: Optimal Values of $q_0(t)$ and $q_1(t)$ with $p = 0.5$

(a) Optimal Values of $q_0(t)$



(b) Optimal Values of $q_1(t)$

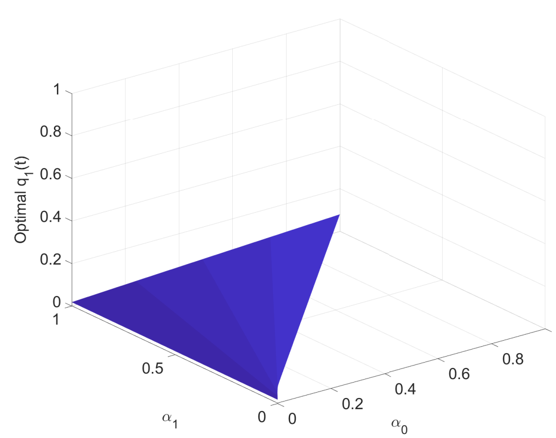
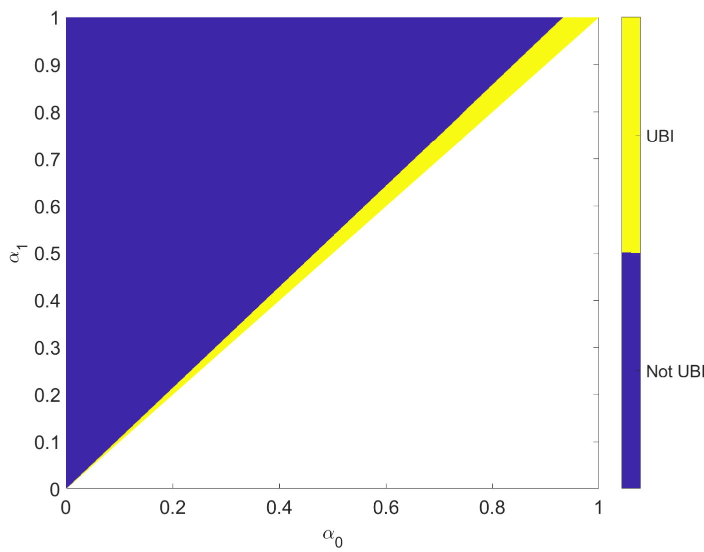


Figure 4 presented the optimal t assuming that $t = 1$ did not provide any cost savings, because the cost savings from $t = 1$ are modelled as a special discontinuous case, and so Figure 6 performs a comparison between the welfare obtained from the optimal t presented in Figure 4 and the welfare from $t = 1$ (including the extra resources made available by not targetting). The blue region represents parameter combinations for which the non-universal t from Figure 4 is indeed optimal, whereas the small yellow region represents situations in which $t = 1$ is the optimal policy due to the savings of resources from not targetting. We can observe from Figure 6 that it is possible for this analysis to lead to a recommendation for a universal basic income, but that it would require that the targetting technology be extremely inefficient, featuring an α_0 that is almost as large as α_1, so that $q_1(t)$ is almost as large as $q_0(t)$ for a given t.

Figure 6: Optimal $t = 1$ with $p = 0.5$



2.2 Imperfect Targetting & Rent-Seeking

If it is difficult to construct a plausible justification for UBI in the model presented above, one might wonder how rent-seeking would alter this conclusion. We now extend the model to include rent-seeking by local government agents, imposing the assumption that individuals have the possibility of paying a bribe to the government agent, which raises their probability of receiving a transfer.

To keep things simple, we do not try to describe the government agent's behaviour, or to microfound the selection process; rather, we assume that for an underlying technology of targetting given by $\hat{q}_i(t)$ for $i \in \{0,1\}$, the actual probability that person j of type i receives a transfer is given by $q_{i,j} = \hat{q}_i^{(E_i(b_{i,j})/b_{i,j})^\gamma}$, where $E_i(b_{i,j})$ is the average value of bribes $b_{i,j}$ across individuals j in type i. That is, we assume that bribery does not alter the relative probability of targetting rich vs poor individuals, but only (potentially) reorganizes who receives the transfers within each group. These are strong assumptions made to generate simple and intuitive results, and the assumption that bribery does not alter inter-group targetting is conservative with regards to the desirability of a UBI, as it implies that a basic income that eliminates bribery would not help to focus transfers on poor rather than rich individuals. When we consider the calibrated continuous-type model in the next section, we will no longer make this conservative assumption.

The utility of individual j in type i is given by $u_{i,j} = y_i + q_{i,j}(b_{i,j})d - b_{i,j}$, and maximizing with respect to $b_{i,j}$ and imposing that in equilibrium $b_i \equiv E_i(b_{i,j}) = b_{i,j} \; \forall \, i,j$, and therefore $q_i \equiv q_{i,j} = \hat{q}_i \; \forall \, i,j$, we find:

$$b_i = -q_i \ln(q_i)\gamma d.$$

The fact that $q_i = \hat{q}_i$ – due to the fact that $E(b_i) = b_i$ in equilibrium – means that the underlying probability of selection is unchanged, but everyone must pay the government agent to not lose their place in line, so to speak.

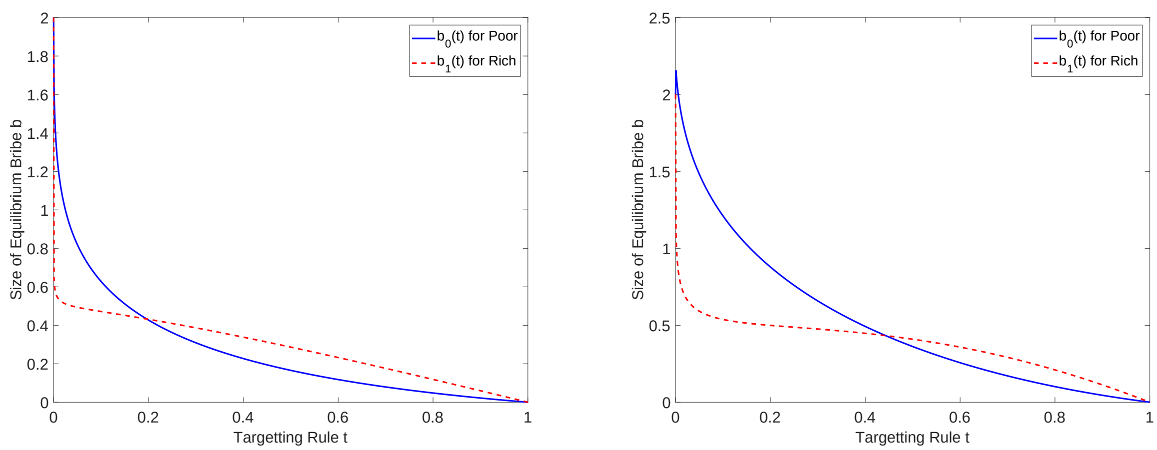
Figure 7 illustrates the bribery functions $b_i(t)$ in the first 2 numerical cases considered above, with $\gamma = 0.5$; the third case (with $p = 0.9$) is generally similar to the first two and so we omit it. We can observe that the amount spent on bribery declines with t, which is logical: if everyone receives the transfer, there is no need to bribe anyone for eligibility.[10] This decline in $b_i(t)$ as t becomes large will be an important part of the results to come in this and the following section; we can prove (results not presented here) that $\frac{db_0}{dt}$ (which is the welfare-relevant effect, as will be seen below) is negative above the optimal t from section 2.1, whereas below that value of t it is theoretically ambiguous. We also find that, expressing

[10] Of course, in practice, we could ask whether making the transfer universal would really eliminate rent-seeking; presumably this would depend on how the transfer was distributed, and whether a semi-independent local government agent played a role in distribution if not selection. See Ghose (2017) for a note of caution on this subject.

the bribe as a fraction of the transfer d, bribes peak at nearly 20% of the transfer size for both groups.

Figure 7: Privately-Optimal Values of $b_0(t)$ and $b_1(t)$ with $p = \gamma = 0.5$

(a) $\alpha_0 = 0.1$ and $\alpha_1 = 0.3$ (b) $\alpha_0 = 0.2$ and $\alpha_1 = 0.6$



If we assume that the government agent is a rich individual, so that their income is valued at a marginal utility of 1, the new welfare function becomes:

$$\begin{aligned}
W &= pu_0(y_0 + q_0(t)d) + (1-p)(y_1 + q_1(t)d) - p(u_0 - 1)b_0(t) \\
&= pu_0 y_0 + (1-p)y_1 + R + \frac{pR(u_0 - 1)q_0(t)(1 + \gamma \ln(q_0(t)))}{pq_0(t) + (1-p)q_1(t)}
\end{aligned}$$

and taking the derivative with respect to t, we find:

$$\begin{aligned}
\frac{dW}{dt} =& \frac{pR(u_0 - 1)}{(pq_0(t) + (1-p)q_1(t))^2} \left[q_0'(t)(1 + \gamma \ln(q_0(t)) + \gamma)(pq_0(t) + (1-p)q_1(t))\right. \\
&\left. -(pq_0'(t) + (1-p)q_1'(t))q_0(t)(1 + \gamma \ln(q_0(t)))\right] \\
=& \frac{pR(u_0 - 1)}{(pq_0(t) + (1-p)q_1(t))^2} \\
&\times \left[(1 + \gamma \ln(q_0(t)))(1-p)(q_0'(t)q_1(t) - q_1'(t)q_0(t)) + \gamma q_0'(t)(pq_0(t) + (1-p)q_1(t))\right]
\end{aligned}$$

In the main square brackets, we can see that two new components have been added: $\gamma \ln(q_0(t))(1-p)(q_0'(t)q_1(t) - q_1'(t)q_0(t))$ and $\gamma q_0'(t)(pq_0(t) + (1-p)q_1(t))$; the latter is always positive, and the former is negative for t below the optimal value in the absence of rents and positive above. Therefore, at the optimal t from section 2.1, the welfare derivative is now positive and the optimal value of t should be to the right. We can prove that the optimal

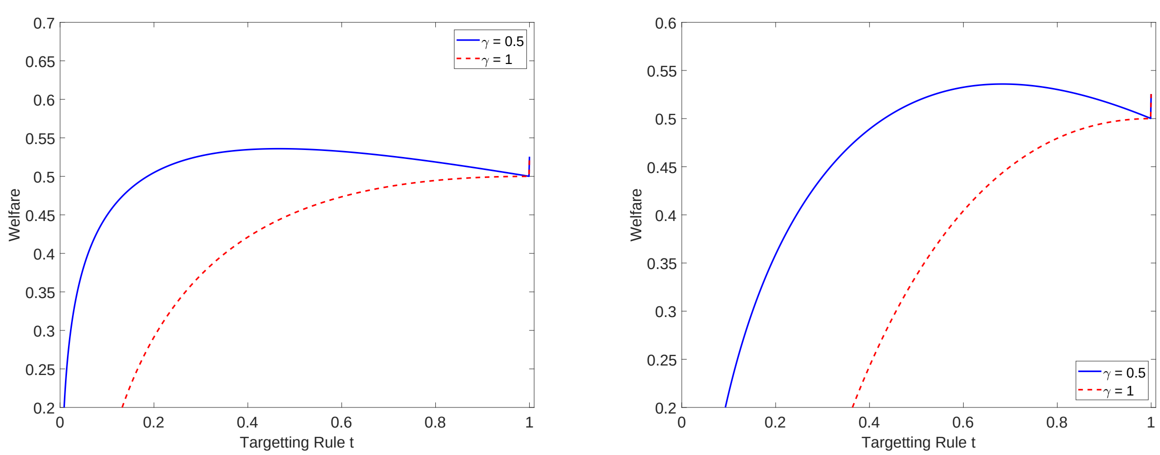
t increases with rent-seeking if $\gamma < \frac{1}{3}$ or if $p > \frac{2\gamma-1}{3\gamma-1}$,[11] because in those cases $\frac{dW}{dt}$ increases everywhere when bribery is introduced; more generally, it is possible that the welfare function could become non-monotone and that there could be multiple local maximum values of t, but that does not occur in the simulations that follow.

Therefore, the implication of our model is that when bribery is introduced, the optimal t should tend to increase and the transfer should tend to become more universal. The intuition is simple: bribery is inefficient – even though in our model it only redistributes resources from poor recipients to a rich government agent, rather than targetting the wrong fraction of rich and poor – and increasing t and making the transfer more universal reduces the incentives for bribery. Thus, a (more) universal transfer could be beneficial, even though it means sharing more resources with the poor, since it means less bribery.

For each of the 3 scenarios already presented in section 2.1, we can calculate the value of welfare for each t as in Figures 1 through 3, using both $\gamma = 0.5$ and $\gamma = 1$, and the results are presented in Figures 8 and 9. Unlike the case without rent-seeking, there is no simple solution for the optimal t in this version of the model, so we can only look for the welfare-maximizing point on the welfare curves in Figures 8 and 9.

Figure 8: Welfare as Function of t with $p = 0.5$ & Rent-Seeking

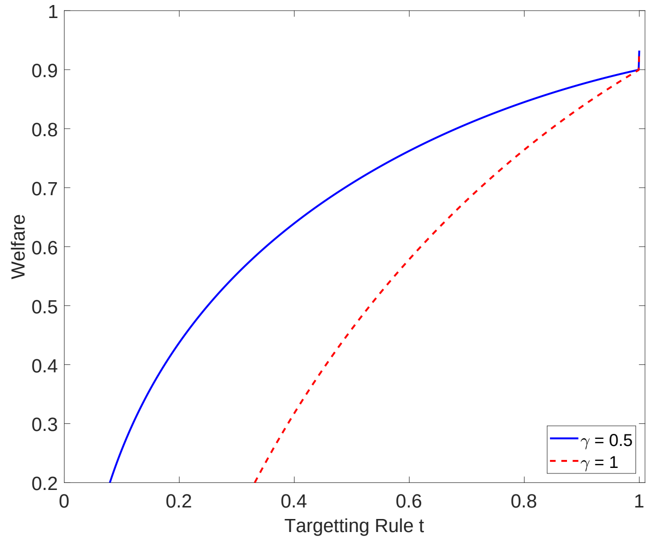
(a) $\alpha_0 = 0.1$ and $\alpha_1 = 0.3$ (b) $\alpha_0 = 0.2$ and $\alpha_1 = 0.6$



In each case, the optimal t increases significantly; for example, for $p = \gamma = 0.5$, the

[11]Note that this condition is not very restrictive for the values of γ that we consider: if $\gamma = 0.5$, for example, we simply need that $p > 0$, whereas the sufficient condition with $\gamma = 1$ would be $p > 0.5$.

Figure 9: Welfare as Function of t with $p = 0.9$, $\alpha_0 = 0.2$, and $\alpha_1 = 0.6$ & Rent-Seeking



optimal t increases to 0.467 if $\alpha_0 = 0.1$ and $\alpha_1 = 0.3$, and to 0.683 if $\alpha_0 = 0.2$ and $\alpha_1 = 0.6$. These policies imply significant increases in the fraction of agents that receive a transfer, to about 75% of poor agents and 44% of rich agents in each case. Even more significantly, the optimal policy in all of the remaining cases is a universal basic income, corresponding to $t = 1$; if rent-seeking is a large problem – if $\gamma = 1$ – or if most agents are poor, the dual benefits of a universal basic income (adminstrative cost savings and elimination of rent-seeking are sufficient to make such a policy optimal.

We can also repeat the analysis that was presented in Figures 4 through 6 for the model without rent-seeking, and the results are found in Figures 10, 11, and 12. As before, Figure 10 presents the optimal value of t ignoring any cost savings from the universal basic income, and Figure 11 shows the values of $q_0(t)$ and $q_1(t)$ for these optimal values of t. Figure 12 presents the cases in which a universal basic income is the optimal policy.

It is apparent from Figure 10 that, even in the absence of cost savings from universality, $t = 1$ is optimal in a significant fraction of cases. Looking at Figure 12, we can see that it is easy now to find cases in which the UBI is optimal, when α_0 is sufficiently large so that targetting of the poor is not highly efficient; in these cases, the combined adminstrative cost savings and welfare gains from elimination of bribery are sufficient to offset the reduced transfer size in the case of universality.

Figure 10: Optimal Targetting Rule t with $p = 0.5$ & Rent-Seeking

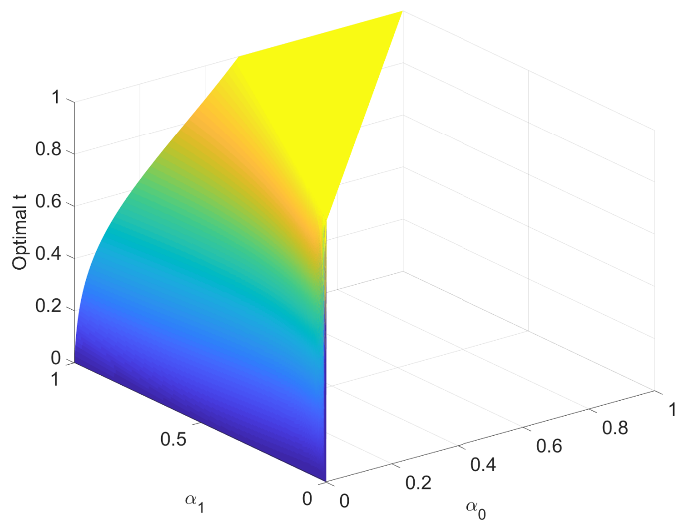
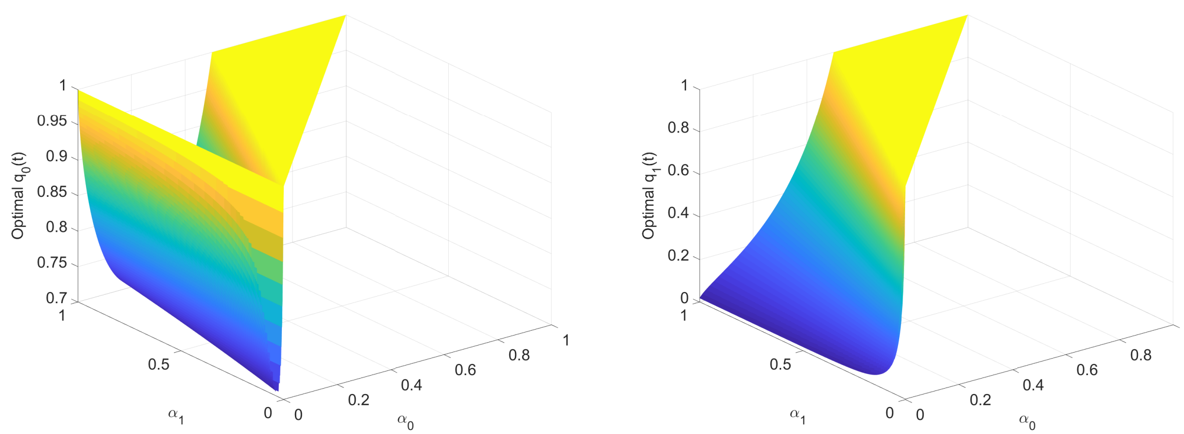


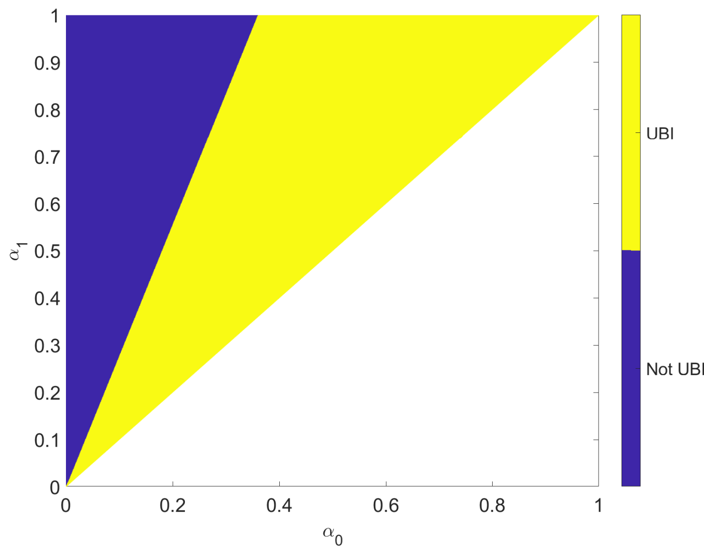
Figure 11: Optimal Values of $q_0(t)$ and $q_1(t)$ with $p = 0.5$ & Rent-Seeking

(a) Optimal Values of $q_0(t)$ (b) Optimal Values of $q_1(t)$



The remaining question is whether the parameter values used in these simulations are reasonable; we have performed simple numerical experiments to illustrate the basic principle of our paper, but the practical applicability remains to be shown. In the next section, we will address this issue by calibrating a continuous-type version of our model to data from two Indian sources.

Figure 12: Optimal $t = 1$ with $p = 0.5$ & Rent-Seeking



3 Calibrated Continuous-Type Model

The simple example studied in the previous section of the paper shows how adding rent-seeking as a source of inefficiency in targetting can alter our conclusions about the optimal redistribution policy. In the current section, we will calibrate a extended continuous-type version of our model to Indian data, under two different assumptions about the efficiency and corruption involved in targetting. India is a useful context to study in our analysis, as several papers have found evidence of poor targetting of social programs, including Asri (2019) and Mane (2006), and we show that it is difficult to match the patterns of benefit receipt found in the data without including rent-seeking in the model. We will also show that in the presence of such rent-seeking, the optimal policy for India does appear to be a universal basic income.

We will use data from two sources in our calibration: data on household income and receipt of BPL cards from the IHDS-II, and (for one version of the calibration) the data from Niehaus et al. (2013) on eligibility for BPL cards. In the version of our model without rent-seeking, we calibrate the targetting technology to the reported receipt of BPL cards in the IHDS-II, and then solve for the optimal targetting scheme in the same dataset. In the version of our model with rent-seeking, we first use the Niehaus et al. (2013) data to calibrate the targetting technology to the estimated eligibility for a BPL card across the income distribution; we then calibrate the bribe function to match the reported receipt of BPL cards in the IHDS-II, and solve for the optimal targetting scheme in the latter dataset as in the no-rent-seeking case.

In choosing our calibration strategy, we had several alternative options: we could instead have calibrated the receipt of BPL cards to the data from Niehaus et al. (2013), but the percentage of households that receive a BPL card in their data is very high and it is difficult to accurately match it. Also, we could have used the measure in Niehaus et al. (2013) of how large a bribe people paid to receive their BPL card; but those reported amounts are very small, and implausibly so if they are measuring the total amount given to the local government agent, as they measure only direct monetary transfers, and not various non-monetary transfers made by households, in the form of voluntary transfers in-kind, transfers of political influence, and even involuntary transfers.[12] Therefore, throughout our analysis, we back out the size of the bribes from the solution to the model, and we will show how sensitive our results are to the sizes of these bribes.

3.1 Calibration and Optimal Policy without Rent-Seeking

As in the previous section, we start with a version of our model without rent-seeking – where the only reason for noisy targetting is an imperfect targetting technology – and calibrate the model to replicate as closely as possible the reported receipt of BPL cards in the IHDS-II data. We use household income as the income measure, and the standard IHDS household weights, and we have observations on 41534 households, which reduces to 40663 when we trim the top and bottom 1 percent of the income distribution. The summary statistics for our sample can be found in Table 1, and a weighted histogram of household income (in rupees per year) is presented in Figure 13.

Rather than a binary model with only two levels of income, we now need to model targetting over the entire distribution of incomes y; this also means that we cannot use our simple targetting specification $q_i(t)$ from the previous section, as targetting needs to be an

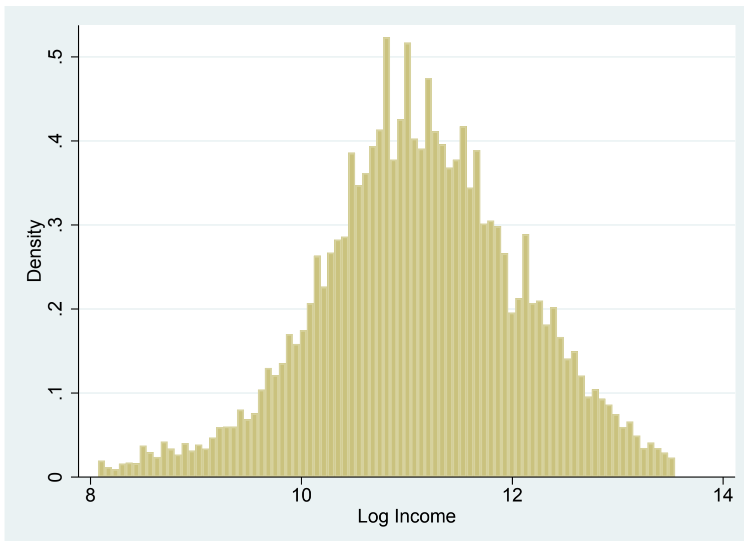
[12] For example, the often-noted fact that households often receive less grain at PDS shops than the amount to which they are entitled.

Table 1: Summary Statistics for IHDS-II Data

Variable	Observations	Mean	Std. Deviation	Minimum	Maximum
household income	40663	104200.5	109431.9	3200	762700
household income per capita	40663	24807.25	29432.69	423.75	665000
BPL card receipt	40663	0.4148	0.4927	0	1

Notes: This table presents weighted summary statistics for our trimmed sample from the IHDS-II. We use the standard IHDS-II household weights, and we trim the top and bottom 1 percent of the household income distribution (keeping tied values in the dataset). All monetary amounts are in rupees per year.

Figure 13: Histogram of Household Income from IHDS-II



explicit function of y. We assume a targetting technology in which the probability that a household of income y receives a BPL card is:

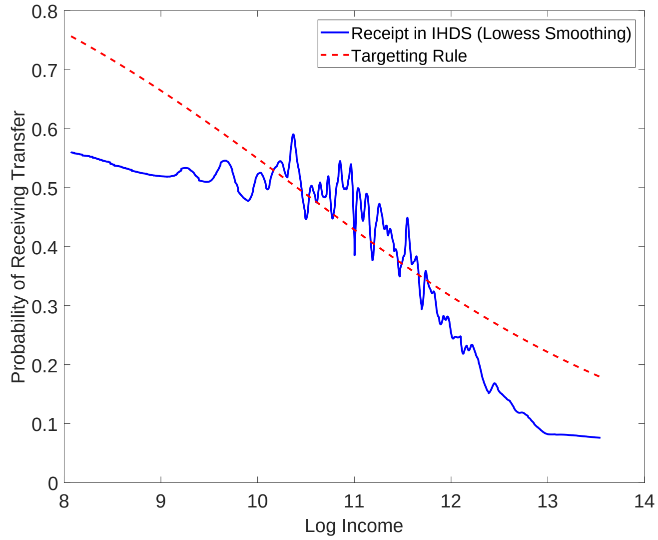
$$q(y;t) = \frac{\exp(-\alpha(\ln(y) - t))}{\exp(-\alpha(\ln(y) - t)) + \beta} \tag{1}$$

where t represents the "targetted" log income level and β is inversely related to a sort of baseline probability at that log income; if $\ln(y) = t$, the probability of receipt is $\frac{1}{1+\beta}$, so t would be the log income at which $q = 0.5$ if $\beta = 1$.

We search for the parameters α, β, and t that best match the actual receipt of BPL cards in the IHDS-II data; specifically, we minimize the weighted sum of squared deviations between $q(y;t)$ and the receipt of BPL cards. The results of our calibration can be found in Figure 14, and feature $\alpha = 0.4857$, $\beta = 1.1913$, and $t = 10.7683$.

The main thing that is apparent from Figure 14 is that it is very hard to match the

Figure 14: Real and Calibrated Distribution of BPL Card Receipt without Rent-Seeking



actual pattern observed in the data without any rent-seeking, or some other reason why low-income households are not particularly likely to receive a BPL card. In particular, we cannot adequately match the low probability of receipt at low incomes, and those households are very important because their low incomes will imply high marginal utility from consumption. This already suggests that we may need to introduce a form of rent-seeking in order to arrive at a reasonable match for the data, highlighting the importance of rent-seeking in the Indian context.[13]

To evaluate the optimal targetting rule, we assume a standard CRRA household utility function from consumption:

$$U(c) = \frac{c^{1-\rho}}{1-\rho}$$

where ρ is the coefficient of relative risk-aversion, and where consumption c will be equal to the measured household income y from the data plus any transfer received from the government. Formally, if the transfer is d and the probability of receiving the transfer is q, we have that the household's expected utility is:

$$V = qU(y+d) + (1-q)U(y)$$

[13]There is apparently some evidence of reduced targetting errors in the PDS after the Food Security Act of 2013; see Drèze et al. (2019).

We assume a coefficient of relative risk-aversion of $\rho = 3$; we then assume a redistribution budget R that is equal to 2.5% of total household income,[14] and an administrative cost of 1.7% of expenditures that is saved by not targetting; if the transfer is not universal, this implies a government budget constraint given by:

$$d \sum_{i}^{40663} w_i q(y_i; t) = 0.983 \times 0.025 \sum_{i=1}^{40663} w_i y_i$$

where i indexes the household and w_i is the household weight. A universal basic income is treated as a special case in which q is equal to one for all households, in which case the available transfer d_u is:

$$d_u = \frac{0.983 \times 0.025 \sum_{i=1}^{40663} w_i y_i}{\sum_{i}^{40663} w_i}.$$

We then search over t for the value that maximizes welfare, defined as the weighted sum of household utility: for any given value of t, we can calculate $q(y_i; t)$ for each observation, and find the value of d that balances the government budget, and then solve for utility for each household given their d and q. We find the results that are presented in Figure 15 for welfare as a function of the percentage of households receiving a transfer (which is a monotonic increasing function of the targetting level t), where the X at the right side of the figure represents a universal basic income, which saves 1.7% of expenditures on administration

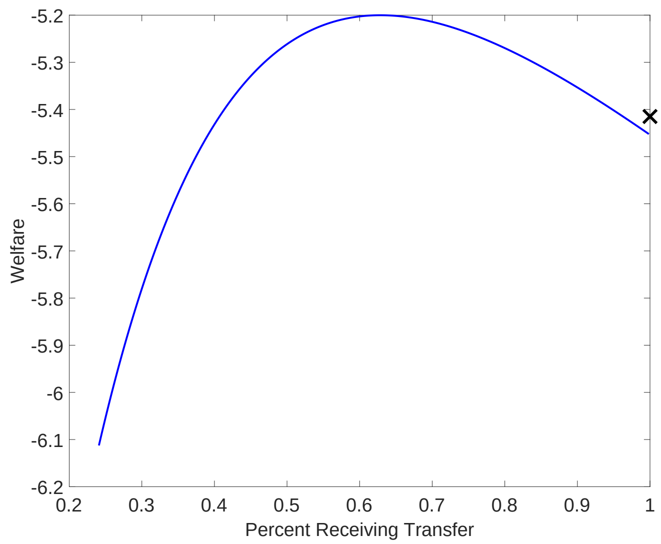
We find that the optimal policy involves setting $t = 12.61$ (significantly higher than the baseline policy), and distributing transfers to about 63% of the population. While this implies a redistribution scheme that is more universal than at baseline, we are still well short of a universal basic income, and even though the universal basic income features higher welfare than a nearly-universal transfer (given the savings of 1.7% on administration), the welfare level is still well below that of the optimal targetted transfer.

3.2 Calibration and Optimal Policy with Rent-Seeking

We now account for two sources for the inefficiency of targetting: an imperfect targetting technology, and rent-seeking by the government agent. To calibrate the model in this setting, the data on reported receipt of BPL cards in the IHDS-II is no longer sufficient, because we

[14] Mundle and Sikdar (March 1, 2017) indicate that "non-merit subsidies" (for things other than food, elementary & secondary education, health, and water supply and sanitation) were about 5% of GDP in 2011-12, so we assume that half of these subsidies can be replaced by our transfer.

Figure 15: Optimal Targetting Rule t without Rent-Seeking



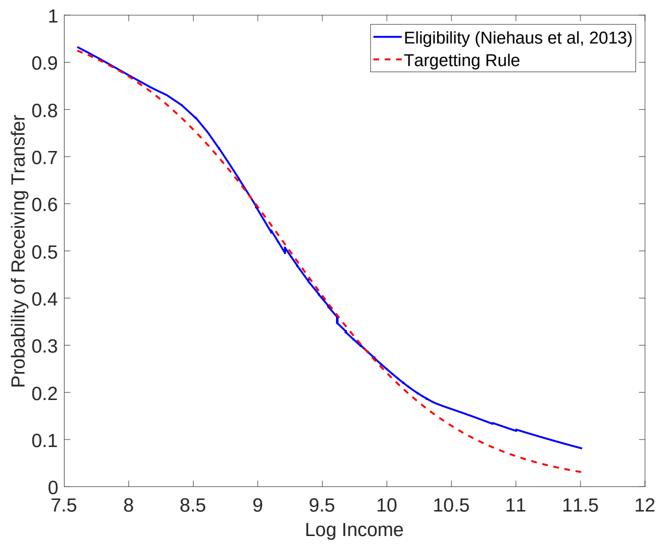
need to divide the failure in targetting into the part that comes from imperfections in the targetting technology and the part that comes from rent-seeking. Therefore, we instead begin with the Niehaus et al. (2013) data on predicted eligibility (using their "more conservative eligibility definition"),[15] smoothed using lowess across log household income; we have this variable for 13277 households.

Using the same functional form from (1) for the targetting technology, we find the values of α, β, and t that best match the estimated BPL eligibility in the Niehaus et al. (2013) data; since the data does not contain sample weights, we minimize the sum of squared deviations between $q(y; t)$ and the measure of predicted eligibility in the data. This calibration gives us $\alpha = 1.5241$, $\beta = 0.3392$, and $t = 8.5383$, with the results presented graphically in Figure 16; unlike in Figure 14 for receipt, it is easy to accurately match these data for eligibility.

We then complete our calibration by finding the value of t and the parameters of a bribery function that best match the actual reported receipt of BPL cards in the IHDS-II data, given our estimates of α and β. However, we need to use a slightly different functional form for the targetting probability after rent-seeking to allow for variation with y and to accurately match the data. Specifically, we use $\hat{q}(y)$ for the targetting probability absent rent-seeking and q for the probability of receiving a transfer after rent-seeking, as before, and we assume

[15] To be precise, we translate their R code into Stata to generate and work with an identical Stata dataset.

Figure 16: Real and Calibrated Distribution of BPL Card Eligibility



that $q(y) = \hat{q}(y)f(y)$, where the function $f(y)$ is given by:

$$f(y) = \frac{\left(\frac{b(y)}{E(b(y))}\right)^{\gamma}\left(\frac{y}{E(y)}\right)^{\delta}}{\hat{q}(y)\left(\frac{b(y)}{E(b(y))}\right)^{\gamma}\left(\frac{y}{E(y)}\right)^{\delta} + (1-\hat{q}(y))}.$$

The functional form chosen for $f(y)$ ensures that $f(y) \leq \frac{1}{\hat{q}(y)}$, so that $q(y)$ can never exceed 1, and that $f(y) = 1$ for an "average" household with $b(y) = E(b(y))$ and $y = E(y)$. Thus, the probability increases with the relative size of bribe $b(y)$ given, but also with the relative wage, to account for the fact that higher-income people receive cards surprisingly often given that they have little incentive to pay a bribe for a BPL card of relatively small value. Essentially, we assume that the local government agent might want to be friendly with the more wealthy (and presumably powerful) citizens in their area, and the relative strength of this force relative to bribe size is given by δ (relative to γ). Without such an assumption, we cannot come close to matching the observed pattern of receipt of BPL cards.[16]

To calibrate the parameters of this function, we have to account for the fact that households choose their bribe size to maximize expected utility:

$$\max_{b} q(b)U(y+d-b) + (1-q(b))U(y-b)$$

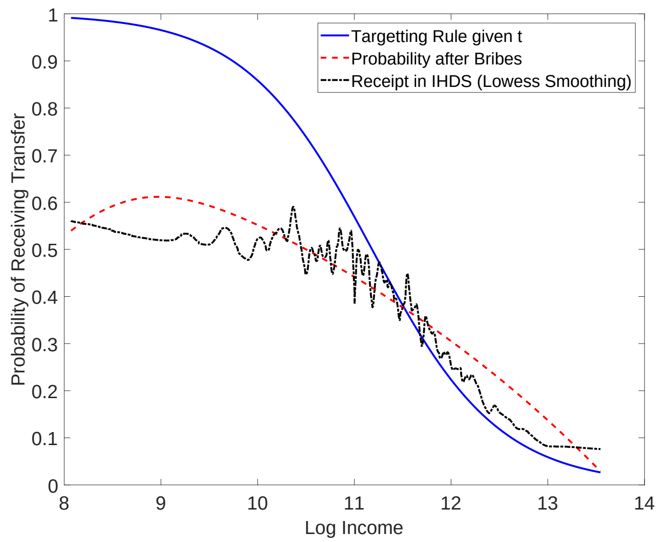
[16]A calibration with δ set to zero gives us $\gamma = 0.0004$ and $t = 10.1198$, which provides a very poor fit to the data.

which leads to the following first-order condition:

$$-q(b)U'(y+d-b)-(1-q(b))U'(y-b)+q'(b)\left(U(y+d-b)-U(y-b)\right)=0. \qquad (2)$$

Accounting for this utility maximization problem, the values of the parameters that best match the actual probability of receiving a BPL card to the predicted value given the bribery function are $\gamma = 1.0000$ (constrained to a maximum of 1 to ensure numerical stability), $\delta = 1.0827$, and $t = 10.4736$. The results are presented graphically in Figure 17, where the blue line shows the official targetting rule at $t = 10.4736$, the red dashed line is receipt in the model, and the dot-dashed black line is smoothed receipt in the IHDS-II data. Clearly, in the presence of rent-seeking, we are able to match the data on receipt of BPL cards much more successfully.

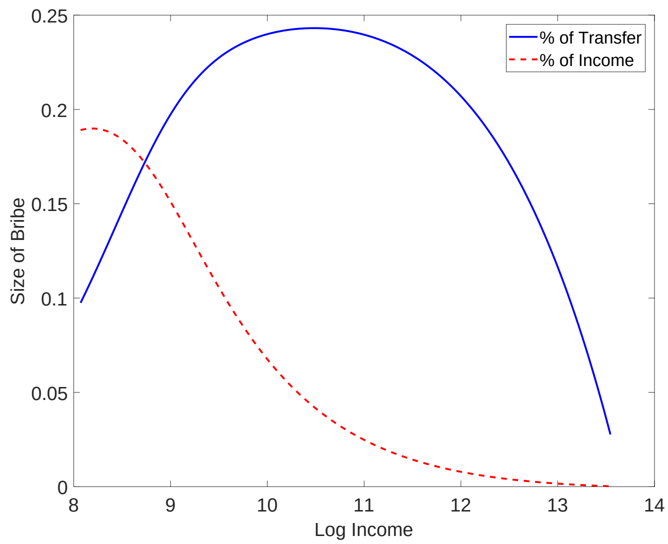
Figure 17: Real and Calibrated Distribution of BPL Card Receipt with Rent-Seeking



The bribes follow a non-monotonic pattern with respect to household income, as shown in Figure 18: as a percentage of the transfer, the bribe starts at 9.8% at the bottom of the income distribution, rises to a maximum of 24.3% at around 36000 rupees, and declines to 2.8% at the top of the income distribution. Meanwhile, as a percentage of income, the bribe peaks at about 19% at a very low income of about 3600 rupees, and then declines monotonically from there to reach 0.02% of income at the top.

As before, we then use the IHDS-II data to evaluate the optimal targetting policy; for

Figure 18: Size of Equilibrium Bribes

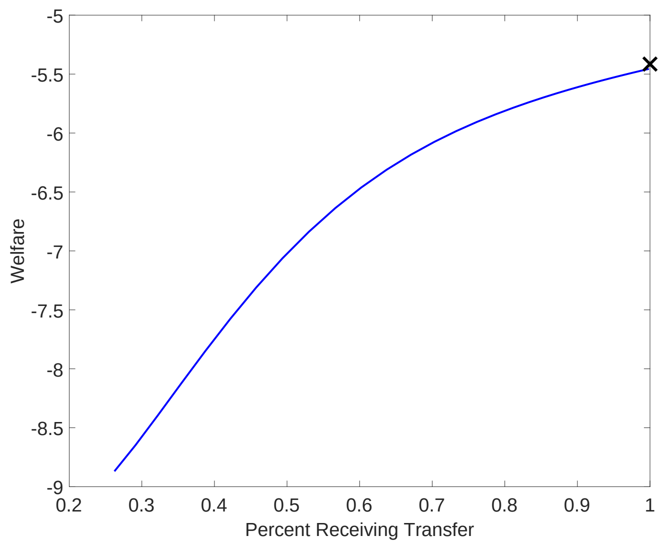


each value of t considered, we have to solve for the privately-optimal function of b with respect to y. Of course, the mean value of bribes tends to decrease with the threshold, because a very high threshold means almost everyone will receive the transfer and it is thus almost surely unnecessary to pay a bribe. We assume that the government agent's income is quite high – equal to the maximum in our sample, in fact – and thus that their marginal utility of income is quite low, so the transfer of resources for households to the government agent represents redistribution in the wrong direction.

The results for optimal policy can be found in Figure 19, where we can see that welfare does indeed increase with t, and thus with the proportion of recipients (which is a monotonic increasing function of t) over a large range. The X at the top right is above the curve, indicating that a universal basic income dominates any other policy, as it combines an elimination of rent-seeking with a saving of administrative expenses. At the baseline policy, $t = 10.4736$ and 41.3% of households receive a transfer, so this is a very large increase in universality.

Fundamentally, there are two new factors here leading to the conclusion that the universal basic income is the optimal policy: the added misallocation that rent-seeking generates – with transfers going to rich households too often and many poor households going without – and the redistribution in the wrong direction (to the government agent) that the bribes represent.

Figure 19: Optimal Targetting Rule t with Rent-Seeking



If we momentarily set aside the redistribution in the wrong direction caused by bribery, then given a level of misallocation of transfers, it doesn't really matter why the transfers are being misallocated – whether it is due to poor targetting technology or to rent-seeking – it just matters that they are misallocated, and that making the transfer more universal would reduce that misallocation, at least in the sense that fewer poor people would be excluded. In that sense, the only difference between rent-seeking and poor targetting technology would be that they have different functional forms, which is a fairly arbitrary modelling choice. However, it is important to note that in our analysis, rent-seeking is important at least in part because it helps us to match the data on receipt of BPL cards. Indeed, we cannot match the poor targetting at the bottom of the income distribution without rent-seeking, so the data seem to rather strongly indicate that rent-seeking is an important part of the reason for misallocation.

This also means that the redistribution in the wrong direction that is caused by bribery could also be important for welfare, so we can ask how the optimal policy conclusion would vary if bribes were smaller. That is hard to do without altering the overall motivation for redistribution, since the equilibrium bribe size is largely dependent on the coefficient of relative risk-aversion; see equation (2). So we suppose that bribes are paid as in the model, but that p percent of each household's bribe is returned to them, but in a lumpsum way conditional on income so that it does not directly affect the incentives to make bribes. Essentially, we suppose that the government agent can only keep part of the bribes they receive – perhaps because excessive wealth would be too conspicuous – and has to redistribute the remainder of it back to the population, doing so in proportion to the bribes paid (to avoid any redistributional effect of returned bribes).

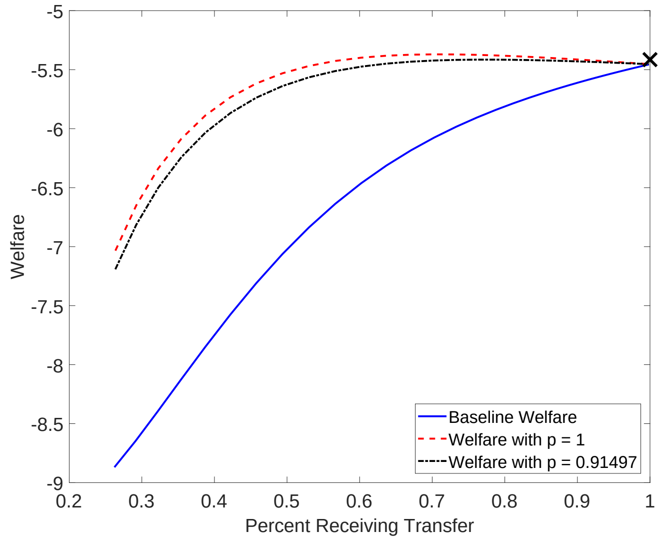
Then we can ask the question: for what value of p does the universal basic income cease to be the optimal policy? Alternatively, how big do (net) bribes have to be to make the bribe-reducing effect of a universal basic income sufficiently desirable? Figure 20 provides the answer to this question: the critical value is $p = 0.915$, so as long as the net bribes are at least 8.5% as large as the bribes in our simulation, the universal basic income is the optimal policy. In other words, since the average bribe in our baseline simulation is 22% of the transfer, then we would still prefer the UBI as long as the the average bribe was at least 1.87% of the transfer. Recall that Niehaus et al. (2013) found that the average bribe – in direct monetary form only – was 14 rupees for a card with an estimated annual value (in 2001) of 294 rupees, suggesting a bribe of 4.76% of the value of the annual transfer, so this suggests that our conclusion of UBI as the optimal policy is quite robust to the size of bribes. Indeed, even if all bribes were completely reimbursed (that is, $p = 1$), so that there was no redistribution in the wrong direction, the optimal transfer would be given to 70.9% of population, which is relatively close to universal; several proposals for India that claim to be a UBI actually propose a transfer to the poorest 75% or so, including Ministry of Finance of India (2017).

4 Conclusion

In this paper, we examine the case for a universal basic income in developing countries, with a particular focus on India. Such a policy would save on administration costs, and would overcome any targetting failures of targetted transfers; but it would also involve giving smaller amounts of money to everyone rather than targetting those resources on the people that seem poor.

However, unlike previous work, we show that rent-seeking is also important: if local government agents who have to perform the targetting have the ability to seek bribes and

Figure 20: Optimal Targetting Rule t with p Percent of Bribes Returned



other rents, targetting failures will not be random and the allocation of transfers and of bribe income may be even less efficient. We show that this provides an additional argument in favour of a universal basic income, which would reduce the power of the local government agent and thus their ability to extract rents.

In both a simple two-type model and a continuous-type model that is calibrated to Indian data, we find that a targetted transfer is optimal in the absence of rent-seeking, but a universal basic income becomes optimal once we model rent-seeking by government agents. We further find that the Indian data cannot be accurately fit by a model that does not incorporate rent-seeking, as there is far too little receipt of BPL cards at very low incomes. Both of these findings indicate that rent-seeking in targetting is a quantitatively important phenomenon that has the power to significantly affect optimal redistribution policy in a country like India.

References

Asri, V. (2019): "Targeting of Social Transfers: Are India's Poor Older People Left Behind?" *World Development*, 115, 46–63.

Banerjee, A., R. Hanna, J. Kyle, B. A. Olken, and S. Sumarto (2018): "Tangible Information and Citizen Empowerment: Identification Cards and Food Subsidy Programs in Indonesia," *Journal of Political Economy*, 126, 451–491.

Banerjee, A., P. Niehaus, and T. Suri (2019): "Universal Basic Income in the Developing World," *Annual Review of Economics*, 11, 959–983.

Bardhan, P. (2017): "Universal Basic Income – Its Special Case for India," *Indian Journal of Human Development*, 11, 141–143.

BBC News (March 25, 2019): "India Election 2019: Congress Pledges Income for 50m Families," `https://www.bbc.com/news/world-asia-india-47690066`, BBC, viewed on January 22, 2020.

Besley, T. (1990): "Means Testing versus Universal Provision in Poverty Alleviation Programmes," *Economica*, 57, 119–129.

Brown, C., M. Ravallion, and D. van de Walle (2018): "A Poor Means Test? Econometric Targeting in Africa," *Journal of Development Economics*, 134, 109–124.

Camacho, A. and E. Conover (2011): "Manipulation of Social Program Eligibility," *American Economic Journal: Economic Policy*, 3, 41–65.

Desai, S. and R. Vanneman (2018): "India Human Development Survey-II (IHDS-II), 2011-12," Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2018-08-08. `https://doi.org/10.3886/ICPSR36151.v6`.

Drèze, J. (2017): "Decoding Universal Basic Income," *Indian Journal of Human Development*, 11, 163–166.

Drèze, J., P. Gupta, R. Khera, and I. Pimenta (2019): "Casting the Net: India's Public Distribution System after the Food Security Act," *Economic and Political Weekly*, 54, 36–47.

Drèze, J. and R. Khera (2010): "The BPL Census and a Possible Alternative," *Economic and Political Weekly*, 45, 54–63.

Ghatak, M. and F. Maniquet (2019): "Universal Basic Income: Some Theoretical Aspects," *Annual Review of Economics*, 11, 895–928.

Ghose, A. K. (2017): "Universal Basic Income in India: Some Comments," *Indian Journal of Human Development*, 11, 177–179.

Hanna, R. and B. A. Olken (2018): "Universal Basic Incomes versus Targeted Transfers: Anti-Poverty Programs in Developing Countries," *Journal of Economic Perspectives*, 32, 201–226.

Hoynes, H. W. and J. Rothstein (2019): "Universal Basic Income in the United States and Advanced Countries," *Annual Review of Economics*, 11, 929–958.

Jhabvala, R. (2017): "A Basic Income for India: Experiences from the Field," *Indian Journal of Human Development*, 11, 160–162.

Kishore, A. and S. Chakrabarti (2015): "Is More Inclusive More Effective? The 'New Style' Public Distribution System in India," *Food Policy*, 55, 117–130.

Klasen, S. and S. Lange (2016): "How Narrowly Should Anti-poverty Programs Be Targeted? Simulation Evidence from Bolivia and Indonesia," Discussion Paper No. 213, Courant Research Centre, Georg-August-Universität Göttingen.

Macdonald, D. (2016): "A Policymaker's Guide to Basic Income," https://www.policyalternatives.ca/publications/reports/policymakers-guide-basic-income, Canadian Centre for Policy Alternatives.

Mane, R. P. (2006): "Targeting the Poor or Poor Targeting: A Case for Strengthening the Public Distribution System of India," *Journal of Asian and African Studies*, 41, 299–317.

Ministry of Finance of India (2017): "Universal Basic Income: A Conversation With and Within the Mahatma," https://www.indiabudget.gov.in/budget2017-2018/e_survey.asp, Government of India, viewed on April 26, 2019.

Mundle, S. and S. Sikdar (March 1, 2017): "Budget Subsidies of the Central Government and 14 Major Indian States: 1987-88 and 2011-12," https://www.ideasforindia.in/topics/macroeconomics/budget-subsidies-of-the-central-government-and-14-major-indian-states-1987-88-and-2011-12.html, Ideas for India, viewed on January 22, 2020.

Niehaus, P., A. Atanassova, M. Bertrand, and S. Mullainathan (2013): "Targeting with Agents," *American Economic Journal: Economic Policy*, 5, 206–238.

Sharma, A. N. (2017): "Debate on Universal Basic Income is Needed: Introduction to the Symposium Issue," *Indian Journal of Human Development*, 11, 139–140.