



Does transparency improve public program targeting? Evidence from India's old-age social pension reforms

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Abstract

Public program targeting is particularly challenging in developing countries. Transparency in eligibility rules for the implementation of social programs could be an effective measure to reduce mistargeting. While prior studies have examined the relevance of transparent delivery mechanisms, we focus on the transparency of eligibility criteria that can be reformed at relatively low cost. India's social pension reforms in the late 2000s provide the opportunity to examine the effect of a change in these criteria. Using two rounds of the India Human Development Survey along with extensive administrative information, we test whether increasing the transparency of eligibility criteria reduces the mistargeting of social pensions. We thereby allow for an error band, and we carefully control for design effects due to a general increase in the number of pensions and eligible individuals. Our results confirm the relationship between transparency of eligibility criteria and targeting performance and are robust to different specifications of the transparency measure and the introduction of a tolerance band.

Keywords: Targeting, transparency, old-age pensions, poverty, India

JEL Codes: I30, I38, H55

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1. Introduction

In many developing countries, wide-spread corruption, local capture, and clientelism prevent the effective delivery of basic social services to the intended beneficiaries. Policy interventions raising the level of transparency have been widely shown to improve poor people's access to these services (Björkman & Svensson, 2009; Francken, Minten, & Swinnen, 2009; Olken, 2007; Peisakhin, 2012; Peisakhin & Pinto, 2010; Reinikka & Svensson, 2004, 2005, 2011). Owing to the lack of reliable income data, the identification of beneficiaries needs to rely on proxy means tests. How to design these proxy means tests and which criteria should be included remains a subject of ongoing debate.

India's old-age social pension reforms in the late 2000s provide us with the opportunity to directly test the relationship between transparency improvements and the targeting performance for the case of social pensions in India. The reforms that we focus on consist of a clearer definition of the eligibility criteria. At the national level, in 2007, the Central Government replaced the previously vague poverty-related criterion "destitution" (no further indication was given how this should be defined) by the need to belong to a "Below Poverty Line" (BPL)-card holding household. This BPL card is also used for numerous other benefits such as food or fuel subsidies despite several criticisms of its beneficiary identification and allocation process (Alkire & Seth, 2013; Hirway, 2003; Jain, 2004; Panda, 2015; Saxena, 2009; Sundaram, 2003). Whether a household is in possession of a BPL card or not is an easily observable criterion and leaves no room for interpretation. In addition, there are state pension schemes, with different eligibility criteria that also changed around the same period. We can thus explore variation over time and across states.

While our study will have implications for access to anti-poverty schemes in general, studying the functioning of old-age social pension schemes is also relevant in itself: In many developing and emerging economies the age structure has started to change (United Nations, 2015), traditional family structures break down (Rajan & Kumar, 2003), and a large share of the elderly population is not yet covered by any contribution-based pension schemes of the formal sector (Sastry, 2004). Social pensions, i.e., pensions provided by governments to the elderly poor independently of prior contributions to social security systems have thus become increasingly relevant (see also Fan, 2010). Nevertheless, the literature on social pensions still remains scarce.

In addition, the limited literature that does exist indicates that mistargeting is an extremely widespread phenomenon (Asri, 2016; Kaushal, 2014) – possibly even more than for other public programs.

In this paper, we analyze how the selection of beneficiaries can be improved and focus on the role of transparency. One potential approach is to facilitate the selection of beneficiaries by making eligibility criteria more transparent and less complex. We focus therefore on the *verifiability of eligibility criteria* and analyze whether more transparent criteria are related to a better targeting performance of social pensions. If this expected relationship could be confirmed, this would suggest a resource effective means to channel the benefits of social security programs to the neediest individuals.

As the reform of eligibility criteria varied in their specific implementation across states, we can test the relationship between the transparency of eligibility criteria and the targeting errors. We use two rounds of the India Human Development Survey (IHDS) along with extensive administrative information to examine the relationship between the change in eligibility criteria and the targeting error over time (before and after the reform). From a political-economy perspective, we are interested in assessing how the relevant politicians and administrative officers can be driven to respect a set of officially defined eligibility criteria as closely as possible. We hence define our criteria of targeting error along the lines of the regulations in official government documents. This is despite the fact that these regulations may not coincide with the approaches that researchers use to identify the deserving individuals, such as comparing consumption expenditures to poverty lines (e.g. Asri, 2016) or using multi-dimensional poverty measures (e.g. Alkire & Seth, 2008, 2013). In doing so, we consider that both sides are complementary: For targeting to be successful, selection criteria must correctly identify the target group, *and* they must be correctly applied. This paper focuses on the second aspect, which has received much less attention in previous studies so far.

The remainder of the paper proceeds as follows: Section 2 presents the literature, theoretical considerations, and the hypothesis derived thereof. Section 3 introduces the Indian case study on old-age pensions and the related reform process. Section 4 presents data and methods followed by the empirical results in Section 5. Section 6 puts our findings in perspective using a measure of poverty that is independent of official targeting criteria. Section 7 concludes.

2. Literature and theoretical background

This paper contributes directly to the literature on the role of transparency for the targeting performance of anti-poverty schemes. While prior studies examined the relevance of transparent delivery mechanisms, we focus on the transparency of eligibility criteria that may be more easily amenable to reform. Most closely related to our study, Niehaus et al. (2013, p.206) analyze how a proxy means test should be designed if the “implementing agent is corruptible”. Theoretically and empirically, the authors show that using more conditions to define eligibility for an anti-poverty scheme is likely to deteriorate the targeting performance. Intuitively their findings indicate that rule breaking becomes more likely if there are more rules that local government official needs to follow for the allocation of benefits. The theoretical model and empirical application in Niehaus et al. applies also to the context of social pensions in India. In addition to the number of conditions that Niehaus et al. are focusing on, we take into account that eligibility conditions also differ substantially in their complexity and verifiability and assess the influence of transparency improvements for specific reforms of social pension eligibility in the late 2000s.

In line with Niehaus’ et al. (2013) findings, Drèze and Khera (2010) show the importance of using eligibility criteria that are easy to follow and suggest replacing the existing complex approach used for the identification of BPL card holders by easily verifiable inclusion and exclusion criteria which allow individuals to state their eligibility based on one criterion such as “I am eligible because I am landless” or “I am not eligible because I own a car” (p.55). Drèze and Khera (2010) argue that this simplification will also help to facilitate participatory monitoring and to prevent fraud.

Increased transparency of eligibility criteria can be achieved by reducing the number and complexity of conditions as well as by applying the criteria with high verifiability. Considering the verifiability of eligibility criteria is extremely important for the implementation of public anti-poverty programs in developing countries where data on income are often imprecise and where high shares of informal sector employment further complicate the measurement of welfare of potential beneficiaries (Baker & Grosh, 1995).

From a theoretical perspective, we expect that increasing the transparency of eligibility criteria affects demand and supply sides of social pension targeting. Transparency improvements

influence the behavior of local government officials in charge of selecting beneficiaries (supply side) and local citizens applying (demand side):

On the supply side, through the increase in transparency, the local government officials face increased costs of preferential treatment as the likelihood of being detected is higher and therefore targeting errors are expected to be reduced. Moreover, using more transparent eligibility criteria reduces the administrative burden of selecting beneficiaries and the chance of human error. The use of more transparent and simpler eligibility criteria also reduces the administrative costs of social protection schemes and thereby allows that at least in theory, these limited resources can be used as transfers to the poor.

On the demand side, increasing the transparency of eligibility criteria facilitates the application for the eligible elderly individuals. Fewer and less complex conditions simplify the application process and make the outcome of the application more predictable. Given that the applicant submits all required documents, the chances of receiving the benefits are higher compared to a situation with less transparent criteria and higher discretionary power for the local government official. Transparency of eligibility criteria moreover facilitates that people are aware of their entitlements and helps individuals to scrutinize the selection of beneficiaries in public meetings improving their influence in the beneficiary selection.²

Based on these theoretical considerations related to the supply and demand side of targeting, we hypothesize that increasing the transparency of eligibility criteria reduces targeting errors.

3. Old-age social pensions in India

In India, social pension schemes exist at the state and national level, whereby the pensions provided by the state governments typically complement the amounts provided under the national scheme and/or widen the group of beneficiaries. The national scheme called Indira Gandhi National Old Age Pensions Scheme (IGNOAPS) was introduced in 1995 with a central government contribution of 75 INR per month. Unlike social pensions in other developing countries like Nepal, Bolivia or South Africa that were paid out to all individuals above a certain age, social pensions in India are targeted only towards the poor (Palacios & Sluchynsky, 2006).

² In the Indian context, public meetings are supposed to be used for scrutinizing the list of beneficiaries for several anti-poverty schemes including old-age social pensions (see e.g. Besley, Pande, & Rao, 2005).

The Ministry of Rural Development is in charge of the social pension scheme but the state governments are responsible for the implementation through *gram panchayats* (village councils) and municipalities. The 1998 guidelines of the National Social Assistance Programme (NSAP) state that “[the] Panchayats/Municipalities will be responsible for implementing the schemes [and] are expected to play an active role in the identification of beneficiaries” (Government of India, 1998, p. 4). Panchayats and municipalities represent the smallest local governance unit in rural and urban India respectively.

IGNOAPS initially targeted elderly persons who should be 65 years or older, and destitute defined as “having little or no regular means of subsistence from his/her own sources of income or through financial support from family members or other sources” (Government of India, 1995, p. 7). At the same time, there was a cap on the number of beneficiaries that effectively limited the number of the destitute to 50% of the elderly below the Tendulkar poverty line (Rajan, 2001, p. 613). While this implicitly shifted the eligibility threshold to the median of the distribution of monthly per capita household consumption expenditure of the elderly poor (Rajan, 2001, p. 613), who did and who did not belong to this group was unobservable in practice, and the vagueness of the 'destitution' criterion left ample discretionary power to local officials. In 2007, the previously used destitution criterion was replaced by the much more easily observable requirement that beneficiaries should live in households that hold a BPL card. In addition, minimum age was reduced to 60 years.

Regarding the complementary state pensions, we also observe several reforms of eligibility criteria tending to reduce the complexity of eligibility criteria and increasing their verifiability. For instance, in Uttar Pradesh eligibility for the state social pension scheme was originally based on land holding in rural areas and individual income in urban areas, while after the reforms it was purely based on BPL card holding. Other states such as Himachal Pradesh, Haryana, Odisha and Karnataka now rely largely on household income to determine the eligibility for their state-run old-age pension schemes. In other states such as Madhya Pradesh, state-run programs simply follow the IGNOAPS criteria. Finally, there are a few states such as West Bengal that fully abstain from running their own state-level programs. For the latter, the reform of IGNOAPS directly defines the overall change in transparency of the relevant eligibility criteria in the state.

While there is a general tendency towards the use of more easily verifiable criteria the number of criteria increased in many states, which may reduce transparency. In any case, the above discussion shows that considerable variety regarding the transparency of eligibility criteria remains between states. This is mainly true for state-run schemes, but even the criteria for IGNOPAS are not always exactly identical across states. Based on a large number of government reports and internet sources, we compiled the exact information for the period before and after the reform for seven states. This information is presented in Appendix 1.

4. Data and methods

4.1 Generation of the data set

To test our hypothesis, we examine the likelihood of individual-level mistargeting depending on the transparency of the relevant eligibility criteria and on a number of controls. To implement this analysis, we combine two data sets with information on (i) individuals, households and communities, and (ii) administrative regulations at the state level. Unfortunately, detailed information on specific eligibility criteria and their change over time could not be compiled for all states, so that the analysis is effectively restricted to the states of Haryana, Himachal Pradesh, Karnataka, Madhya Pradesh, Odisha, West Bengal and Uttar Pradesh (see Appendix 1). For the individual- and community level data we rely on two waves of the India Human Development Survey (IHDS) in 2004-05 and 2011-12 that were conducted by the National Council of Applied Economic Research (NCAER) and University of Maryland (Desai et al., 2007, 2015), i.e., before and after the relevant reforms.

The IHDS is a nationally representative individual-level survey including a broad range of modules regarding demographics, health, public welfare programs, fertility, agriculture, employment, gender relations and women's status, beliefs, education, social networks, institutions, etc. related to individuals, households and communities. The survey covers 41,554 households in 1503 villages and 971 urban neighborhoods across India. Sampling was based on a stratified, multistage procedure in 2004-05 (IHDS-I) and households were re-interviewed in 2011-12 (IHDS-II) (Desai et al., 2007, 2015).

As we use individual-level fixed effects regression models to control for individual heterogeneity in our econometric analysis, and the data collection includes only two periods, our dataset is

effectively reduced to those individuals who were surveyed in both rounds. In addition, given that our focus is on old-age pensions, we exclude all individuals that are more than ten years younger than the eligibility age.³ Finally, our dependent variable capturing the likelihood of targeting error at the individual level can only be identified for individuals in seven states for which sufficient information is available on state-level pension schemes, i.e., the seven states listed above. As a consequence, for our analysis the sample is reduced to 6,807 elderly individuals observed in both rounds of the survey within these seven states, i.e., to a total of 13,614 observations.

We combine the IHDS data with state-level administrative data on the specific social pension schemes drawn from a large number of government websites and reports.⁴ As a complement to quantitative data, we also collected qualitative information through interviews with policy makers, ministerial officials, social activists and scholars specialized on social pensions for elderly. The information drawn from these interviews primarily refers to the administrative processes and was used for checking the collected administrative information. The interviews will not be analyzed directly in this paper, but they provided important background information that help in the interpretation of empirical results. We provide a list of conducted interviews in Appendix 6.

4.2 Operationalization

4.2.1 Dependent variable

As we intend to measure a possible improvement in targeting, a natural choice for the dependent variable seems to be the targeting error. This error can refer both to unjustified exclusion or unjustified inclusion. Exclusion error is defined as the share of eligible individuals who are excluded, while inclusion error is defined as the share of ineligible individuals who are included (see Coady, Grosh, & Hoddinott, 2004). Given that the correct application of the threshold still leaves many poor and deserving elderly uncovered, exclusion error tends to be regarded as the primary concern in the Indian context. This was revealed in many of our interviews. In addition, IHDS data show that the prevalence of inclusion error is much smaller. In fact the number of wrongly included individuals, particularly in the 2004-05 survey is so limited that credible

³ This cut-off is based on the age distribution of social pension beneficiaries presented in Appendix 2.

⁴ The data source for each variable is presented in Appendix 3.

statistical inference appears problematic. We therefore focus on exclusion error here. At the individual level, the overall share can obviously not be computed, but we can observe whether a person is ‘wrongly excluded’ or ‘wrongly included’. We hence generate dummy variables to reflect the targeting error at the individual level.

As mentioned earlier, in contrast to most of the extant literature (e.g. on social pensions in India Asri, 2016), we do not impose any external normative assessment of what is ‘wrong’. Rather, we consider the official criteria that public officials are supposed to follow, and try to match them as closely as possible with our data. Since the criteria vary across states and over time, a person with the same characteristics could be wrongly excluded in one place (or one point of time), and rightly excluded in another. Along with the age criterion, we hence need to consider a number of variables in this context, related to consumption expenditure, income, BPL, land holding, and/or residential status. The destitution criterion relevant primarily for the early implementation of IGNOAPS (and some state-level social pension schemes) is measured by per-capita consumption (net of social pension receipts) below the median consumption of the elderly poor (Rajan, 2001, p. 613), whereby poverty is defined based on the Tendulkar poverty line (separately for rural and urban areas), and median consumption of the elderly is approximated by the per-capita consumption (net of old-age pensions) of the household in which they live. Since respondents to the IHDS do not distinguish between different social pension schemes, when eligibility criteria differ between IGNOAPS and the relevant state scheme, we consider that an individual is rightly included if she receives the pension and fulfills the criteria for either of these schemes. Along the same lines, anyone who fulfills the criteria of either of the schemes but is not included, is considered as wrongly excluded.

Picking up the perspective of relevant politicians and administrative officers also leads to an additional consideration: For some of the relevant criteria, they may only be able to observe roughly and not exactly whether they are met. It thus appears appropriate to carry out the analysis with a tolerance band around the exact thresholds. This may also be useful because respondents to the survey (on which we rely to determine age and the degree of poverty) may not always give exact answers. For instance, they may provide their approximate, rather than their exact age. And finally, targeting error that only comes at the margins of given thresholds appears substantially much less relevant than misallocation that leaves some of the poorest and most deserving individuals without pension coverage. We thus complement the traditional computation of the

error with an additional analysis allowing for a small error margin around the official threshold. Since methodologically, it is not possible to create a statistical error band around some arbitrary number, we instead construct a 95% confidence band around the cut-offs using the sampling distribution of the estimator of the corresponding percentile of the distribution.

As most of the underlying variables are continuous, the computational procedure is straightforward. For the BPL criterion, however, we need to first reconstruct the underlying distribution of asset ownership and other socio-economic characteristics of the household. We do so by estimating a probit model to obtain the probability of holding a BPL card. The explanatory variables of this model are derived from the 13-item census questionnaire used for the 2002 BPL assessment (Ministry of Rural Development, 2002). We then compute the 95% confidence interval around the mean prediction for those individuals who effectively possess a BPL card. The cut-offs for the errors with tolerance band then jointly constitute the limits of the confidence interval for BPL card holding itself. For a detailed explanation of the construction of the cut-off points including tolerance bands, see Appendix 4.

4.2.2 Explanatory variables and controls

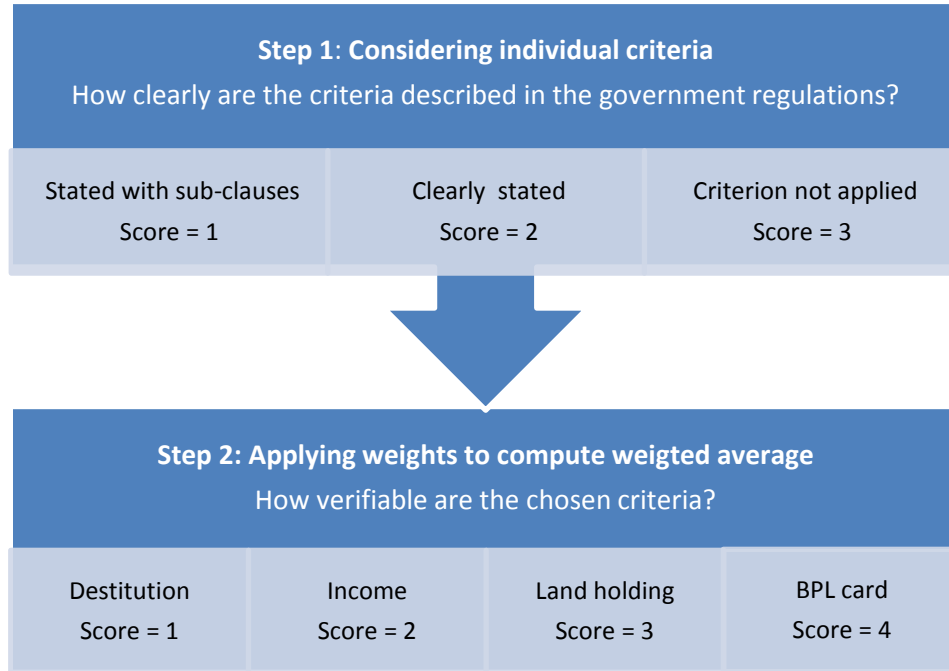
Our explanatory variables describe the transparency of eligibility criteria. Based on the administrative information described above, we develop three alternative state and time specific transparency scores. In general, the transparency score increases if eligibility criteria are fewer in number, easier to verify and less complex to implement. Following Niehaus et al. (2013), our first indicator (Transparency A) simply counts the different criteria and related conditions taken into account to define eligibility. The idea is that the sheer number of these criteria matters, because any addition of criteria and related sub-clauses renders the selection process more difficult to understand and thereby reduces transparency. However, not all criteria are equally difficult to assess, and this may be even more relevant for transparency than the number of criteria itself. Building on Drèze and Khera (2010) we hence suggest an additional indicator (Transparency B) that considers how easily verifiable the criteria are.⁵

Finally, we compute a more sophisticated version of the transparency measure (Transparency C), which combines both aspects within a single indicator (see Figure 1). This indicator assigns

⁵ See Appendix 5 for a more detailed explanation of the construction of Transparency A and B.

higher scores to state level regulations that use fewer eligibility criteria, state the relevant criteria clearly and choose to use eligibility criteria that are more verifiable.

Figure 1: Coding of transparency measure C



Source: Authors' illustration.

After examining government regulations, we classify eligibility criteria into four categories, namely destitution, income, land holding and BPL card holding. In addition, there are criteria regarding minimum age (see Annex 1), but we ignore them for our transparency indicators, as their existence is uniform across states and over time. Depending on states, eligibility criteria include one or several of the above-mentioned categories. We start by evaluating transparency within each category. For example, if a state level regulation does not specify anything related to land-based eligibility, the score for this category is 3. If it mentions a single clause related to land-based eligibility, the score is 2. If there are several clauses and sub-clauses related to land based eligibility thereby reducing clarity and increasing complexity, the score is 1. We follow the same scoring scheme for each of the four categories: destitution, income, land and BPL.

We develop the overall transparency index C based on the weighted scores for all categories. We thereby compute the weights based on the qualitative data collected during our interviews with members of parliament, government officials and other experts, and based on the existing

literature on targeting in India that helped us to gauge how verifiable an eligibility criterion is. The two steps for coding the transparency measure are visualized in Figure 1.

We further consider a number of control variables. Given that our dependent variables are based on thresholds the construction of which involves a number of possibly relevant controls, the latter may be endogenous. We thus distinguish between two sets of control variables – a first set, in which we exclude such potentially endogenous factors, and a second set in which we take them into account. The first set includes information on household size, widowhood, education and employment, access to media, urban or rural locality, and the share of the elderly, the share of Muslims, and the share of Scheduled Castes, Scheduled Tribes and Other Backward Castes in the district and political variables. The complementary set of control variables additionally includes the working status of the elderly individual, an indicator of household assets, an indicator of landlessness, and further variables at district level, i.e., the Gini index, the overall share of Tendulkar poor (based on per-capita consumption net of old-age pensions), the share of literate adults, and the shares of households that express confidence in local government officials and state government.

4.3 Statistical methods

Our econometric analysis is based on fixed effects regressions with observations weighted using corresponding probability weights. Hausman tests clearly reject the alternative use of random effects. Since our dependent variables are binary, the use of a linear specification leads to a linear probability model. We use cluster-robust error terms (clustered at the individual level) in order to mitigate the resulting heteroscedasticity problems. Given that our time series is very short, the alternative use of probit with fixed effects suffers from an incidental parameter problem leading to biased coefficient estimates. Fixed effects (conditional) logit is a possible alternative and will be used for robustness checks. Our empirical model is:

$$Y_{it} = \beta_0 + \beta_1 \text{Year}_{2012} + \beta_2 \text{TS}_{st} + \mathbf{x}'\boldsymbol{\gamma} + a_i + u_{it} \quad (1)$$

where Y_{it} is a binary variable capturing whether individual i is wrongly excluded in period t , Year_{2012} is a period dummy that takes the value of one in the second round of the survey, TS_{st} is the transparency score for state s in period t , a_i is individual fixed effect capturing unobserved heterogeneity and \mathbf{x} is a set of control variables. Our focus is on parameter β_2 .

An important issue with this regression design may be that β_2 could fully or partially reflect a simple design effect. Since a higher number of pensions were allocated in the second period, at a given number of eligible individuals, the probability of being wrongly excluded should decline, even if pensions were allocated randomly. As the increase of pensions varies across states the simple inclusion of the period dummy will not suffice to control for this. Since it is highly plausible that the number of pensions made available by each state are correlated with the transparency of the eligibility criteria (e.g. because a state that cares for the elderly poor will try to improve both, coverage and transparency), our estimator of β_2 may be biased, and the effect of transparency itself may be much less pronounced than our initial regression outcomes would suggest.⁶

At the same time, the number of eligible individuals rises between the two periods, and again this increase is not uniform across states. The effect is exactly opposite to the above since this leads to a reduction of available pensions relative to eligible individuals, and should hence increase exclusion error even if pensions were allocated randomly. Again, part of this problem can be solved by controlling for the share of elderly in the population, but issues remain, because the number of eligible individuals also increases due to the reform of the eligibility conditions, notably through the reduction of minimum age. Again these design features of the pension system are plausibly determined together with other changes in the criteria, and hence cannot be considered as independent from the transparency variable.

We solve this issue by comparing our outcomes to the outcomes we obtain when randomly allocating pensions and eligibility within each state and period.⁷ In other words, we use the true probability to (a) receive a pension, and (b) to be eligible to determine pseudo-eligible individuals and pseudo-pension recipients by drawing from a Bernoulli distribution with the corresponding probability (by state and period). From these two random variables, we create a new dummy variable mimicking wrong exclusion for this pseudo case. We then re-run regression (1) based on the new dependent variable.

$$Y_pseudo_{it} = \tilde{\beta}_0 + \tilde{\beta}_1 Year_{2012} + \tilde{\beta}_2 TS_{st} + \mathbf{x}'_i \tilde{\boldsymbol{\gamma}} + \tilde{a}_i + \tilde{u}_{it} \quad (2)$$

⁶ We thank Stefan Klonner for having pointed this out to us.

⁷ Note that to be closer to reality, the random draw for 2011-2012 is carried out in a way that pensions and eligibility cannot be withdrawn. Hence the random draw is kept from the previous period and augmented by a new random draw of additionally eligible individuals and additional pensions only.

If the estimate of $\tilde{\beta}_2$ is insignificant, we can safely conclude that our initially estimated effect is not driven by the mere increase in pensions and/or eligible individuals. If it remains significant, we have to consider the difference of the coefficients between the initial regression and the pseudo regression ($\beta_2 - \tilde{\beta}_2$). This difference corresponds to the effect of transparency cleaned for the design effects discussed above. Running a third regression based on the difference between (1) and (2) can show whether this difference is significant.

$$Y_{it} - Y_{pseudo_{it}} = (\beta_0 - \tilde{\beta}_0) + (\beta_1 - \tilde{\beta}_1)Year_{2012} + (\beta_2 - \tilde{\beta}_2)TS_{st} + \mathbf{x}'(\boldsymbol{\gamma} - \tilde{\boldsymbol{\gamma}}) + (a_i - \tilde{a}_i) + (u_{it} - \tilde{u}_{it}) \quad (3)$$

5. Results

5.1 Descriptive statistics

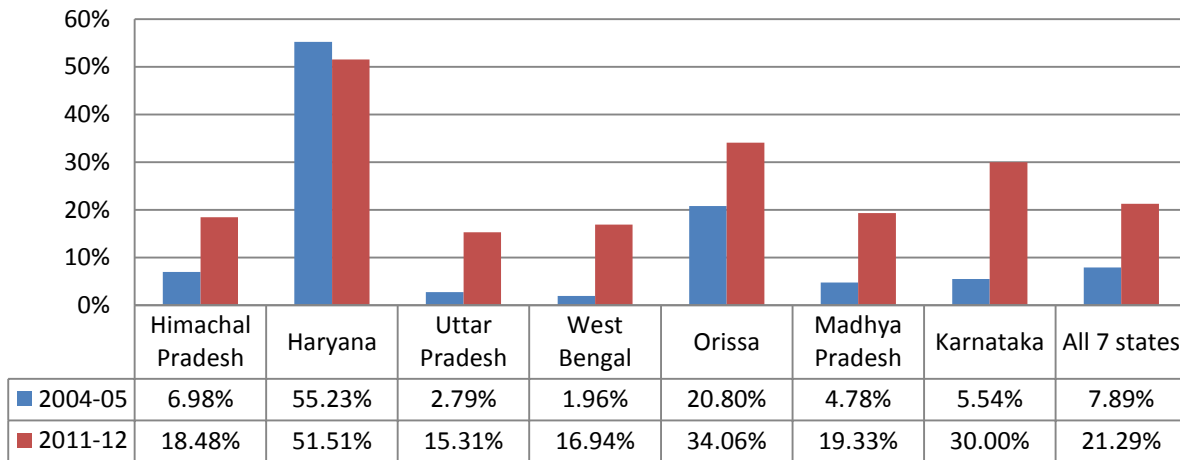
We start by providing a general overview of the development of coverage and mistargeting based on descriptive statistics. For presenting the empirical results, we stick to the balanced panel of observations also used later for the regression analysis to ensure comparability.

Figure 2 (a) presents social pension coverage of the elderly, which reveals strong differences across states and over time. In particular, in Haryana, coverage has always been much higher than in other states. These other states, however, have increased their coverage considerably between the two periods of observation. As mentioned above, this change in coverage is an important factor to keep in mind as it reduces the exclusion error even if pensions are allocated randomly.

As the prevalence of poverty varies significantly between states, it appears useful, however, to compare the above values with the values if the sample is restricted to the elderly poor. Figure 2 (b) shows how the picture changes when we only consider the elderly below the Tendulkar poverty line: All rates increase, but particularly so in Uttar Pradesh, West Bengal and Madhya Pradesh.

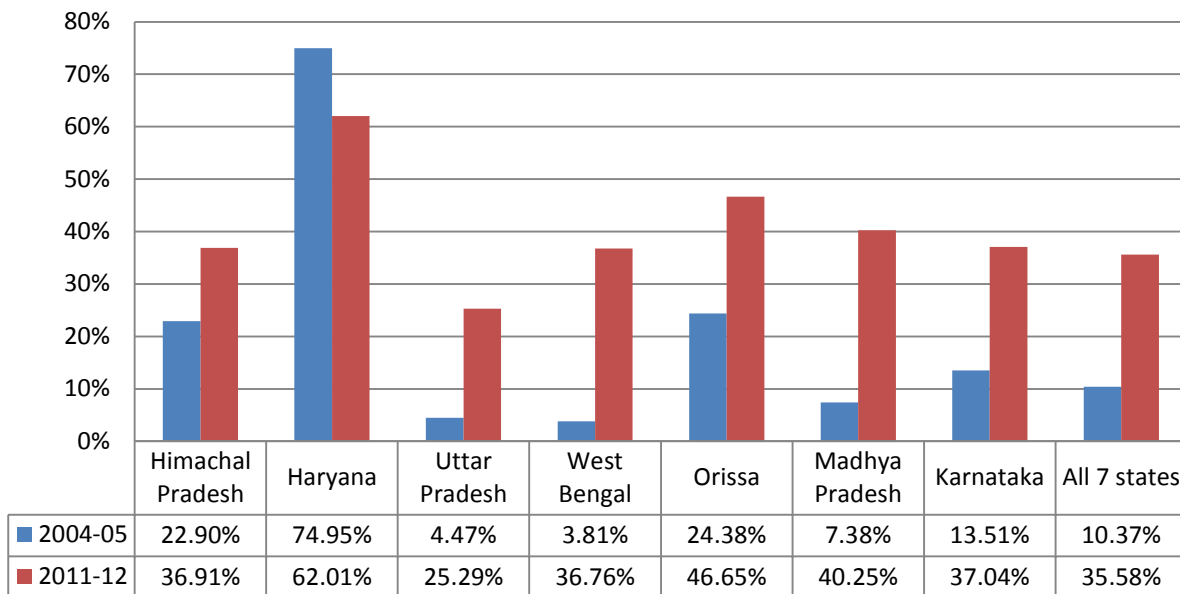
Figure 2: Coverage

(a) Social pension coverage of elderly, by state and year



Notes: Based on observations from balanced panel. The elderly population includes all individuals who are at least as old as the local eligible age.

(b) Social pension coverage of elderly poor, by state and year



Notes: Based on observations from balanced panel. The elderly poor include all individuals who are at least as old as the local eligibility age with consumption expenditure net of social pension benefits received below the Tendulkar poverty line.

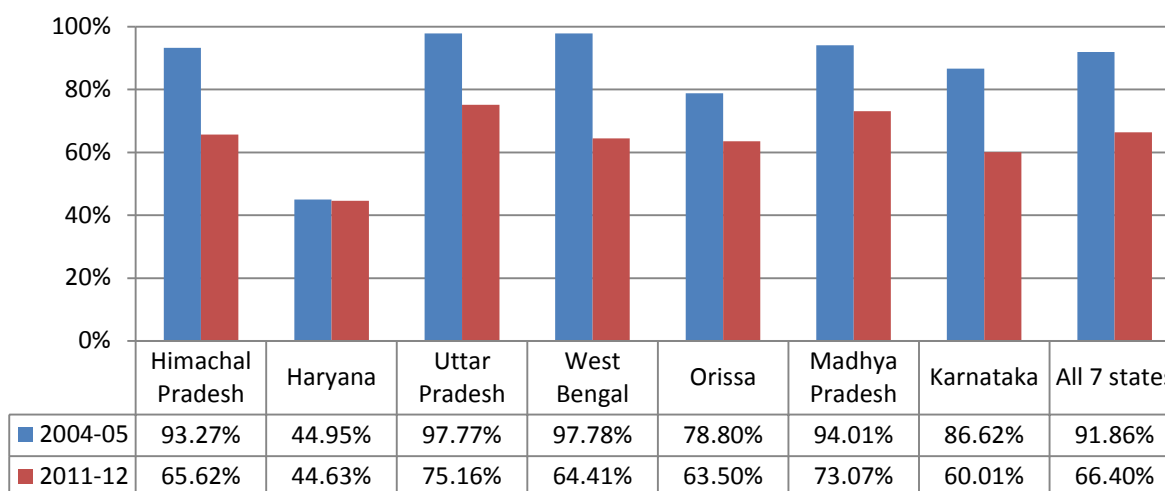
Source: IHDS I for 2004-05 and IHDSII for 2011-12.

We now look at the exclusion error within each state, and how it evolved over time. Figure 3 shows the exclusion error using the sharp criteria in panel (a), and the tolerance band in panel (b). We observe that the exclusion error is extremely high, in 2004-05 in some states even close to 100%. In all states except Haryana where the pension coverage was highest in both time periods,

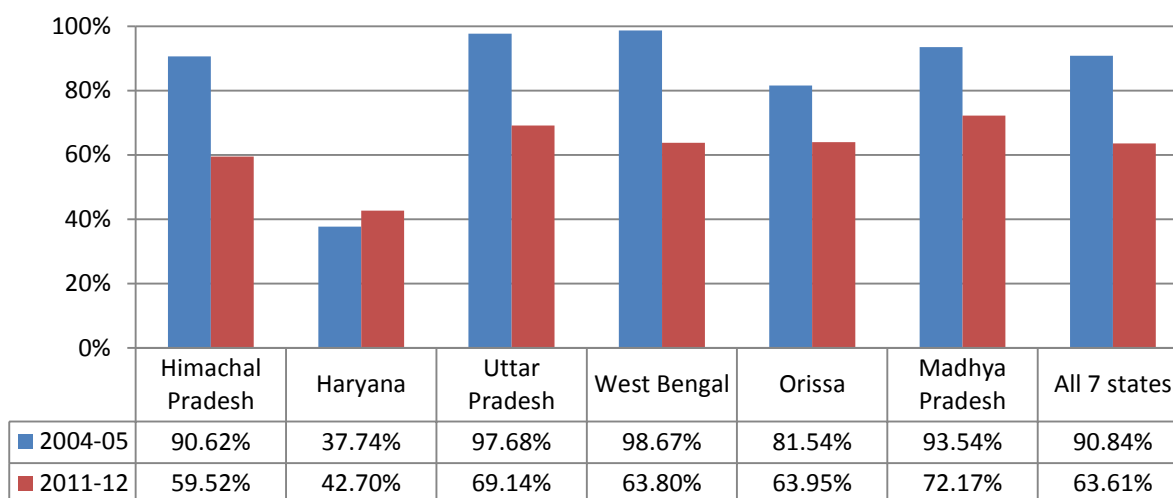
the exclusion error in 2004-05 was above 75% and still above 60% in 2011-12. The exclusion error calculated with the tolerance band is slightly different but shows a similar pattern. In all states except Haryana, the exclusion error decreased substantially over time.

Figure 3: Exclusion error

(a) Based on sharp eligibility criteria



(b) Based on criteria with tolerance band



Notes: This figure does not include any statistics for Karnataka as applying the tolerance band, slightly fewer individuals are counted as eligible and in the case of Karnataka there are 0 “included must” individuals in 2004-05.

Source: IHDS I for 2004-05 and IHDS II for 2011-12.

5.2 Econometric analysis

Our econometric analysis now allows us to relate these outcomes to differences in the transparency of the eligibility criteria. The empirical results are in line with our expectations. The fixed-effects regressions consistently show that higher transparency is associated with a lower likelihood of being wrongly excluded from social pension benefits (see Table 1 as well as Table A5.2 in Appendix 5). In Table 1 below we present the specification using our most comprehensive transparency indicator, namely Transparency C. In the first specification, we control only for the time dummy. In the second specification, we include all clean control variables and in the third specification, we include all control variables (including those that are potentially endogenous to social pension receipt). The probability of being wrongly excluded decreases by 6-7 percentage points in all models if the transparency score increases by 1 unit ($\approx \frac{1}{2}$ standard deviation). The results are robust to the different specification of the transparency measure and to the use of the tolerance band (see also Appendix 5).⁸

Table 1: Transparency of eligibility criteria and the likelihood of being wrongly excluded

(a) Sharp eligibility criteria, transparency measure C

VARIABLES	(1) Wrongly excluded	(2) Wrongly excluded	(3) Wrongly excluded
Year ₂₀₁₂	-0.096*** (0.016)	-0.163*** (0.027)	-0.214*** (0.039)
Transparency C	-0.066*** (0.005)	-0.063*** (0.005)	-0.062*** (0.005)
Individual fixed effects	Yes	Yes	Yes
Household variables	No	Yes, clean controls	Yes, all controls
District characteristics	No	Yes, clean controls	Yes, all controls
Political variables	No	Yes, clean controls	Yes, all controls
Observations	13614	13614	13614
Number of id	6807	6807	6807
R-squared	0.076	0.099	0.105

Notes: Statistical significance is shown by ** $p < 0.05$, *** $p < 0.01$ with cluster-robust p-values in parentheses.

⁸ Results are also robust to the use of a conditional logit specification. In this case, odds ratios for Transparency C are 0.74, 0.735, and 0.728 for the equations without, with clean, and with all controls respectively. All are statistically significant at $p < 0.001$.

(b) Using tolerance band, transparency measure C

VARIABLES	(1) Wrongly excluded with band	(2) Wrongly excluded with band	(3) Wrongly excluded with band
Year ₂₀₁₂	-0.039*** (0.014)	-0.110*** (0.028)	-0.164*** (0.035)
Transparency C	-0.054*** (0.005)	-0.050*** (0.005)	-0.052*** (0.004)
Individual fixed effects	Yes	Yes	Yes
Household variables	No	Yes, clean controls	Yes, all controls
District characteristics	No	Yes, clean controls	Yes, all controls
Political variables	No	Yes, clean controls	Yes, all controls
Observations	13614	13614	13614
Number of id	6807	6807	6807
R-squared	0.062	0.089	0.096

Notes: Statistical significance is shown by ** $p < 0.05$, *** $p < 0.01$ with cluster-robust p-values in parentheses.

5.3 Placebo tests

As discussed in Section 4.3, the robust negative relationship observed between transparency and the probability to be wrongly excluded, may simply reflect a design effect due to variation in the number of pensions and in the number of eligible individuals that could be correlated with transparency. Our alternative dependent variable based on the random draw of both pensions and eligible individuals $Y_{pseudo_{it}}$ should allow us to identify this design effect since the only information it includes is the corresponding change in the numbers of eligible persons and pensions received.

Results indicate that indeed, the transparency scores continue to be robustly related to this pseudo probability of being wrongly excluded. The coefficient estimates continues to be negative and significant. However, the size of the point estimates is only about half of the size of the estimates in Table 1. In the differenced regression (following equation 3 above), the difference between the original estimates and the placebo estimates is still sizeable and highly significant.

We present the different coefficient estimates with respect to Transparency C in Table 2 below, and with respect to Transparency A and B in Appendix 5, Table A5.3 (all results are only for the

sharp eligibility criteria as the band cannot be created around a random draw of eligible individuals). As before, the columns present the different specifications (without controls, with clean controls, and with all controls). The rows compare the coefficient estimates for the transparency variable in equations 1, 2, and 3. The numbers referring to equation 3 can be considered as the net effect of transparency as they are computed by subtracting the design effect from the overall effect. According to these results, an increase of Transparency C by 1 unit ($\approx \frac{1}{2}$ standard deviation) leads to a net decrease in the probability to be wrongly excluded by 3 percentage points. In other words, an increase in transparency by one standard deviation reduces the probability of any individual to be wrongly excluded by 6 percentage points. This corresponds to the effect size we find for the alternative measures A and B in Appendix 5.

Table 2: Net effect of transparency

	(1)	(2)	(3)	Notes
Coefficients estimated	Individual and year fixed effects, no controls	Fixed effects and clean controls	Fixed effects and all controls	
β_2	-0.066*** (0.005)	-0.063*** (0.005)	-0.062*** (0.005)	Estimates from equation 1, (copied from Table 1)
$\tilde{\beta}_2$	-0.036*** (0.003)	-0.033*** (0.002)	-0.034*** (0.003)	Estimates from equation 2 (placebo: design effect)
$(\beta_2 - \tilde{\beta}_2)$	-0.030*** (0.006)	-0.029*** (0.006)	-0.029*** (0.006)	Estimates from equation 3: Net effect of transparency

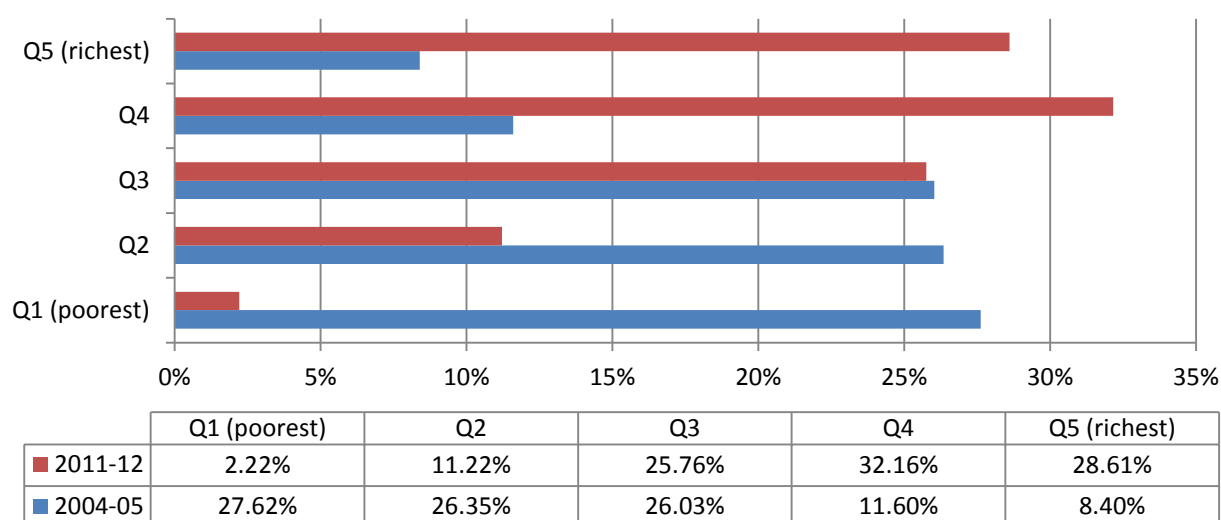
Notes: Statistical significance is shown by ** $p < 0.05$, *** $p < 0.01$ with cluster-robust p-values in parentheses.

6. Discussion

Our results have demonstrated that transparent criteria tend to be more systematically applied and hence reduce targeting error. However, even a clear and consistently applied criterion is useful only if it correctly identifies the intended beneficiaries. As explained above, the BPL criterion has been widely criticized in this respect. If better-off households rather than the poor possess BPL cards, then the above described changes in eligibility criteria and the related improvements in targeting will not necessarily lead to greater access of the elderly poor to the social pension benefits. It may, in fact, primarily increase the access of the well-to-do. Dutta (2010) as well as Asri (2016) suggest that this may indeed be the case.

We briefly study this question by examining the consumption quintiles of the ‘wrongly excluded’ cases in the elderly population. Figure 4 shows the distribution of those considered as ‘wrongly excluded’ according to the official criteria before and after the reform. The graphical illustration confirms the misfit of the official criteria. About 60% of those considered as ‘wrongly excluded’ in the period after the reforms belong to the two highest consumption quintiles (29% to the highest and 32% to the second highest quintile). While they may be ‘wrongly excluded’ from an official perspective (as they fulfill the official criteria such as holding a BPL card), this exclusion appears clearly justified from a distributional perspective. On a positive note, the share of those wrongly excluded with very low consumption expenditures in the lowest quintile has gone down from 28% to 2% indicating a better inclusion of poor elderly among the beneficiaries after the reforms compared to before.

Figure 4: Consumption quintiles of wrongly excluded



Source: IHDS- I for 2004-05 and IHDS- II for 2011-12.

Clearly, the reformed eligibility criteria do not solve the problematic mismatch between official eligibility and actual poverty. While local government officials do a better job in allocation social pensions in line with official rules since the criteria have become more transparent, BPL card holding as one frequently used criterion suffers from significant targeting error itself. This remains a challenge that needs to be addressed in future reforms.

It should be noted that the Indian government is well-aware of the problems related to BPL (Government of India 2009, p. 17ff.). In 2011, the Socio-Economic and Caste Census (SECC) was launched with the primary objective to revise the identification of BPL households. It uses a variety of asset- and income-based criteria along with direct exclusion and inclusion conditions. The new criteria were formally adopted by the Ministry of Rural Development in January 2017 (Press Information Bureau / Government of India, 2017). It remains to be seen to what extent they will improve upon the status quo.

7. Conclusion

Public program targeting represents a strong challenge, notably in the context of many developing countries where corruption, clientelism and elite capture are high. In such contexts, social and political connectedness appears to be highly correlated to the benefits received. These problems must be expected to be even greater for programs like social pensions targeted to the elderly poor, who are generally less well-educated, less mobile and less vocal when it comes to claiming their rights. India's reform of its old-age social pension schemes in the late 2000s provides the opportunity to examine the effect of the introduction of a large scale transparency improvement in this context. Given the variation in the reforms between states and over time, we are able to assess whether (and to what extent) increasing the transparency of eligibility criteria helps to reduce the mistargeting of old-age social pensions. Our panel fixed effects regressions show that the likelihood of being wrongly excluded decreases with more transparent eligibility criteria, and our results are robust to different specifications and the inclusion of a tolerance band.

A placebo regression reveals, however, that the mere increase in pension numbers along with the increased number of eligible individuals biases the initial estimates. To obtain the net effect of transparency, the influence of these changes in numbers (design effect) needs to be purged out of our estimates. Final (net) results indicate that the increase in any of our alternative transparency indicators by 1 standard deviation leads to a reduction of the probability for wrong exclusion by about 6 percentage points. This represents a sizeable effect. Our results thus suggest a means to improve targeting that is more easily implemented and more resource efficient than other reforms that attempt to address the officials' behavior directly, e.g. by increased monitoring and tighter vigilance.

However, increasing the compliance with targeting criteria is beneficial only to the extent that the criteria correctly identify the elderly poor. In our context, BPL status as a frequently used indicator to identify beneficiaries shows only a modest correlation with old-age poverty. In order to achieve the intended distributional effects, this mismatch needs to be addressed. In India, reforms are currently under way regarding the redefinition of BPL, but their effect remains yet to be seen.

All in all, our results suggest that increasing the transparency of eligibility criteria can play an important role in reducing the under-coverage of social pension benefits. Yet, reforms should not stop at this point. First substantial targeting error remains once the more transparent criteria have been introduced. Second, the criteria need to be well-defined in order to properly match the intended target group. Otherwise, there may be no formal targeting error, but nevertheless, the neediest individuals in the population are not reached. As currently debated among academicians and development practitioners, clear-cut exclusion criteria that manage to prevent clearly non-poor individuals from access to anti-poverty benefits seem to be the best option for targeting of social pensions in India.

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Appendix 1: Eligibility criteria in the seven states included in the analysis

State	Name of scheme	Eligibility criteria 2004-05	Eligibility criteria 2011-12	Source of information
Himachal Pradesh	IGNOAPS	Age 65 years or above, destitute	Age 60 years or above, BPL card holding	Government of Himachal Pradesh (undated (a),(b),(c)),
	State Old Age Pension Scheme	Age 60 years or above, individual annual income \leq Rs. 6000 and if the elderly has adult children their income should not exceed Rs. 11000	Age 60 years or above, individual does not have anyone to take care of him/her, individual annual income \leq Rs. 9000 or total annual family income \leq Rs. 15000 excluding his/her own income	
Haryana	IGNOAPS	Age 60 years or above, personal income from all sources together with spouse's income \leq Rs. 50.000 per annum, domicile requirement	Age 60 years or above, BPL card holding	Government of Haryana (2006, 2011, undated(a),(b))
	Old Age Samman Allowance Scheme (since November 2005)	Scheme did not exist.	Age 60 years or above, personal income from all sources together with spouse's income \leq Rs. 200,000 per annum for rural and urban areas	
Uttar Pradesh	IGNOAPS	Age 65 years or above, destitute, domicile requirement	Age 60 years or above, BPL card holding for rural areas, BPL or Antyodaya card holding for urban areas, resident of UP	Government of Uttar Pradesh (2010a,b,c, undated), Comptroller & Auditor General of India (2009)
	KISAN PENSION SCHEME (valid up to May 2007)	Age 60-64 years, land holding \leq 3.25 acre for rural areas or individual income $<$ Rs. 12000 per annum for urban areas, domicile requirement	Scheme did not exist.	
	MAHAMAYA (valid during 2007-12)	Scheme did not exist.	Age 60 years or above, BPL card holding for rural areas, BPL or Antyodaya card holding for urban areas, domicile requirement	
West Bengal	IGNOAPS	Age 65 years or above, destitute	Age 60 years or above, BPL card holding	Government of West Bengal (undated)
Madhya Pradesh	IGNOAPS	Age 65 years or above, destitute	Age 60 years or above, BPL card holding	Government of Madhya Pradesh (undated (a),(b), (c))
	Samagra Social Security Pension Scheme	Age 60 or above, destitute	Age 60 years or above, BPL card or landless and destitute	
Odisha	IGNOAPS	Age 65 years or above, destitute	Age 60 years or above, BPL card holding	Government of Odisha

	Madhu Babu Pension Yojana (since 2008)	Scheme did not exist.	Age 65 years or above, destitute or Age 60 years or above and annual household income from all sources \leq Rs. 24000, domicile requirement	(undated (a), (b), 2008)
Karnataka	IGNOAPS	Age 65 years or above, BPL card holding, annual income < Rs. 6000 per annum	Age 60 years or above, BPL card holding	Government of Karnataka (undated,), Rajasekhar et al (2009), webindia123.com (2007), Chathukulam et al (2012)
	Sandhya Suraksha Yojana (since 2007)	Scheme did not exist.	Age 60 years or above, annual household income \leq Rs 20000	

Notes: All listed conditions separated with commas are “and”-conditions. If they are “or”-conditions, we have specifically mentioned this.

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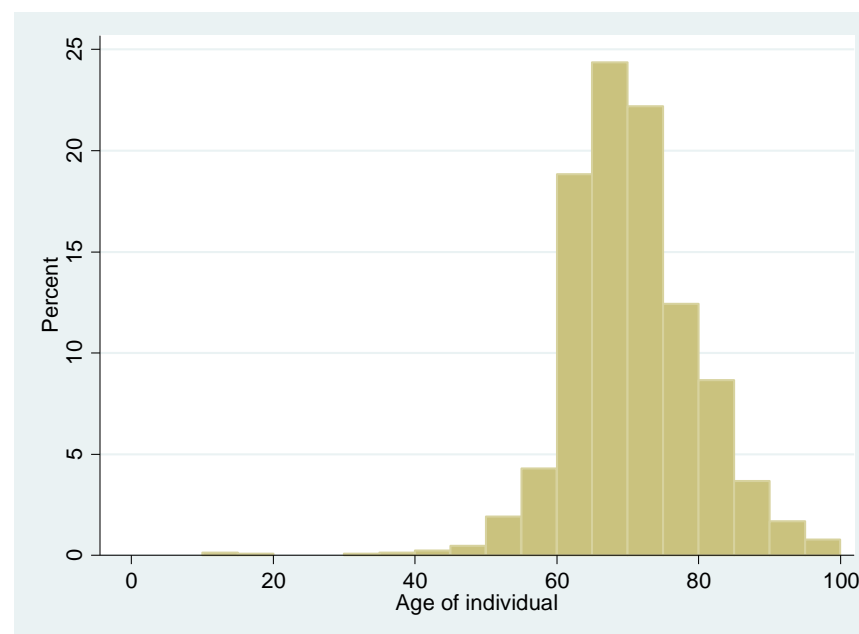
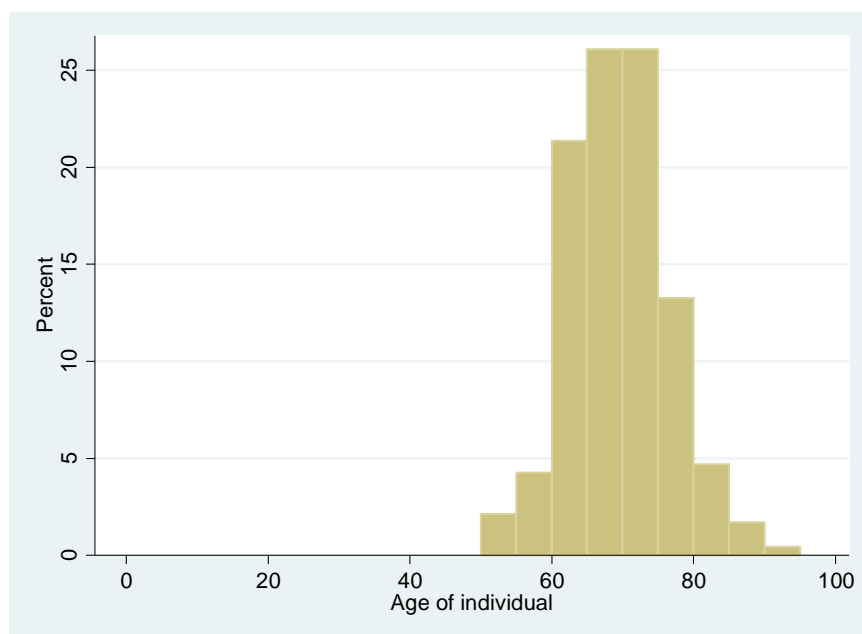
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Appendix 2: Age distribution of social pension beneficiaries

(a) 2004-05

(b) 2011-12



Source: Authors' illustration, descriptive statistics based on IHDS-I for 2004-05 and IHDS-II for 2011-12.

Appendix 3: Variable description and sources

VARIABLES	2004-05		2011-12		Measurement level	Definition	Data source
	mean	se	mean	se			
Error excluded	0.367	0.011	0.296	0.008	Individual	Dummy equal to 1 if individual does not receive social pension but fulfills the locally relevant eligibility criteria	IHDS & administrative information
Error excluded band	0.221	0.01	0.205	0.007	Individual	Dummy equal to 1 if individual does not receive social pension but fulfills the locally relevant eligibility criteria using tolerance band	IHDS & administrative information
Transparency A	2.804	1.180	2.247	0.897	State	Transparency score A= 5 – number of eligibility criteria (clauses and sub-clauses). Range is 1-4. For a detailed explanation, see Appendix 5.	Administrative information
Transparency B	1.267	0.442	2.370	1.212	State	Transparency score B = verifiability score of the least verifiable category of eligibility criteria applied. Range is 1-4. For a detailed explanation, see Appendix 5.	Administrative information
Transparency C	24.623	1.903	23.534	1.909	State	Transparency score C = Weighted sum of eligibility criteria whereby weights are based on verifiability score. Range is 20-26.	Administrative information
Year ₂₀₁₂	0	0	1	0	Year	Dummy for the second survey period (2011-2012)	IHDS
Pension recipient	0.047	0.003	0.202	0.007	Individual	Dummy equal to 1 if individual receives social pension	IHDS
Age	62.49	0.167	69.34	0.168	Individual	Age of the individual	IHDS
Female	0.492	0.01	0.494	0.01	Individual	Dummy equal to 1 if individual is female	IHDS
Literate	0.379	0.01	0.381	0.009	Individual	Dummy equal to 1 if individual can read and write a sentence	IHDS
Widowed	0.245	0.009	0.363	0.009	Individual	Dummy equal to 1 if individual is widowed	IHDS
Working	0.611	0.01	0.328	0.01	Individual	Dummy equal to 1 if individual is working at least 240 hours per year	IHDS
BPL card					Household	Dummy equal to 1 if household holds a BPL card	IHDS
Household assets	10.708	0.103	12.93	0.116	Household	Number of household assets owned	IHDS
Landless	0.359	0.01	0.384	0.009	Household	Dummy equal to 1 household is landless	IHDS
Household maximum education	7.78	0.107	7.991	0.111	Household	Education level of the most educated person in the household	IHDS
Permanent job	0.105	0.006	0.339	0.01	Household	Dummy equal to 1 if any household member has a permanent job	IHDS
Newspaper	0.186	0.007	0.512	0.01	Household	Dummy equal to 1 if household members read newspaper	IHDS
TV	0.368	0.009	0.718	0.01	Household	Dummy equal to 1 if household members watch TV	IHDS
Household size	6.5	0.072	5.511	0.058	Household	Number of persons sharing one kitchen	IHDS
Urban	0.189	0.006	0.235	0.006	Household	Dummy equal to 1 if household lives in urban area	IHDS

Local government confidence	0.302	0.005	0.284	0.006	Village/block	Share of households having confidence in the local government	IHDS
State confidence	0.233	0.003	0.349	0.003	District	Share of households having confidence in the state government	IHDS
Share of elderly in population	0.086	0.001	0.11	0.001	District	Percentage of elderly population of total population	IHDS
Share of SC, ST, OBC in population	0.72	0.004	0.725	0.003	District	Percentage of SC, ST, OBC population of total population	IHDS
Share of Muslims in population	0.134	0.002	0.138	0.003	District	Percentage of Muslims of total population	IHDS
Share of literate adults in population	0.569	0.002	0.63	0.002	District	Percentage of literate adults among adult population	IHDS
Gini coefficient	0.347	0.001	0.337	0.001	District	Gini coefficient based on consumption expenditures adjusted for social pension benefits	IHDS
Head count ratio	0.344	0.003	0.164	0.002	District	Head count ratio estimated based on consumption expenditures adjusted for social pension benefits	IHDS
Local government connection	0.105	0.006	0.339	0.01	Household	Dummy equal to 1 if household has a direct connection to the local government	IHDS
Political competition (Herfindahl)	0.668	0.002	0.673	0.001	District	Political competition in the Lok Sabha constituency based on the Hirschman-Herfindahl concentration index	Statistical reports of 2004 and 2009 Lok Sabha Elections from Election Commission of India
Participation in public meeting	0.297	0.004	0.252	0.004	Village/block	Share of households participating in public meetings	IHDS
Number of observations	6807	6807					

Appendix 4: Defining tolerance bands for eligibility criteria

Though the eligibility cut-offs for age, income, and land possession are clearly defined and unambiguous in official documents of the seven analyzed states, their implementation in reality is problematic because many of the rural elderly may not provide documentary proof of their eligibility. This leaves some type of subjective “margin of error” in deciding who should be (in)eligible for pensions. For example, if someone is 59 years old (cut-off 60 years) and applies for old-age pension without any documentary proof of her age, there is a chance of her being included. In comparison with someone who is much younger than the cut-off age, this case is clearly not a gross violation of eligibility criteria. One way of distinguishing these two cases is to construct a band around eligibility cut-offs. It is obvious that we cannot find any statistical error band around some arbitrary number. However, we may find the standard error of an estimator of the corresponding distributional parameter. To incorporate this “margin of error” we construct a 95% confidence band around the cutoffs using the sampling distribution of the estimator of the corresponding percentile of the distribution. The steps to find the band are given below.

Age: We find the percentage of the population who are below 60 years (or 65 years depending on year and state). Let this be x percent. Therefore, our age cut-off is x th percentile of the age distribution. We now find standard error and 95% confidence band of the estimate of x th percentile. We do this separately for each state in two periods. If someone is above the upper limit of this band, she is considered as ‘clearly eligible’ (i.e., must be included) in terms of age. If someone is below the lower limit, he is considered as ‘clearly ineligible’ (i.e., must be excluded). We follow the same method to find bands around income and land-holding criteria.

Destitute: The destitution criterion is not as objective as age or BPL criteria. However, we know that around 50% of the poor households are considered under different benefit schemes for the destitute. Therefore, we interpret the bottom-half of the poor as destitute. First, we convert nominal monthly per capita consumption expenditure (MPCE) to real using block specific poverty line deflators (Tendulkar poverty line). The consumption expenditure considered here is net of social pension receipts. Then we find the median of the real MPCE of the poor (Tendulkar). Finally, the standard error and 95% confidence band around the median are found separately for each state in two periods.

BPL: Below Poverty Line (BPL) cards are distributed based on a census carried out by the Government of India in 2002. This census assessed several socio-economic conditions of the poor households including asset holding, housing, clothing, sanitation, education, occupation, employment, and indebtedness and migration status. We first estimate a Probit model of BPL card holding status based on the above socio economic conditions using IHDS survey data for 2012. This model is estimated separately for each state. We then find the cut-off for the positive outcome based on the mean of the propensity scores of the BPL card holders in each state separately. The standard error of the estimated mean is used to construct the 95% confidence band around the cut-off.

Since this is only an approximation, it may happen that an actual BPL card holder does not fall into this interval. To ensure that the band is not more restrictive than the original indicator, we consider both criteria jointly to define who is clearly eligible or ineligible: A person is considered as ‘clearly eligible’ (must be included) if he does hold a BPL card *and* has an asset-based propensity of holding a BPL card greater than the upper limit of the confidence band. At the same time, a person is considered as ‘clearly ineligible’ (must be excluded) if she does not hold a BPL card *and* has an asset-based propensity of holding a BPL card smaller than the lower limit of the confidence band.

Appendix 5: Alternative transparency measures

This appendix first provides further details on the construction of transparency measures A and B, and then presents the results based on a replication of Tables 1 and 2 using these alternative transparency scores.

As explained in the text, Transparency A is based solely on the number of conditions through which eligibility is defined in each state and period. Age criteria are not taken into account as they are required everywhere and at all times. For the remainder, we have already defined four categories of frequently used criteria, namely destitution, income, land holding and BPL card. Within these, there can be different sub-clauses, namely different regulations for rural and urban areas, or for male and female individuals. In addition, some states use further criteria outside the four general categories, e.g. domicile requirements. When summing up the different clauses and sub-clauses, we get to a maximum of four per state and year. To let the final transparency score start from 1 (lowest level of transparency) and to increase with lower levels of complexity, it is computed as:

$$(\text{Transparency A})_{jt} = 5 - (\text{number of conditions})_{jt}, \forall \text{ state } j \text{ and period } t. \quad (\text{A5.1})$$

For example in Uttar Pradesh 2011-12 we have two types of conditions for BPL (see Appendix 1), hence a count of 2 for the BPL category. There are no other conditions in any other categories. So the overall count is 2, and Transparency A is $5 - 2 = 3$.

Transparency B does not consider the number of conditions, but only their verifiability. The verifiability scores for each category of conditions are the same as used for the weights used for the construction of Transparency C and explained in Section 4. These scores are: destitution=1 (most vague, most difficult to assess), income=2, land holding=3, and BPL card holding=4 (easiest to assess). When computing the score, we consider that if one condition is vague, eligibility as a whole becomes vaguely defined and hence transparency is low. Transparency B is thus defined by the criterion used that obtains the lowest score in terms of verifiability:

$$(\text{Transparency B})_{jt} = \min(\text{verifiability score of criteria applied})_{jt}, \forall \text{ state } j \text{ and period } t. \quad (\text{A5.2})$$

For example in Karnataka 2004-05 income and BPL are used as criteria (see Appendix 1). Income has a verifiability score of 2, while BPL has a verifiability score of 4. Income is the least verifiable among the two. Hence the value of Transparency B is 2.

Table A5.1 below compares the two complementary measures, both with each other and with the combined measure Transparency C explained in Section 4.

Table A5.1: Transparency scores by state and year

	Transparency A		Transparency B		Transparency C	
	2004-2005	2011-2012	2004-2005	2011-2012	2004-2005	2011-2012
Himachal Pradesh	2	1	1	2	20	22
Haryana	3	3	2	2	24	22
Uttar Pradesh	1	2	1	4	24	26
West Bengal	4	4	1	4	26	24
Madhya Pradesh	4	2	1	1	26	22
Odisha	4	1	1	1	26	21
Karnataka	3	3	2	2	26	26

The correlation between the different indices is low for Transparency A and B ($\rho_{A,B} = 0.06$) since they are based on different conceptual ideas. At the same time each of them is highly correlated with Transparency C since they contribute to the computation of the latter ($\rho_{A,C} = 0.57$, $\rho_{B,C} = 0.41$). Noticeably, the effect of the reforms in the late 2000s seems to be reflected in improved transparency only when looking at Transparency B. While they led to an improvement in the verifiability of the criteria (stronger focus on BPL), the number of clauses and sub-clauses was often not reduced and even increased in several states.

Table A5.2 presents the regression results using Transparency A and B rather than Transparency C (cf. Table 1), each time with and without the use of the tolerance band. The effect of the transparency measure remains negative and significant throughout, i.e. no matter which dimension of transparency we consider.

Table A5.2: Results using alternative transparency measures

(a) Sharp eligibility criteria, transparency measure A

	(1)	(2)	(3)
VARIABLES	Wrongly excluded	Wrongly excluded	Wrongly excluded
Year ₂₀₁₂	-0.086*** (0.000)	-0.044* (0.064)	-0.055* (0.090)
Transparency A	-0.109*** (0.000)	-0.112*** (0.000)	-0.111*** (0.000)
Individual fixed effects	Yes	Yes	Yes
Household variables	No	Yes, clean controls	Yes, all controls
District characteristics	No	Yes, clean controls	Yes, all controls
Political variables	No	Yes, clean controls	Yes, all controls
Observations	13614	13614	13614
Number of id	6807	6807	6807
R-squared	0.058	0.069	0.073

(b) Using tolerance band, transparency measure A

	(1)	(2)	(3)
VARIABLES	Wrongly excluded with band	Wrongly excluded with band	Wrongly excluded with band
Year ₂₀₁₂	-0.030** (0.028)	-0.000 (0.989)	-0.022 (0.413)
Transparency A	-0.087*** (0.000)	-0.086*** (0.000)	-0.090*** (0.000)
Individual fixed effects	Yes	Yes	Yes
Household variables	No	Yes, clean controls	Yes, all controls
District characteristics	No	Yes, clean controls	Yes, all controls
Political variables	No	Yes, clean controls	Yes, all controls
Observations	13614	13614	13614
Number of id	6807	6807	6807
R-squared	0.043	0.054	0.061

Notes: Statistical significance is shown by ** $p < 0.05$, *** $p < 0.01$ with cluster-robust p-values in parentheses.

(c) Sharp eligibility criteria, transparency measure B

VARIABLES	(1) Wrongly excluded	(2) Wrongly excluded	(3) Wrongly excluded
Year ₂₀₁₂	0.156*** (0.000)	0.187*** (0.000)	0.142*** (0.000)
Transparency B	-0.124*** (0.000)	-0.124*** (0.000)	-0.133*** (0.000)
Individual fixed effects	Yes	Yes	Yes
Household variables	No	Yes, clean controls	Yes, all controls
District characteristics	No	Yes, clean controls	Yes, all controls
Political variables	No	Yes, clean controls	Yes, all controls
Observations	13614	13614	13614
Number of id	6807	6807	6807
R-squared	0.079	0.089	0.095

(d) Using tolerance band, transparency measure B

VARIABLES	(1) Wrongly excluded with band	(2) Wrongly excluded with band	(3) Wrongly excluded with band
Year ₂₀₁₂	0.174*** (0.000)	0.195*** (0.000)	0.146*** (0.000)
Transparency B	-0.105*** (0.000)	-0.105*** (0.000)	-0.120*** (0.000)
Individual fixed effects	Yes	Yes	Yes
Household variables	No	Yes, clean controls	Yes, all controls
District characteristics	No	Yes, clean controls	Yes, all controls
Political variables	No	Yes, clean controls	Yes, all controls
Observations	13614	13614	13614
Number of id	6807	6807	6807
R-squared	0.071	0.082	0.092

Notes: Statistical significance is shown by ** $p < 0.05$, *** $p < 0.01$ with cluster-robust p-values in parentheses.

Table A5.3 shows the results for the placebo regression and the net effects when subtracting the design effect determined by the latter. Just as for Transparency C, the resulting net effects correspond to about half of the originally measured effects (Table A5.2). For both measures A and B, a 1-unit increase in transparency (≈ 1 standard deviation) corresponds to a net decrease of

the probability to be wrongly excluded by 5-6 percentage points. The two complementary dimensions of transparency hence contribute to the reduction of mistargeting to a similar extent.

Table A5.3: Net effects using alternative transparency measures

(a) Transparency measure A

	(1)	(2)	(3)	
Coefficients estimated	Individual and year fixed effects, no controls	Fixed effects and clean controls	Fixed effects and all controls	Notes
β_2	-0.109*** (0.000)	-0.112*** (0.000)	-0.111*** (0.000)	Estimates from equation 1, (copied from Table A5.2a)
$\tilde{\beta}_2$	-0.060*** (0.000)	-0.054*** (0.000)	-0.052*** (0.000)	Estimates from equation 2 (placebo: design effect)
$(\beta_2 - \tilde{\beta}_2)$	-0.049*** (0.000)	-0.058*** (0.000)	-0.059*** (0.000)	Estimates from equation 3: Net effect of transparency

(b) Transparency measure B

	(1)	(2)	(3)	
Coefficients estimated	Individual and year fixed effects, no controls	Fixed effects and clean controls	Fixed effects and all controls	Notes
β_2	-0.124*** (0.000)	-0.124*** (0.000)	-0.133*** (0.000)	Estimates from equation 1, (copied from Table A5.2c)
$\tilde{\beta}_2$	-0.069*** (0.000)	-0.066*** (0.000)	-0.070*** (0.000)	Estimates from equation 2 (placebo: design effect)
$(\beta_2 - \tilde{\beta}_2)$	-0.056*** (0.000)	-0.058*** (0.000)	-0.063*** (0.000)	Estimates from equation 3: Net effect of transparency

Notes: Statistical significance is shown by ** $p < 0.05$, *** $p < 0.01$ with cluster-robust p-values in parentheses.

Appendix 6: List of interviews conducted in Delhi, March - April 2016

Name	Designation	Date
Mr Ladu Kishore Swain	Member of Parliament, Aska, Odisha (Party: Biju Janata Dal)	16 March 2016
Mr Konda Vishweshwar Reddy	Member of Parliament, Chelvella, Telangana (Party: Telangana Rashtra Samiti)	21 March 2016
Mr Udit Raj	Member of Parliament, North West Delhi, Delhi (Party: Bharatiya Janata Party)	21 March 2016
Mr Jagdambika Pal	Member of Parliament, Domariyaganj, Uttar Pradesh (Party: Bharatiya Janata Party)	22 March 2016
Mr Nikhil Dey	Social Activist, Mazdoor Kisan Shakti Sangathan, Rajasthan	28 March 2016
Prof Arvind Panagariya	Vice-Chairman, National Institute for Transforming India (former Planning Commission), New Delhi	28 March 2016
Dr Ashok K. Jain	Adviser, Rural Development, National Institute for Transforming India (former Planning Commission), New Delhi	28 March 2016
Dr Rinku Murgai	Economist, World Bank, New Delhi	12 April 2016