Do more transparent eligibility rules 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 clarity and verifiability of eligibility criteria. India's social pension reforms in the late 2000s provide the opportunity to examine the effect of a change in these criteria within and across states. Using two rounds of the India Human Development Survey along with extensive administrative information collected for the different states, we test whether increasing the transparency of eligibility criteria reduces the mistargeting of social pensions. We thereby allow for a tolerance band, and account for changes in social pension coverage. Our results confirm the expected relationship between the transparency of eligibility criteria and targeting performance and are robust to different specifications of the transparency measure and various robustness checks. Since eligibility criteria can be changed at low cost, this suggests a viable route for reform in many developing countries.

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

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1 Introduction

In many developing countries, not only wide-spread corruption, local political capture, clientelism, but also a lack of information and lack of administrative capacity prevent the effective delivery of basic social services to the intended beneficiaries (Asri et al., 2020). Policy interventions raising the level of transparency have been widely shown to improve poor people's access to these services (Björkman and Svensson, 2009; Francken et al., 2009; Olken, 2007; Peisakhin, 2012; Peisakhin and Pinto, 2010; Reinikka and Svensson, 2004, 2005, 2011). So far, these studies focus on service delivery processes. At the most basic level, however, transparency starts with the definition of eligibility criteria. These criteria are transparent if they are clear and easy to verify. Owing to the lack of reliable income data, the identification of poverty 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 to which we wish to contribute in this paper.

India's old-age social pension reforms in the late 2000s provide us with the opportunity to directly test the relationship between changes in eligibility criteria and targeting performance. Social pensions are non-contributory pensions, i.e., direct government cash transfers to the elderly. Reforms of eligibility criteria were implemented both for national and state pension schemes. At the national level, for instance, the central government replaced the previously vague poverty-related criterion "destitution" (without any operational definition) by the requirement 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 and health care. Whether a household is in possession of a BPL card or not is an easily observable criterion and leaves no room for interpretation.

Note that whether the BPL card itself is correctly targeted to the poor is a different question that has been discussed elsewhere in the literature (Alkire and Seth, 2013; Hirway, 2003; Jain, 2004; Panda, 2015; Government of India et al., 2009; Sundaram and Tendulkar, 2003), and that we cannot cover here. However, our study will have implications for access to anti-poverty schemes in general, and thus also be indirectly relevant for future reforms of eligibility for BPL cards.

Theoretically, one would expect a trade-off between the specificity and detail of eligibility criteria, and their transparency, whereby the former ensures that the criteria correctly characterize the most vulnerable beneficiaries, while the latter ensures that they are implementable in practice. In this study, we assess the relevance of the latter. If we find a sizable effect of transparency on the correct implementation of service delivery regulations, then the above trade-off needs to be taken seriously in policy reforms. Attempts to refine criteria so as to best capture the intended target population should consider the negative side-effects such detailed definitions may have on actually reaching the poor. At the same time, simplifying existing criteria may provide a resource-effective means to channel the benefits of social security programs to the neediest individuals.

To assess the effect of transparent eligibility rules on actual implementation, we will proceed in the following way: First, we develop a new indicator of eligibility-criteria-related transparency combining the insights of previous studies (Niehaus et al., 2013; Khera and Drèze, 2010). Second, we define targeting error strictly along the lines of the regulations in official government documents, rather than on the basis of externally imposed poverty measures. This requires a detailed assessment of the rules applicable at national and sub-national level and their change over time. Third, we consider a tolerance band around the eligibility cut-off points. When criteria are intransparent, i.e., either vague or very complex, it may be difficult for a local government official to exactly define the correct target group. But as long as the selected beneficiaries are close to those intended, this may still be better than using easy but broad criteria in the first place. Our computation and application of a tolerance band takes this consideration into account and leads to a more conservative assessment of the effect of transparent, i.e., usually more simplified and verifiable eligibility conditions.

Beyond the detailed administrative data collected from national and sub-national documents and web search, we use two rounds of the India Human Development Survey (IHDS) to examine the relationship between the change in eligibility criteria and the targeting error over time. We find statistically and economically significant results that are robust to variations in the specification of the transparency measure and various robustness checks.

2 Literature and theoretical background

So far, the literature on the role of transparency for the targeting performance of anti-poverty schemes has primarily examined the relevance of transparent delivery mechanisms (Björkman and Svensson, 2009; Francken et al., 2009; Olken, 2007; Peisakhin, 2012; Peisakhin and Pinto, 2010; Reinikka and Svensson, 2004, 2005, 2011). In contrast, 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) analyze how a proxy means test should be designed if the "implementing agent is corruptible" (p. 206). The authors focus on complexity through the number of conditions. They show both theoretically and empirically 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 a local government official needs to follow for the allocation of benefits. In a context of widespread corruption, the officials can make use of the ambiguity created by the higher complexity to allocate benefits in line with their own preferences. While the accuracy of a poverty indicator often increases with the number of specific conditions, these conditions may simply not be enforceable.

As corruption is an important concern in large parts of the developing world (and beyond), these findings are highly relevant for the implementation of welfare schemes. Other important concerns in developing countries are the lack of information and the lack of government capacity (UNCDF and UNDP, 2012; UNDP, 2016; World Bank, 2004, 2016*b*,*a*). They may reinforce the above-mentioned implementation problems. For instance, when poor people do not know the eligibility criteria, they cannot claim their rights and hold corrupt agents responsible. For corrupt government officials themselves, lack of information or capacity may provide a good excuse in case they are caught while transgressing the rules. Furthermore, even if officials are not corrupt, lack of capacity and of relevant information may create a situation in which complex eligibility criteria cannot be enforced. Asri et al. (2020) show that this may be the case for social pension allocation in Bangladesh, where the lack of relevant information, notably on the characteristics of applicants, forces local government officials to select beneficiaries among those people they are personally acquainted with. This shows that the considerations in Niehaus et al. (2013) are very broadly applicable in developing country contexts, even beyond the context the authors themselves had in mind.

However, using the simple count of eligibility criteria as the measure of complexity is a rough simplification. Individual conditions may themselves differ in their level of complexity, i.e., there may be several sub-conditions, and the individual criteria may be more or less difficult to assess and verify.

Already in the mid 1990s, Baker and Grosh (1995) underscore that the verifiability of eligibility criteria is extremely important for the implementation of all kinds of public anti-poverty programs in developing countries where data on income are imprecise. In their work on the identification of BPL card holders, Khera and Drèze (2010) also focus on verifiability. In line with Niehaus et al.'s findings, they show the importance of using eligibility criteria that are easy to follow. But rather than to reduce the number of criteria, they suggest replacing the existing complex approach by easily verifiable inclusion and exclusion criteria which allow individuals to indicate their eligibility based on statements such as “I am eligible because I am landless” or “I am not eligible because I own a car” (p. 55). Khera and Drèze (2010) argue that this simplification will also help to facilitate participatory monitoring and to prevent fraud.

In our study, we will integrate the different aspects of complexity based on the number of criteria and their verifiability into a combined transparency indicator, while simultaneously showing the results for each of its components. In line with the authors cited above, we expect that increasing the transparency of eligibility criteria positively affects both the demand and supply sides of social pension targeting. As already illustrated in the above examples, transparency improvements influence the behavior of local government officials in charge of selecting beneficiaries (supply side) and local citizens applying for social benefits (demand side). Overall, the theoretically expected advantages are as follows:

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 likelihood of human error. The use of more transparent 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.[1]

Testing the effect of increased transparency of eligibility criteria in the context of social pensions in India might be a rather hard case. While the context of widespread corruption and lack of information and government capacity is certainly given in India, focusing on social

[1]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 et al. (2005)).

pensions may make it relatively difficult to detect the effect of any change in eligibility criteria. This is because the elderly themselves are often highly constrained through physical weaknesses preventing their participation in public life and through illiteracy and lack of access to modern communication – so constrained that they may not be able to understand and/or may not be properly informed even about highly transparent criteria (unless they receive external support by family members or NGOs). This may reduce the working of the demand channel. If our estimates indicate that increasing the transparency of eligibility criteria considerably reduces targeting errors for social pensions, the effect may thus be even stronger for other welfare schemes, where the demand side is less constrained in terms of public participation, access to information and mobility.

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 person per month. Unlike social pensions in other developing countries like Nepal, Bolivia or South Africa that are paid out to all individuals above a certain age, for budgetary reasons, social pensions in India are targeted only towards the poor considering that this is the population for which support provides the greatest welfare benefits (Palacios and Sluchynsky, 2006). 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 panchayats and municipalities are responsible for the implementation of the schemes and that they shall be actively involved 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, 1998, 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 with consumption expenditures 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), those who did and 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. In most cases, the reforms at state level also reduced the complexity of eligibility criteria and thereby increased their transparency. 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 yet 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 IGNOAPS 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 A.

4 Data and methods

4.1 Generation of the data set

To test the hypothesis that transparent criteria improve targeting, 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 A). For the individual- and community level data we rely on two waves of the India Human Development Survey (IHDS) that were conducted by the National Council of Applied Economic Research (NCAER) and the University of Maryland (Desai and Vanneman, 2010, 2015) in 2004-05 and 2011-12, 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 2004-05 and 42,152 households in 2011-12 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 and Vanneman, 2010, 2015).

Given our focus on old-age pensions, in both rounds we exclude all individuals who are younger than the state specific eligibility age.[2] 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 consists of 5,015 elderly surveyed in 2004-05 and 7,399 elderly surveyed in 2011-12, i.e., a total of 12,414 observations. In principle, the data allow us to create a balanced panel over the two rounds, so that individual fixed effects can be used to control for unobservable heterogeneity among the elderly. However, given that the age of those covered in the first period is already high, we lose a high number of them before the second round. The sample for the panel regression would thus not be representative for all the elderly anymore. For this reason, we focus on a pooled cross section from 2004-05 and 2011-12 in the main part of the regression analysis, and exploit the panel aspect of the data only in our robustness checks.

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.[3] As a complement to quantitative data, we also collected qualitative information through interviews with policy

[2] The complete age distribution of social pension beneficiaries is presented in Appendix B.

[3] The data source for each variable is presented in Appendix C.

makers, ministerial officials, social activists and scholars specialized in 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 provide important background information that helps in the construction of the main explanatory variable and interpretation of empirical results. We provide a list of interviews in Appendix D.

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. Given that the correct application of the threshold still leaves many poor and deserving elderly uncovered, exclusion errors tend 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 errors is much smaller. In fact, due to very limited social pension coverage, the number of wrongly included individuals, particularly in the 2004-05 survey, is so limited that credible statistical inference appears problematic, which is why we focus on exclusion errors in this paper.

While exclusion error is generally defined as the share of eligible individuals who are excluded from social pension benefits (see Coady et al., 2004), the dependent variable in our regressions is measured at the individual level. This excludes the computation of population shares. Instead, we simply create an indicator variable that takes the value of one if a person is 'wrongly excluded', and zero otherwise.[4]

As mentioned earlier, in contrast to the previous literature (e.g. Asri, 2019), 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

[4]It should be noted that the average for 'wrongly excluded' in our sample does not correspond to the standard measure of exclusion error either. This is because our dataset does not only include eligible individuals, but also some non-eligible elderly (as long as they are in the eligible age group).

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, 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 median of consumption expenditures (net of old-age pensions) of the household in which they live. This procedure to assess destitution corresponds to the official process used to compute the number of pensions allocated to each state (Rajan, 2001, p.613).

Respondents to the IHDS do not distinguish between different social pension schemes and simply report whether or not they receive a social pension.[5] Qualifying for any existing scheme, should, in principle, lead to social pension receipt. When eligibility criteria differ between IGNOAPS and the relevant state scheme, anyone who fulfills the criteria of either of the schemes but does not receive a pension, is therefore considered as wrongly excluded.

In addition to the indicator variable for wrong exclusion, we construct a second dependent variable that is more lenient regarding minor errors. Using this alternative variable guarantees that econometric results will not be driven by only a minor divergence from official cut-off points for any of the eligibility criteria.

In principle, if local government officials were strongly committed to applying government criteria and relatively well informed, vague or complex criteria might just introduce such minor errors. Officials may not be able to assess the exact information, but still get things right at least roughly, for instance if they have to define operational proxies themselves, or if the beneficiaries cannot provide clear answers to some of many different criteria. As long as the selection of beneficiaries remains close to the target, the eligibility criteria used may still be preferable to more transparent, but less accurate ones.

Our alternative dependent variable takes such concerns into account by introducing a tolerance band around the exact thresholds of all eligibility criteria. Only if a person is clearly eligible, i.e., beyond the tolerance band for all criteria, and still not included among the beneficiaries, this person is considered as wrongly excluded according to this indicator with band.

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

[5]Based on this experience, NCAER adjusted the initially more specific formulation to a general one in the second round of the IHDS.

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 E.

4.2.2 Explanatory variables and other covariates

Our explanatory variables describe the transparency of eligibility criteria. As the computation of corresponding transparency indicators necessarily includes some subjective judgments regarding both the information included and the method of aggregation, we propose alternative indicators here that we describe in detail below and in Appendix F. Making use of the detailed administrative information collected at national and state level for both periods under review (see Appendix A), we develop three complementary 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.

For all three indicators, we first classify eligibility criteria into four main categories, namely destitution, income, land holding, and BPL card holding. In some cases, there are also additional other criteria or sub-criteria. Furthermore, there are obviously age-related criteria. The latter are relevant for the assessment of mistargeting, but we can ignore them for our transparency indicators, as their existence (as opposed to their value) is uniform across states and over time. Following Niehaus et al. (2013), our first indicator (Transparency A) simply counts the different eligibility criteria officially relevant for any specific pension scheme at a given point in time. We slightly refine this measure by also considering sub-criteria. The idea is that the sheer number of these criteria and sub-criteria matters, because any addition of conditions renders the selection process more difficult to understand (i.e. increases opacity). The transparency score is then computed by subtracting the number of relevant conditions from their empirical maximum ($= 4$). We finally add $+1$ to avoid zero numbers (for details, see Appendix F).

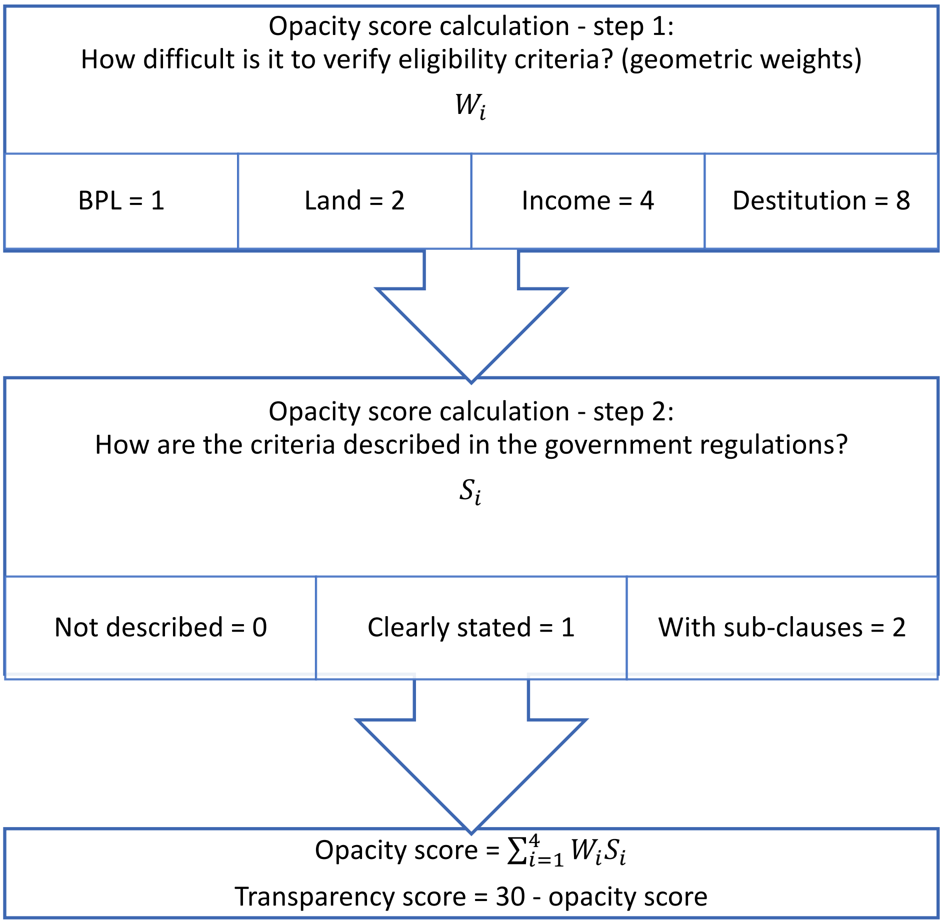
However, not all criteria are equally difficult to assess, and this may be even more relevant for transparency than the number of criteria itself. Building on Khera and Drèze (2010), we hence suggest an additional indicator (Transparency B) that considers how easily verifiable the criteria are. To construct this indicator, we assign geometric weights to each of the four categories of criteria mentioned above, increasing with the difficulty of verification (opacity). Based on our insights from our qualitative interviews, we classify BPL card holding as least difficult to verify (1 point), land holding as second-least difficult to verify (2 points), income as second-most difficult to verify (4 points) and destitution as most difficult to verify (8 points). We aggregate the numbers to a transparency score by subtracting the highest value for any criterion used in a specific pension scheme from the empirical maximum value across all observations (=8), and again add +1 to avoid an overall score of zero (for details, see Appendix F).

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 higher scores to state-level regulations that use fewer eligibility criteria and eligibility criteria that are more easily verifiable. To compute this indicator, we proceed in three steps. The first two steps generate an opacity score which we convert into a transparency score in the third step. Figure 1 below visualizes the calculation step by step.

We first focus on the difficulty to verify eligibility criteria and apply the same geometric weights as for Transparency B. We denote the verifiability weight of criterion i by W_i, $i \in \{BPL, land, income, destitute\}$. In the second step, we consider how clearly the criterion is described in the government regulations. Again in terms of opacity, we assign 0 points when the criterion is not stated, 1 point if the criterion is clearly stated and 2 points if the criterion is stated with sub-clauses. Let S_i be the opacity score of criterion i. The overall opacity score is the weighted sum $\sum_{i=1}^{4} W_i S_i$. If a state specifies all four types of eligibility criteria with maximum level of opacity, the weighted sum is $2\sum_{i=1}^{4} W_i = 30$. Finally, to obtain the transparency score C, we subtract the opacity score from the empirical maximum value (29), and again add +1, i.e.,

$$Transparency\ C = 30 - \sum_{i=1}^{4} W_i S_i.$$

Figure 1: Coding of transparency measure C



Source: Authors' illustration.

We further consider a number of covariates to control for confounding factors. In this context one important factor may be pension coverage, which often changes simultaneously with the introduction of new eligibility criteria. Indeed without an appropriate control for the change in coverage, any change in exclusion error that we might attribute to the influence of transparency, may actually reflect the effect of a change in the number of pensions relative to the number of eligible elderly. As a higher number of pensions was 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 in the number of pensions varies across states, the simple inclusion of a period dummy will not suffice to control for this. Since it is highly plausible that the number of pensions made available by each state is 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), without a control for coverage, our estimator may be biased, and the effect of transparency itself may be much less pronounced than our initial regression outcomes would suggest.

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, 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.

Since this is an important concern, we will also go beyond a simple linear control variable and suggest additional non-linear specifications to deal with this problem in our robustness tests.

Apart from coverage, our data allow us to control for a large number of other possible confounders. However, some caution is necessary when selecting the control variables. Given that our dependent variables is 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 education, literacy, widowhood, gender, household's maximum education, household's employment situation, access to media, household size, rural or urban locality, Scheduled Castes (SC), Scheduled Tribes (ST) and Other Backward Castes (OBC), muslim, household size, political participation, share of elderly, share of SC, ST, OBC, share of muslims, share of electrified households, share of literate voters in the district.

The complementary set of control variables additionally includes the working status of the elderly person, an indicator of household assets, an indicator of landlessness, and further variables at district level, i.e., Gini index, poverty head count ratio and the share of households that express confidence in local government officials and state governments. At the state level, we further control for share of tax revenue and judicial speed as indicators of state capacity and quality of state-level governance, two factors that might simultaneously influence the transparency of eligibility criteria and the correct selection of beneficiaries. The summary statistics and definitions of all variables are displayed in Appendix C.

4.3 Statistical methods

As mentioned above, our main econometric analysis is based on pooled cross sectional regressions allowing our sample to be representative for the total population of the elderly, age-wise eligible for social pension receipt, in both periods of observation. However, results from a panel model with individual fixed effects will be shown in the robustness tests. In all regressions, observations are weighted using corresponding probability weights.

Since our dependent variable is binary, we essentially estimate the probability of being wrongly excluded. We opt for a linear probability model for ease of interpretation. To avoid related heteroscedasticity problems, we use heteroskcedasticity-robust error terms clustered at the district level. For readers preferring the use of non-linear probability models, we replicate the core analysis using a logistic specification in Appendix G. We present marginal effects in both cases to facilitate the comparison.

As a default, our regression models always include an indicator variable for the survey period, which is coded one for the second round of the IHDS (2011/12) and zero for the first round (2004/05). In most specifications we also include state dummies. The year and state fixed effects account for unobservable period- or state-specific heterogeneity. Our empirical model therefore becomes:

$$Y_{it} = \beta_0 + \beta_1 Year_{2012} + \beta_2 TS_{st} + \mathbf{X}'_{it}\gamma + a_s + u_{it} \tag{1}$$

where Y_{it} is a binary variable capturing whether individual i is wrongly excluded in period t, $Year_{2012}$ is the period dummy, TS_{st} is the transparency score for state s in period t, a_s is the state fixed effect and $\mathbf{X}$ is a vector of control variables. Our focus is on parameter β_2.

5 Results

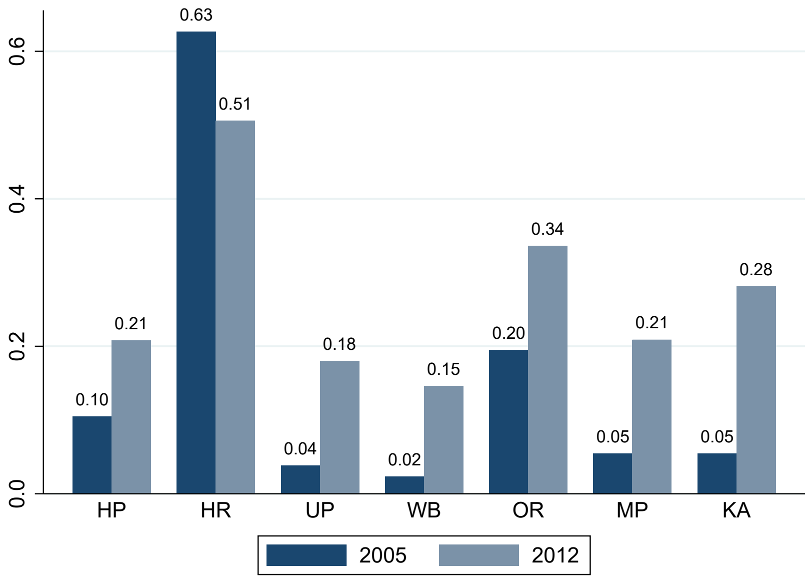
5.1 Descriptive statistics

Before we get to the results of our econometric analysis, we present some relevant descriptive statistics based on the same database. Figure 2 shows social pension coverage of the elderly, which reveals strong differences across states and over time. Noticeably, in Haryana, coverage is much higher than in other states. This may be driven by a focus on the elderly within Haryana's social security system following the introduction of the new state pension scheme in 2005 (see Appendix A). However, social pension coverage decreased over time (from 63% in 2005 to 51% in 2012) while it increased in all other states during the same period.

Differences between states and over time could also be related to differences in the prevalence of poverty. However, Figure 3 shows that this is not the case. As opposed to the previous figure,

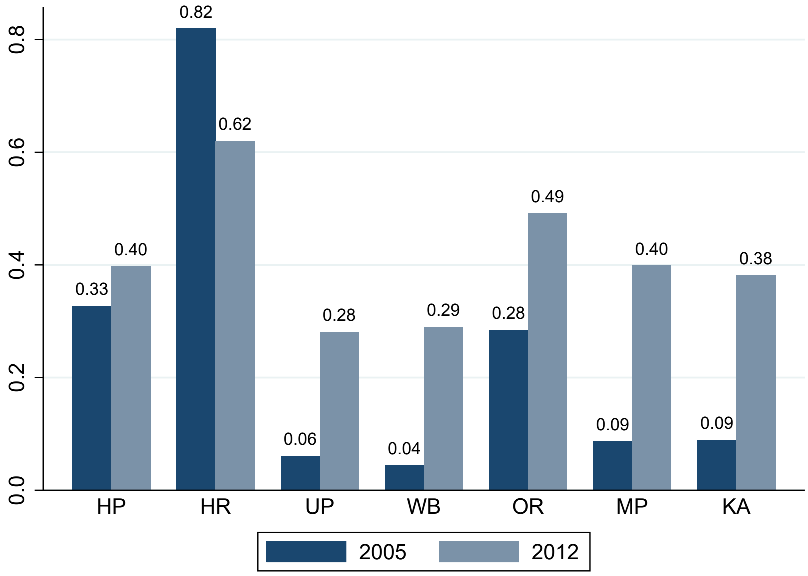
Figure 3 only considers those elderly living in poor households, namely in households with consumption expenditures below the Tendulkar poverty line. Since this reduces the denominator of the coverage indicator, all rates are higher compared to those in Figure 2, but the development over time and the relationships between states remain very similar in the restricted sample. Only Himachal Pradesh and Madya Pradesh move up from the lower end to the middle range among the states covered by our data once poverty is accounted for.

Figure 2: Social pension coverage of elderly, by state and year



Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP), Karnataka (KA). Based on observations from pooled cross section. The elderly population includes all individuals who are at least as old as the local eligible age.
Source: IHDS I for 2004-05 and IHDS II for 2011-12.

Figure 3: Social pension coverage of elderly poor, by state and year

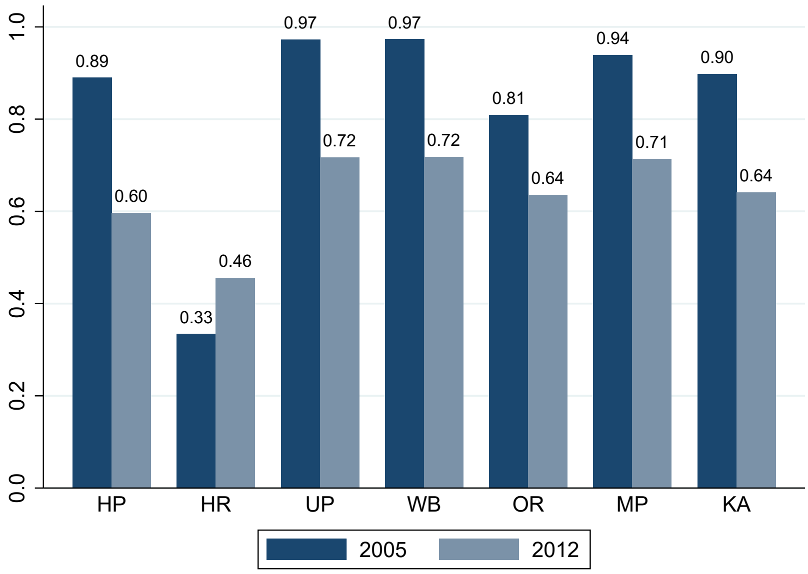


Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP), Karnataka (KA). Based on observations from pooled cross section. The elderly population includes all individuals who are at least as old as the local eligible age.
Source: IHDS I for 2004-05 and IHDS II for 2011-12.

We now look at the exclusion error within each state, and how it evolved over time. Figure 4 shows the exclusion error using the sharp criteria, while Figure 5 applies the tolerance band.[6] We observe that the exclusion error is extremely high, in 2005 in Uttar Pradesh and West Bengal even close to 100%. In all states except Haryana, the exclusion error in the first period was above 80% and still at or above 60% in 2011-12. The general trends are reversely related to pension coverage. This is what one would expect, since, when the number of available pensions is very low relative to the number of eligible elderly, a large part of them cannot be covered, even if no funding is diverted to ineligible people. The exclusion error calculated with the tolerance band is slightly different but shows a similar pattern.

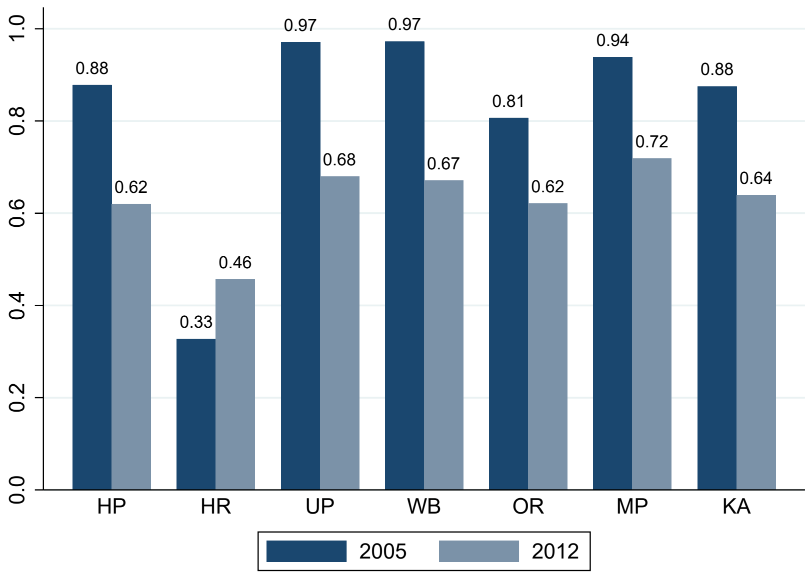
[6]While the exclusion error without band is the ratio of the number of eligible individuals in a state not receiving the social pension divided by the number of eligible people, for the exclusion error with band, we consider only clearly eligible people (beyond the tolerance band) both in the numerator and the denominator of this ratio.

Figure 4: Exclusion error based on sharp eligibility criteria



Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP), Karnataka (KA). Based on observations from pooled cross section.
Source: IHDS I for 2004-05 and IHDS II for 2011-12.

Figure 5: Exclusion error based on criteria with tolerance band



Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP), KA (Karnataka). Based on observations from pooled cross section.
Source: IHDS I for 2004-05 and IHDS II for 2011-12.

5.2 Main econometric outcomes

Our econometric analysis allows us to assess the determinants of exclusion error beyond the obvious link to pension coverage. In particular, it allows us to relate being wrongly excluded measured at the individual level to differences in the transparency of the eligibility criteria. Overall, the empirical results are in line with our expectations. The regressions consistently show that higher transparency is associated with a substantially lower likelihood of being wrongly excluded from social pension benefits. In the following, we present our main results for the representative sample of elderly in the seven Indian states in 2005 and 2012 using the data from the pooled cross section.

In Table 1 we show the specifications using our most comprehensive transparency indicator, namely Transparency C. We first run a regression controlling only for the time period. In the second specification we add state fixed effects. After that, we progressively add the different types of controls discussed above, namely pension coverage (Column 3), exogenous covariates (Column 4) and potentially endogenous covariates (Column 5).

The probability of being wrongly excluded decreases by 2-3 percentage points in all models if the transparency score increases by 1 unit (≈ 0.2 standard deviations). In other words, a one standard deviation increase in the transparency score C is associated with a 10-15-percentage point reduction in the probability of being wrongly excluded. For a typical change in eligibility criteria, such as for the national pension scheme IGNOAPS that replaced the destitution criterion by BPL card holding, Transparency C improves by 7 units. According to our estimations, a state following this development (e.g., West Bengal) would decrease the probability of wrong exclusion by 14-21 percentage points. At the higher end, this corresponds to almost half of the average predicted value of 46%.[7]

While these effects are large, no matter which equation we choose, it should be noted that the smallest value comes up in the regression with no covariates except the year dummy. This neglects a number of possibly relevant confounders. For this reason, we believe that the higher values for regressions in which at least state fixed effects, pension coverage and the set of clearly exogeneous controls are taken into account, provide the more plausible estimates.

Table 2 shows the same set of specifications, but with our alternative dependent variable including the tolerance band. As expected, this more conservative estimation that does not consider anyone as wrongly excluded if the error remains very small, leads to slightly smaller estimates for the effect of transparency. However, the difference between the two estimations is rather negligible. It ranges between 0.006 and 0.5 percentage points. Clearly, an improvement of transparency regarding eligibility criteria is associated with statistically and economically

[7] As explained above, this sample average is lower than the exclusion error in the descriptive statistics because the sample also includes a number of non-eligible individuals who, by definition, cannot be wrongly excluded.

significant improvements in targeting that go way beyond small changes around the eligibility thresholds.

Table 1: Transparency measure C and error wrongly excluded without band

	(1)	(2)	(3)	(4)	(5)
Year 2012	-0.190***	-0.178***	-0.125***	-0.143***	-0.0954**
	(0.0184)	(0.0169)	(0.0278)	(0.0303)	(0.0297)
Transparency C	-0.0202***	-0.0243***	-0.0230***	-0.0250***	-0.0282***
	(0.0020)	(0.0030)	(0.0031)	(0.0030)	(0.0026)
Adj. R-Squared	0.11	0.12	0.13	0.15	0.17
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.46	0.46	0.46	0.46	0.46
Between 0 and 1	1.00	1.00	1.00	1.00	1.00
Observations	12414	12414	12414	12412	12412

Dependent variable is wrong exclusion without tolerance band. Standard errors shown in parentheses are clustered at the district level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results are robust to the use of different specifications of the transparency measure. Based on the full model with all controls, Tables 3 and 4 compare the marginal effects for Transparency C with those of Transparency A (looking only at the count of criteria) and Transparency B (considering only their verifiability). Both of these measures – which have been combined as different dimensions of transparency into Transparency C – are also important on their own. Both are statistically and economically significant. According to Table 3, an increase in the number of criteria by one increases the probability of wrong exclusion by 15.5 percentage points (Column 1) and, at a given number of criteria, moving from the most intransparent criterion (destitution) to the clearest criterion (BPL card holding) is associated with a reduction of this probability by about 40 percentage points (7x5.75).

Just as for Transparency C, the more conservative estimation including the tolerance band in Table 4 only marginally reduces the size of these effects. All relevant coefficients remain large and highly significant.

Table 2: Transparency measure C and error wrongly excluded with band

	(1)	(2)	(3)	(4)	(5)
Year 2012	-0.214***	-0.222***	-0.162***	-0.176***	-0.103**
	(0.0214)	(0.0184)	(0.0303)	(0.0290)	(0.0299)
Transparency C	-0.0196***	-0.0197***	-0.0182***	-0.0196***	-0.0238***
	(0.0019)	(0.0027)	(0.0027)	(0.0026)	(0.0021)
Adj. R-Squared	0.13	0.15	0.15	0.18	0.21
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.36	0.36	0.36	0.36	0.36
Between 0 and 1	1.00	1.00	1.00	0.99	0.99
Observations	12414	12414	12414	12412	12412

Dependent variable is wrong exclusion with tolerance band. Standard errors shown in parentheses are clustered at the district level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Transparency measures A, B, C, and error wrongly excluded without band

	(1)	(2)	(3)
Year 2012	-0.192***	0.00412	-0.0954**
	(0.0299)	(0.0348)	(0.0297)
Transparency A	-0.155***		
	(0.0145)		
Transparency B		-0.0575***	
		(0.0057)	
Transparency C			-0.0282***
			(0.0026)
Adj. R-Squared	0.17	0.17	0.17
State fixed effects	Yes	Yes	Yes
State coverage	Yes	Yes	Yes
Exogenous covariates	Yes	Yes	Yes
Endogenous covariates	Yes	Yes	Yes
Avg. predicted value	0.46	0.46	0.46
Between 0 and 1	1.00	1.00	1.00
Observations	12412	12412	12412

Dependent variable is wrong exclusion without tolerance band. Standard errors shown in parentheses are clustered at the district level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Transparency measures A, B, C, and error wrongly excluded with band

	(1)	(2)	(3)
Year 2012	-0.184***	-0.0174	-0.103***
	(0.0327)	(0.0303)	(0.0299)
Transparency A	-0.128***		
	(0.0122)		
Transparency B		-0.0496***	
		(0.0045)	
Transparency C			-0.0238***
			(0.0021)
Adj. R-Squared	0.21	0.21	0.21
State fixed effects	Yes	Yes	Yes
State coverage	Yes	Yes	Yes
Exogenous covariates	Yes	Yes	Yes
Endogenous covariates	Yes	Yes	Yes
Avg. predicted value	0.36	0.36	0.36
Between 0 and 1	0.99	0.99	0.99
Observations	12412	12412	12412

Dependent variable is wrong exclusion with tolerance band. Standard errors shown in parentheses are clustered at the district level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3 Robustness tests

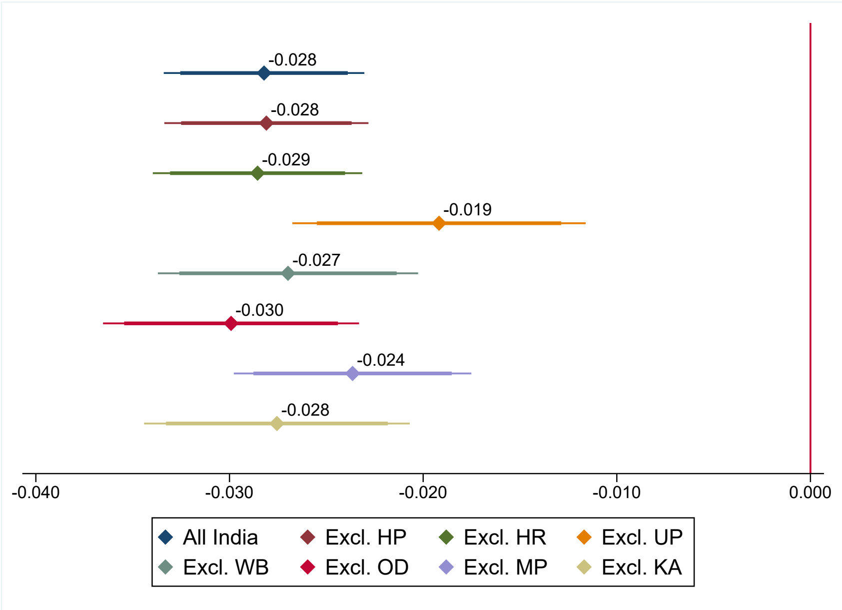
To test the robustness of our results, we conduct a number of complementary analyses. First, we examine whether any specific states drive our results. Second, we examine whether they are robust to a specification using a panel model with individual fixed effects. Third, we use a non-linear specification to control for the changes in coverage. Forth, we examine to what extent unobserved factors correlated with the transparency of eligibility criteria and with the likelihood of being wrongly excluded may influence our results. Fifth, we test whether our findings also hold when we consider a conceptually different measure of the targeting performance of social pensions, and sixth, we apply wild-cluster bootstrapping to account for the fact that our independent variable varies only at the state level and over time. Further robustness tests applying a logistic, rather than a linear probability model are provided in Appendix G.

5.3.1 Outliers at the state level

Potentially, the observed relationship between the transparency of eligibility criteria and the exclusion error could be driven by one particular state. Since Haryana was quite an outlier in the descriptive statistics, showing much better results than the other states in our sample, both regarding coverage and regarding the exclusion error, this may be a possible candidate responsible for driving the results. To see whether such differences are important, we re-run the regression analysis from Table 1, Column 5 (full model including all covariates). However, this time, we systematically exclude each of the states one-by-one. Figure 6 presents the coefficient estimates for Transparency C for each of the seven regressions. It shows that independently of the state being excluded, we always observe a highly significant and negative coefficient for the net effect of Transparency C ranging from -0.03 (omitting Odisha) to -0.019 (omitting Uttar Pradesh).

Showing the same results for an analysis including the tolerance band again reduces the coefficient estimates, but still shows a sizeable effect of improvements in transparency, no matter which state is excluded (see Figure 7). In this more conservative set-up, the effect of Transparency C ranges from -0.026 (omitting Odisha) to -0.011 (omitting Uttar Pradesh).

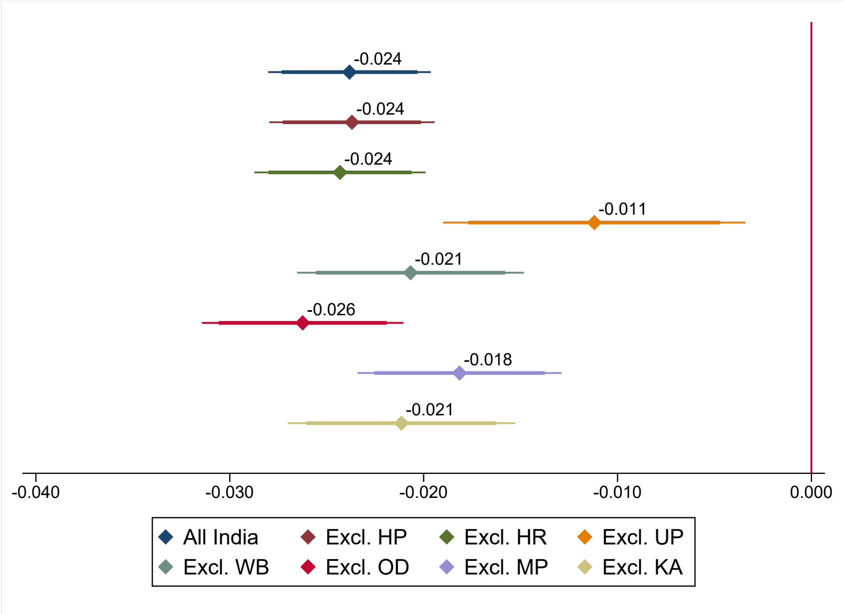
Figure 6: Sensitivity of results to included states - without tolerance band



Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP)

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

Figure 7: Sensitivity of results to included states - with tolerance band



Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP)

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

The two figures also show that, despite its differences regarding social pension coverage and aggregate exclusion error, Haryana is not an outlier when it comes to the effect of transparency. If at all, Uttar Pradesh might be an outlier here: in both figures the point estimates have a visibly smaller absolute value when Uttar Pradesh is excluded, suggesting that an increase in transparency might be even more relevant there than in other states. However, at least in the estimation without tolerance bands, the confidence intervals for all point estimates largely overlap, so that such differences might simply be an artifact of the specific sample of elderly used in our analysis.

5.3.2 Panel regression

To address potential concerns related to omitted variable bias at the individual level, we now present a panel model that takes into account individual time-invariant heterogeneity through individual fixed effects. As mentioned earlier, the disadvantage of this approach is that the sample is no more representative for the elderly. We have two options to construct the panel. Either we include those that meet the age threshold already in the first period, and who are still alive in the second. This reduces the number of observations considerably. Or we also include all those that become of eligible age only in the second period. This creates some noise as, by definition, these people cannot be wrongly excluded in 2004/5. At the same time, the number of observations in this setting becomes comparable to the number of observations in the repeated cross section models used before. For this reason, we opt for the second choice. Tables 5 and 6 show the replication of our main results. There are only four columns because state fixed effects are absorbed automatically in the individual fixed effects (perfect multicollinearity).

The estimates are very similar to our earlier results, but with a noticeable reduction in the range of coefficient estimates, which vary little across the different specifications. They come close to those estimates previously obtained for the model with all but the set of potentially endogenous controls. As before, the estimated effect is slightly smaller, but still sizable, when the tolerance band is applied to the computation of the dependent variable.

Table 5: Panel regressions without band

	(1)	(2)	(3)	(4)
Year 2012	0.110^{***}	0.0458	-0.0631	-0.159^{*}
	(0.0199)	(0.0351)	(0.0619)	(0.0616)
Transparency C	-0.0251^{***}	-0.0261^{***}	-0.0236^{***}	-0.0241^{***}
	(0.0027)	(0.0027)	(0.0029)	(0.0028)
Adj. R-Squared	0.07	0.08	0.10	0.12
Individual FE	Yes	Yes	Yes	Yes
State coverage	No	Yes	Yes	Yes
Exogenous covariates	No	No	Yes	Yes
Endogenous covariates	No	No	No	Yes
Avg. predicted value	0.34	0.34	0.34	0.34
Between 0 and 1	1.00	1.00	0.98	0.58
Observations	12908	12908	12908	12908
Number of id	6454	6454	6454	6454

Dependent variable is wrong exclusion without tolerance band. Standard errors shown in parentheses are clustered at the district level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Panel regressions with band

	(1)	(2)	(3)	(4)
Year 2012	0.0939***	0.0649	0.0160	-0.0228
	(0.0168)	(0.0357)	(0.0576)	(0.0567)
Transparency C	-0.0217***	-0.0221***	-0.0201***	-0.0208***
	(0.0022)	(0.0023)	(0.0025)	(0.0023)
Adj. R-Squared	0.07	0.07	0.10	0.12
Individual FE	Yes	Yes	Yes	Yes
State coverage	No	Yes	Yes	Yes
Exogenous covariates	No	No	Yes	Yes
Endogenous covariates	No	No	No	Yes
Avg. predicted value	0.24	0.24	0.24	0.24
Between 0 and 1	1.00	1.00	0.96	0.64
Observations	12908	12908	12908	12908
Number of id	6454	6454	6454	6454

Dependent variable is wrong exclusion with tolerance band. Standard errors shown in parentheses are clustered at the district level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3.3 Alternative control for coverage

As we have seen in the descriptive statistics, social pension coverage changed considerably between the two periods of observation, and this change may affect our results if changes in coverage are correlated with reforms of the eligibility criteria. So far, we have taken this into account by simply controlling for state-wise coverage rates. However, if the effect of coverage is non-linear, this simple control strategy may leave some room for remaining omitted variable bias. We thus propose an alternative non-linear approach to eliminate the effect of increased coverage from our estimation.

Tables 7 and 8 show the regressions including the covariate state coverage with its polynomials up to the third degree. Specifications (1)-(3) are without covariates, while (4)-(6) include all but the state-level covariates. The issue is that we do not have much variation at the state level so that additional variables for state coverage along with all the previously included state-level covariates lead to severe collinearity problems.

Table 7: Polynomial coverage control without band

	(1)	(2)	(3)	(4)	(5)	(6)
Year 2012	-0.137***	-0.179***	-0.179***	-0.170***	-0.136**	-0.149***
	(0.018)	(0.030)	(0.035)	(0.023)	(0.039)	(0.040)
Transparency C	-0.022***	-0.022***	-0.013***	-0.024***	-0.024***	-0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Adj. R-Squared	0.12	0.12	0.13	0.15	0.15	0.16
Avg. predicted value	0.46	0.46	0.46	0.46	0.46	0.46
$State\_coverage$	Yes	Yes	Yes	Yes	Yes	Yes
$State\_coverage^2$	No	Yes	Yes	No	Yes	Yes
$State\_coverage^3$	No	No	Yes	No	No	Yes
Exogenous covariates	No	No	No	Yes	Yes	Yes
Endogenous covariates	No	No	No	Yes	Yes	Yes
Between 0 and 1	1.00	1.00	1.00	1.00	1.00	1.00
Observations	12414	12414	12414	12412	12412	12412

Dependent variable is wrong exclusion without tolerance band. Standard errors shown in parentheses are clustered at the district level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

While adding the square term in Columns (2) and (5) does not change the earlier results, the point estimate of the transparency measure shrinks considerably when adding the third polynomial. Adding a forth and fifth polynomial does not lead to relevant further changes (not shown). While the point estimates are smaller, they remain relevant, both economically and statistically.

Table 8: Polynomial coverage control with band

	(1)	(2)	(3)	(4)	(5)	(6)
Year 2012	-0.194***	-0.247***	-0.246***	-0.217***	-0.176***	-0.193***
	(0.018)	(0.030)	(0.034)	(0.025)	(0.038)	(0.041)
Transparency C	-0.020***	-0.020***	-0.009**	-0.021***	-0.021***	-0.009**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Adj. R-Squared	0.13	0.13	0.15	0.17	0.17	0.18
Avg. predicted value	0.36	0.36	0.36	0.36	0.36	0.36
$State\_coverage$	Yes	Yes	Yes	Yes	Yes	Yes
$State\_coverage^2$	No	Yes	Yes	No	Yes	Yes
$State\_coverage^3$	No	No	Yes	No	No	Yes
Exogenous covariates	No	No	No	Yes	Yes	Yes
Endogenous covariates	No	No	No	Yes	Yes	Yes
Between 0 and 1	1.00	1.00	1.00	0.99	0.99	0.99
Observations	12414	12414	12414	12412	12412	12412

Dependent variable is wrong exclusion with tolerance band. Standard errors shown in parentheses are clustered at the district level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

If we again take the relatively typical example of West Bengal where Transparency C changes by 7 points, even the smallest point estimates suggests a corresponding reduction of the probability of wrong exclusion by 9.1 percentage points (Table 7, Column (3)), and of 4.9 percentage points when allowing for the tolerance band (Table 8, Columns (3) and (6)).

5.3.4 Selection on unobservables

Despite our efforts to control for observable factors at individual, household, village, district and state level, the estimated effects can still be biased by unobservables. If these unobservable factors are correlated with the transparency measure and with the likelihood of being wrongly excluded, we might just observe a spurious correlation. We closely follow Nunn and Wantchekon (2011) to assess how likely it is that our estimates are biased by unobservable factors. The basic idea goes back to Altonji et al. (2005) showing that selection on observables can be seen as a measure to assess selection on unobservables.

The relevant measure called Selection Ratio can be derived from two regressions. One regression includes a restricted set of control variables and the other one a full set of control variables. Let us call the estimated coefficient of interest from the regression with the restricted set of control variables $\hat{\beta_R}$ (R for restricted), and from the regression with the full set of control variables $\hat{\beta_F}$ (F for full). Based on these coefficients we can calculate the Selection Ratio:

$$\text{Selection Ratio} = |\frac{\hat{\beta_F}}{\hat{\beta_R} - \hat{\beta_F}}| \quad (2)$$

The Selection Ratio indicates how strong selection on unobservables would have to be to explain away the estimated effect. The ratio increases in absolute values of $\hat{\beta_F}$ since a larger coefficient for the variable of interest implies that selection on unobservables would need to explain a larger effect. It decreases in absolute values of $\hat{\beta_R} - \hat{\beta_F}$ because a smaller difference between the coefficient of interest from the restricted model and the coefficient of interest from the full model means that the estimate is less affected by the addition of control variables. Therefore, the selection on unobservables compared to selection on observables needs to be stronger to explain the full effect (Nunn and Wantchekon, 2011, p. 3238). In the following, we present the Selection Ratio for two restricted sets of control variables and two full sets of control variables.

The first restricted set (R1) includes only year fixed effects. The second restricted set (R2) includes year and state fixed effects. The first full set (F1) includes year fixed effects, state fixed effects, state coverage and exogenous control variables. The second full set (F2) includes year fixed effects, state fixed effects, state coverage as well as exogenous and endogenous control variables. All these coefficients have already been computed for the presentation of our main results in Table 1.

Table 9 again reports these regression coefficients now labeled $\hat{\beta_R}$ and $\hat{\beta_F}$, and the corresponding Selection Ratios. The ratio varies between 3.52 when we compare the coefficients for R1 and F2 (second row) and 38.64 when we compare the coefficients for R2 and F1. This implies that the effect of selection on unobservables would have to be at least 3.52 times larger than the effect of the selection on observables to explain away the estimated effects.

With the inclusion of multiple control variables at various levels including controls for social pension coverage, state governance and population size (and many others), we have already accounted for a large number of potentially confounding factors. We thus believe that it is highly unlikely that selection on unobservables entirely drives the estimated effect of transparency on the likelihood of being wrongly excluded.

Table 9: Test for selection on unobservables

Controls in the restricted set	**Controls in the full set**	$\hat{\beta_R}$	$\hat{\beta_F}$	**Selection Ratio**
R1: Year FE	F1: Year FE, state FE, state coverage and exogenous controls	-0.020	-0.025	5.23
R1: Year FE	F2: Year FE, state FE, state coverage, exogenous controls, and endogenous controls	-0.020	-0.025	4.95
R2: Year FE and state FE	F1: Year FE, state FE, state coverage and exogenous controls	-0.024	-0.025	38.64
R2: Year FE and state FE	F2: Year FE, state FE, state coverage, exogenous controls, and endogenous controls	-0.024	-0.025	25.62

5.3.5 Alternative dependent variable: correct selection

While we have already considered two dependent variables - wrong exclusion based on sharp eligibility criteria and wrong exclusion measured with a tolerance band - both are based on the same general concept of mistargeting. As the limited number of pensions available in 2004-05 prevents us from studying wrong inclusion, this is no possible alternative. However, as a complement to wrong exclusion, we can also examine correct inclusion, or, more generally, correct selection into the pension schemes.

While wrong exclusion is currently the predominant concern, this complementary measure may provide a relevant additional perspective for several reasons. First, it may be a less noisy targeting indicator in a situation where much of the wrong exclusion is simply driven by the fact that the number of available pensions does not match the number of eligible elderly. Second, many individuals might be counted as wrongly excluded because they fulfill the eligibility criteria, but simply do not apply. Whether this happens because they are discouraged from applying or because they are too poor, uneducated and vulnerable to apply (or do not even know about the pension schemes), they rightly increase the measure for wrong exclusion. However, given numerous problems with the targeting of the BPL card, people may well be formally eligible in terms of age and BPL status, but not actually be poor. This share is indeed non-negligible, as we show in Figure A2 of Appendix H. For some of these people, applying for the limited benefits provided by the social pension scheme may simply not be worth the effort, and they may hold the BPL card for other reasons (e.g., tax evasion or access to subsidized food). In this case, the exclusion error will appear more problematic than it actually is. The measures of correct inclusion or generally, correct selection, are not affected by such problems.

We thus re-run our main set of equations measuring targeting performance by correct selection into the pension schemes. Observations for which the value of this variable is 1 refer either to individuals who are eligible according to official eligibility criteria and receive social pension benefits, or to those who are ineligible and do not receive social pension benefits. The value of this variable is 0 otherwise.

Table 10 confirms that an increase in the transparency of the eligibility criteria has an economically and statistically significant effect on targeting performance. In fact, the coefficient estimates are not very different from those we obtained before. The sign change is only due to the fact that our dependent variable is now formulated in a positive way, rather than as an error. Increasing the transparency of eligibility criteria by one unit is associated with an increase in the likelihood of a correct selection decision (correct inclusion or correct exclusion) by 1.7-2.4 percentage points. Put differently, a one standard deviation increase in the transparency score is associated with an 8.5-12 percentage points increase in the likelihood of correct selection. The comparable values we had obtained using wrong exclusion as the dependent variable were 10-15 percentage points.

Table 10: Alternative dependent variable

	(1)	(2)	(3)	(4)	(5)
Year 2012	0.185***	0.177***	0.162***	0.163***	0.161***
	(0.0170)	(0.0162)	(0.0299)	(0.0307)	(0.0295)
Transparency C	0.0166***	0.0194***	0.0190***	0.0208***	0.0210***
	(0.0022)	(0.0028)	(0.0028)	(0.0027)	(0.0028)
Adj. R-Squared	0.09	0.10	0.10	0.12	0.13
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.51	0.51	0.51	0.51	0.51
Between 0 and 1	1.00	1.00	1.00	1.00	1.00
Observations	12414	12414	12414	12412	12412

Dependent variable is correctly included. Standard errors shown in parentheses are clustered at the district level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3.6 Wild-cluster bootstrapping

Finally, we address the concern that clustering of errors at district levels could lead us to be overly confident of the statistical significance of our results. Indeed, since our indicators of transparency do not vary across districts, our estimated standard errors clustered at the district level may lead to downward biased estimates of the standard errors (Angrist and Pischke, 2008). While traditional clustering at the state level is not possible in our context, because the number of clusters would be too small to reasonably expect convergence, wild-cluster bootstrapping circumvents this problem (Cameron et al., 2008). Tables 11 and 12 show our results when using this bootstrapping procedure for clusters at the state level. As compared to Tables 1 and 2, the presentation omits the specification without state fixed effects since the latter are particularly important in any setting that cares for possible similarities between observations within states. The top-row in Tables 11 and 12 report the relevant coefficients along with the original standard errors, while the following line shows the bootstrapped standard errors used for the present analysis. While the standard errors change, the relevant coefficient estimates remain the same, and all of them remain significant at the 1% level.

Table 11: Estimation with wild cluster-bootstrapping standard errors - without tolerance band

	(1)	(2)	(3)	(4)
Transparency C	-0.0243***	-0.0230***	-0.0250***	-0.0253***
	(0.0030)	(0.0031)	(0.0030)	(0.0030)
Bootstrapped SE	0.0041	0.0051	0.0043	0.0044
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State coverage	No	Yes	Yes	Yes
Exogenous controls	No	No	Yes	Yes
Endogenous controls	No	No	No	Yes
Observations	12414	12414	12412	12412

Dependent variable is wrong exclusion without tolerance band. Standard errors shown in parentheses are clustered at the district level. The bootstrapped standard error indicates the standard error after applying wild cluster bootstrapping.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Estimation with wild cluster-bootstrapping standard errors - with tolerance band

	(1)	(2)	(3)	(4)
Transparency C	-0.0197***	-0.0182***	-0.0196***	-0.0196***
	(0.0027)	(0.0027)	(0.0026)	(0.0026)
Bootstrapped SE	0.0052	0.0064	0.0062	0.0062
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State coverage	No	Yes	Yes	Yes
Exogenous controls	No	No	Yes	Yes
Endogenous controls	No	No	No	Yes
Observations	12414	12414	12412	12412

Dependent variable is wrong exclusion with tolerance band. Standard errors shown in parentheses are clustered at the district level. The bootstrapped standard error indicates the standard error after applying wild cluster bootstrapping.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.4 Discussion

In sum, none of the robustness tests challenges any of our results. Clearly, the transparency of eligibility criteria matters for social pension targeting, and it does so in both dimensions: the number of criteria and their clarity or verifiability.

As our analysis focuses on a physically weak and often uneducated target group, namely the elderly poor, even with more transparent criteria, it may be difficult for them to claim their rights and monitor correct selection processes unless they receive external support through family members or NGOs. Hence, the effects we observe here may represent a lower bound for the effect that a reform of eligibility criteria might achieve in other social welfare schemes that target working age population or entire households.

If eligibility is determined based on criteria that themselves require appropriate targeting – such as, in our case, BPL card holding – the targeting of these underlying criteria should be similarly reformed. This is in line with current policy efforts in India. Indeed, the Indian government is well-aware of the problems related to BPL identification processes (Government of India et al., 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 that are meant to simplify the assessment. The new criteria were formally adopted by the Ministry of Rural Development in January 2017 (Government of India, 2017). It remains to be seen to what extent they will improve upon the status quo.

6 Conclusion

Due to wide-spread corruption, local elite capture, clientelism, lack of information and lack of administrative capacity, the targeting of public welfare programs remains a daunting challenge in many developing countries. These problems can be expected to be even greater and harder to remedy, 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.

Based on the exploration of extensive administrative information, two rounds of data from the India Human Development Survey, and numerous interviews helping us to interpret the information at hand, we analyzed the question whether the targeting of social pensions could be improved by using more transparent eligibility criteria. Drawing together different dimensions of transparency discussed in the literature into a single indicator, we show that indeed, the effect of an improvement in the transparency of eligibility criteria is both statistically and economically significant. In our main specifications, the effect of a one-standard deviation increase in the transparency indicator is associated with a reduction of the probability to be wrongly excluded by 10-15 percentage points. We can show that these effects are due to different dimensions of transparency, notably a reduced number of different criteria as well as better verifiability for each criterion applied. Each of them has a substantial effect on targeting performance. We also show that this strong effect is not just related to avoiding errors at the margin. To do so, we construct a new measure for wrong exclusion that applies a tolerance band around all relevant eligibility criteria. The resulting more conservative measure for the effect of transparency is only slightly smaller than the one based on the initial estimation.

These results are robust to a large number of additional specifications. In particular, they do not depend on the inclusion of individual states, they hold in a repeated cross section analysis as well as in a panel model with individual fixed effects, they remain valid when we use a non-linear approach to control for pension coverage, and they are robust to different approaches of clustering. In addition, we can show that it is highly unlikely that unobserved confounders are driving these effects, and that the results also hold when we consider an alternative dependent variable, which is not based on wrong exclusion, but on correct selection into the pension scheme.

This suggests a systematic reform of eligibility criteria, not just for social pensions, but also for other social welfare schemes. Given the particularities of the target population for a pension scheme, the effects on other schemes might be even stronger. In any case, the proposed reform is not very costly as it only consists in selecting a more transparent set of criteria and disseminating the related information. In the long run, due to reduced assessment cost, when using the simplified criteria, such a reform may even be financially rewarding. This suggests that the cost-effectiveness of such a reform would be very high.

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A State-level eligibility criteria

State	Name of scheme	Eligibility criteria 2004-05	Eligibility criteria 2011-12
Himachal Pradesh	IGNOAPS	Age 65 years or above, destitute	Age 60 years or above, BPL card holding
	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, individualdoes 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
Sources:		Gov. of HP (undated(a))	Gov. HP (undated(b))
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
	Old Age Samman Allowance (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
Sources:		Gov. of HR (2006, 2011)	Gov. of HR (undated(a))
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
	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 - 2012)	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
Sources:		Gov. of UP (undated), Comptroller and Auditor General of India, (2009)	Gov. of UP (2010a, 2010b, 2010c)

State	Name of scheme	Eligibility criteria 2004-05	Eligibility criteria 2011-12
West Bengal	IGNOAPS	Age 65 years or above, destitute	Age 60 years or above, BPL card holding
Sources:		Gov. of WB (undated)	
Madhya Pradesh	IGNOAPS	Age 65 years or above, destitute	Age 60 years or above, BPL card holding
	Samagra Social Security Pension Scheme	Age 60 or above, destitute	Age 60 years or above, BPL card holding or landless and destitute
Sources:		Gov. of MP (undated)	Gov. of MP (2012, 2013)
Odisha	IGNOAPS	Age 65 years or above, destitute	Age 60 years or above, BPL card holding
	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
Sources:		Gov. of OR (2008)	Gov of OR (undated (a), (b))
Karnataka	IGNOAPS	Age 65 years or above, BPL card holding, annual income $<$ Rs.6000 per annum	Age 60 years or above, BPL card holding
	Sandhya Suraksha Yojana (since 2007)	Scheme did not exist.	Age 60 years or above, annual household income $\leq$ Rs 20000
Sources:		Rajasekhar et al. (2009), Gov of KA (undated)	Chathukulam et al. (2012) webindia123.com (2007)

A.1 References for state-level eligibility criteria

We collected the administrative information on state-level eligibility criteria primarily from state government websites. Since state websites are updated frequently, we provide below the references with links to the web archive (http://web.archive.org/) to ensure that they function in the longer run. We further provide all sources for administrative information on state-level eligibility criteria used for this paper in an online-appendix: State-level eligibility criteria and sources

A.2 Himachal Pradesh

A.2.1 Himachal Pradesh 2004-05

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A.2.2 Himachal Pradesh 2011-12

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A.4.2 Uttar Pradesh 2011-12

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A.7 Odisha

A.7.1 Odisha 2004-05

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A.8.1 Karnataka 2004-05

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A.8.2 Karnataka 2011-12

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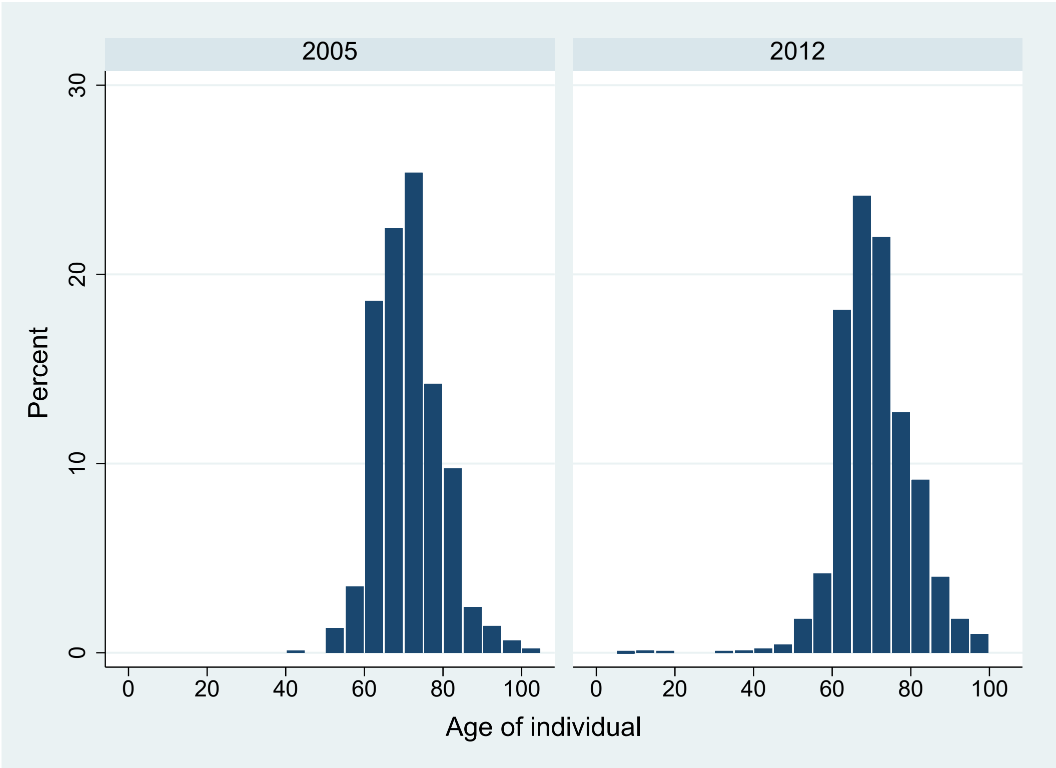
B Age distribution

Figure A1: Age distribution of social pension beneficiaries



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

C Variable description and sources

VARIABLES	2004-05 mean	2004-05 se	2011-12 mean	2011-12 se	Measurement level	Definition	Data source
Error excluded	0.646	0.012	0.355	0.008	Individual	Dummy equal to 1 if individual does not receive social pension but fulfills the locally relevant eligibility criteria	IHDS & admin. info
Error excluded band	0.560	0.012	0.248	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 & admin. info
Correctly included or excluded	0.331	0.012	0.600	0.009	Individual	Dummy equal to 1 if individual receives a social pension and fulfills the locally relevant eligibility criteria or does not receive a social pension and does not fulfill the locally relevant eligibility criteria	IHDS & admin. info
Transparency A	2.465	0.037	2.432	0.016	State	Transparency score A= 5 - number of eligibility criteria (clauses and sub-clauses). Range is 1-4. For a detailed explanation, see Appendix D.	Admin. info
Transparency B	1.654	0.023	5.727	0.049	State	Transparency score B = Verifiability score of the least verifiable category of eligibility criteria applied. Range is 1-8. For a detailed explanation, see Appendix D.	Admin. info
Transparency C	19.573	0.086	24.595	0.087	State	Transparency score C = Weighted sum of eligibility criteria whereby weights are based on verifiability score. Range is 13-29.	Admin. info
Pension recipient	0.095	0.006	0.224	0.007	Individual	Dummy equal to 1 if individual receives social pension	IHDS
Age	71.210	0.187	70.271	0.152	Individual	Age of the individual	IHDS
Female	0.470	0.013	0.497	0.009	Individual	Dummy equal to 1 if individual is female	IHDS
Literate	0.338	0.011	0.378	0.008	Individual	Dummy equal to 1 if individual can read and write	IHDS
Widowed	0.403	0.012	0.403	0.009	Individual	Dummy equal to 1 if individual is widowed	IHDS
Working	0.396	0.013	0.299	0.009	Individual	Dummy equal to 1 if individual is working at least 240 hours per year	IHDS
BPL card	0.277	0.011	0.434	0.009	Household	Dummy equal to 1 if household holds a BPL card	IHDS
Household assets	10.908	0.128	13.136	0.113	Household	Number of household assets owned	IHDS
Landless	0.349	0.011	0.410	0.009	Household	Dummy equal to 1 household is landless	IHDS
Permanent job	0.099	0.006	0.144	0.006	Household	Dummy equal to 1 if any household member has a permanent job	IHDS

VARIABLES	2004-05 mean	se	2011-12 mean	se	Measurement level	Definition	Data source
Household max. education	7.725	0.133	8.179	0.098	Household	Education level of the most educated person in the household.	IHDS
Local government connection	0.100	0.006	0.328	0.009	Household	Dummy equal to 1 if household has a direct connection to the local government	IHDS
Household size	6.533	0.090	5.586	0.050	Household	Number of persons sharing one kitchen	IHDS
Urban	0.192	0.007	0.259	0.006	Household	Dummy equal to 1 if household lives in urban area	IHDS
Share state confidence	0.245	0.005	0.337	0.003	District	Share of households having confidence in the state government	IHDS
Share of elderly	0.090	0.002	0.111	0.001	District	Percentage of elderly population	IHDS
Share of SC, ST, OBC	0.718	0.005	0.713	0.003	District	Percentage of SC, ST, OBC population	IHDS
Share of Muslims	0.128	0.003	0.145	0.002	District	Percentage of Muslims	IHDS
Share of literate voters	0.568	0.003	0.637	0.002	District	Percentage of literate adults among adult population	IHDS
Gini coefficient	0.343	0.002	0.338	0.001	District	Gini coefficient based on consumption exp. adj. for social pension benefits	IHDS
Head count ratio	0.442	0.004	0.232	0.003	District	Head count ratio based on consumption exp. adj. for social pension benefits	IHDS
Political competition	0.669	0.002	0.662	0.001	District	Political competition in the Lok Sabha constituency based on the Hirschman-Herfindahl concentration index	Election Commission of India
Participation in public meeting	0.296	0.003	0.253	0.002	District	Share of households participating in public meetings	IHDS

VARIABLES	**2004-05**		**2011-12**		**Measure-ment level**	**Definition**	**Data source**
	mean	**se**	**mean**	**se**			
Share electrified	0.589	0.006	0.739	0.005	District	Share of households having electricity	IHDS
Share bureaucratic difficulties	0.070	0.002	0.064	0.001	District	Share of households having bureaucratic difficulties with ration card	IHDS
Share tax revenue	0.064	0.000	0.074	0.000	State	Ratio of real own tax revenue of the state (at 2004-05 prices) to its real gross state domestic product (at 2004-05 prices), indicator of state capacity	Reserve Bank of India
Judicial speed	0.370	0.004	0.305	0.005	State	Disposal rate as indicator of judicial speed or institutional efficiency	Reserve Bank of India
Coverage	0.100	0.002	0.215	0.001	State	Social pension coverage of age-wise eligible elderly	Reserve Bank of India
Number of observations	5015		7399				

D Qualitative research

Table A1: List of interviews conducted in Delhi in Spring 2016

Name	**Designation**	**Date**
Mr Ladu Kishore Swain	Member of Parliament, Aska, Odisha (Party: Biju Janata Dal)	16 March 2016
Mr Konda Vishewar 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

E 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 xth percentile of the age distribution. We now find standard error and 95% confidence band of the estimate of xth 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. We follow the same method to find bands around income and land-holding criteria.

Destitute: The destitution criterion is not as objective as the age or BPL criteria. However, we know that pensions were available for 50% of the elderly below the Tendulkar poverty line. 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 the relevant year. 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.

Persons are considered as wrongly excluded according to our measure allowing for the tolerance band if and only if they do not receive the pension while they are 'clearly eligible' according to all eligibility criteria of either the national or the relevant state scheme.

F 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 an empirical 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:

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

For example in Uttar Pradesh 2011-12 we have two types of conditions for BPL (see Appendix A), 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 weight for each category of conditions are the same as used for the construction of Transparency C and explained in Section 4. Higher verifiability weight means more difficult to verify. These weights, W_i are: destitution=8 (most vague, most difficult to assess), income=4, land holding=2, and BPL card holding=1 (easiest to assess). When computing the transparency 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 determined (inversely) by the criterion used that obtains the maximum weight:

$$Transparency\ B = 9 - \max_i \{W_i I_i\}$$

where $I_i = 1$ if criterion i is specified, 0 otherwise. Transparency B is the lowest $(= 1)$ when destitution is specified in the list of all criteria, it is the highest $(= 8)$ when BPL is the only criterion. For example in Karnataka 2004-05 income and BPL are used as criteria (see Appendix 1). Income has a verifiability weight of 4, while BPL has a weight of 1. Income is the least verifiable among the two. Hence the value of Transparency B is $9 - \max\{4, 1\} = 5$. Table A2 below compares the two complementary measures, both with each other and with the combined measure Transparency C explained in Section 4.

Table A2: Transparency scores by state and year

	Transparency A		Transparency B		Transparency C	
	2004-05	2011-12	2004-05	2011-12	2004-05	2011-12
Himachal Pradesh	2	1	1	5	14	21
Haryana	2	2	5	5	22	21
Uttar Pradesh	1	2	1	8	16	28
West Bengal	4	4	1	8	22	29
Madhya Pradesh	4	2	1	1	22	19
Odisha	4	1	1	1	22	13
Karnataka	3	3	5	5	25	25

The correlation between the different indexes is relatively low for Transparency A and B ($\rho_{A,B} = 0.05$) 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 ($\rho_{A,C} = 0.54$, $\rho_{B,C} = 0.815$). 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.

The tables A3-A6 below present the regression results using Transparency A and B rather than Transparency C (cf. Table 1 and 2), each time first with sharp eligibility criteria and then with the use of the tolerance band. With one exception, the effect of the transparency measure remains negative and significant throughout, i.e. no matter which dimension of transparency we consider. The exception is the case of Transparency A with band in the regression without any controls. Since this is the least reliable regression, this does not affect the general conclusion. However, it may be interesting to note that Transparency A is generally much less robust to changes in the set of controls than Transparency B or C.

Table A3: Transparency measure A and error wrongly excluded without band

	(1)	(2)	(3)	(4)	(5)
Year 2012	-0.292***	-0.310***	-0.181***	-0.205***	-0.192***
	(0.0205)	(0.0233)	(0.0343)	(0.0334)	(0.0299)
Transparency A	-0.0208**	-0.0819***	-0.0718***	-0.0806***	-0.155***
	(0.0069)	(0.0130)	(0.0130)	(0.0131)	(0.0145)
Adj. R-Squared	0.08	0.11	0.11	0.13	0.17
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.46	0.46	0.46	0.46	0.46
Between 0 and 1	1.00	1.00	1.00	1.00	1.00
Observations	12414	12414	12414	12412	12412

Dependent variable is wrong exclusion without tolerance band. Standard errors shown in parentheses are clustered at the district level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Transparency measure A and error wrongly excluded with band

	(1)	(2)	(3)	(4)	(5)
Year 2012	-0.313***	-0.326***	-0.193***	-0.212***	-0.184***
	(0.0200)	(0.0211)	(0.0347)	(0.0343)	(0.0327)
Transparency A	0.00182	-0.0508***	-0.0404**	-0.0456***	-0.128***
	(0.0074)	(0.0118)	(0.0119)	(0.0123)	(0.0122)
Adj. R-Squared	0.10	0.14	0.14	0.16	0.21
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.36	0.36	0.36	0.36	0.36
Between 0 and 1	1.00	1.00	1.00	0.99	0.99
Observations	12414	12414	12414	12412	12412

Dependent variable is wrong exclusion with tolerance band. Standard errors shown in parentheses are clustered at the district level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Transparency measure B and error wrongly excluded without band

	(1)	(2)	(3)	(4)	(5)
Year 2012	-0.104***	-0.0485	-0.0650	0.0521	0.00412
	(0.0223)	(0.0244)	(0.0349)	(0.0352)	(0.0348)
Transparency B	-0.0458***	-0.0610***	-0.0621***	-0.0550***	-0.0575***
	(0.0050)	(0.0066)	(0.0066)	(0.0057)	(0.0057)
Adj. R-Squared	0.13	0.14	0.16	0.17	0.17
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.46	0.46	0.46	0.46	0.46
Between 0 and 1	1.00	1.00	1.00	1.00	1.00
Observations	12414	12414	12412	12412	12412

Dependent variable is wrong exclusion without tolerance band. Standard errors shown in parentheses are clustered at the district level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Transparency measure B and error wrongly excluded with band

	(1)	(2)	(3)	(4)	(5)
Year 2012	-0.111***	-0.0908***	-0.0471	-0.0616	-0.0174
	(0.0246)	(0.0258)	(0.0309)	(0.0314)	(0.0303)
Transparency B	-0.0495***	-0.0560***	-0.0539***	-0.0546***	-0.0496***
	(0.0041)	(0.0065)	(0.0064)	(0.0062)	(0.0045)
Adj. R-Squared	0.16	0.17	0.17	0.19	0.21
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.36	0.36	0.36	0.36	0.36
Between 0 and 1	1.00	1.00	1.00	0.99	0.99
Observations	12414	12414	12414	12412	12412

Dependent variable is wrong exclusion with tolerance band. Standard errors shown in parentheses are clustered at the district level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

G Alternative regression model

Table A7: Logit model - transparency measure C and error wrongly excluded without band

	(1)	(2)	(3)	(4)	(5)
Wrongly excluded without band					
Year 2012	-0.797***	-0.756***	-0.543***	-0.639***	-0.435**
	(0.0795)	(0.0746)	(0.1244)	(0.1419)	(0.1397)
Transparency C	-0.0869***	-0.106***	-0.101***	-0.114***	-0.130***
	(0.0090)	(0.0148)	(0.0148)	(0.0145)	(0.0125)
PSeudo R-Squared	0.08	0.09	0.09	0.12	0.14
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.46	0.46	0.46	0.46	0.46
Observations	12414	12414	12414	12412	12412

Dependent variable is wrong exclusion without tolerance band. Marginal effects are shown.
Standard errors shown in parentheses are clustered at the district level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Logit model - transparency measure C and error wrongly excluded with band

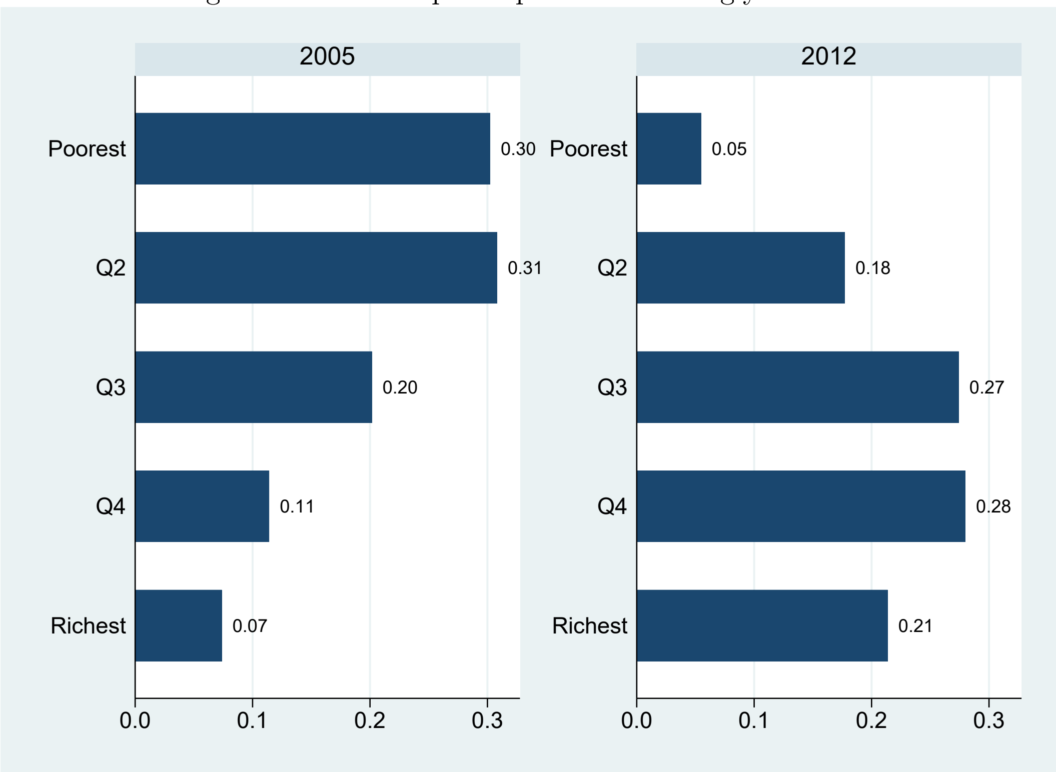
	(1)	(2)	(3)	(4)	(5)
Wrongly excluded with band					
Year 2012	-0.944***	-1.009***	-0.743***	-0.827***	-0.542***
	(0.0924)	(0.0826)	(0.1354)	(0.1390)	(0.1504)
Transparency C	-0.0934***	-0.104***	-0.0979***	-0.109***	-0.130***
	(0.0087)	(0.0146)	(0.0145)	(0.0148)	(0.0113)
Pseudo R-Squared	0.10	0.12	0.12	0.15	0.18
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.36	0.36	0.36	0.36	0.36
Observations	12414	12414	12414	12412	12412

Dependent variable is wrong exclusion with tolerance band. Marginal effects are shown. Standard errors shown in parentheses are clustered at the district level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

H Consumption expenditure as alternative poverty indicator

Figure A2: Consumption quintiles of wrongly excluded



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