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The pursuit of simplicity: Can simplifying eligibility criteria improve social pension targeting?☆

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ABSTRACT

Governments in developing countries struggle to reach intended beneficiaries when targeting social transfers towards vulnerable populations. Rates of eligible individuals not receiving social transfers and ineligible individuals receiving them tend to be high, constraining the effectiveness of such anti-poverty programs. While interventions to incentivize or monitor local agents in charge of selecting beneficiaries are typically expensive, an important complementary and cost-effective approach could be to reform eligibility criteria to facilitate the selection of beneficiaries. Whether reforms should focus on reducing the number of rules, or selecting criteria which are easy to verify, or do both remains an unanswered question. We address this knowledge gap based on India's social pension scheme for elderly poor. We find that making eligibility criteria easier to verify has the potential to achieve a substantial improvement in the targeting performance through a reduction in the exclusion error. Those who meet the relevant criteria have a much higher chance of actually becoming beneficiaries. Since eligibility criteria can be changed at low cost, this suggests a viable route for reform in many developing countries. However, a major caveat remains that criteria must sufficiently well reflect actual poverty if the more accurate selection of beneficiaries according to formal criteria shall also translate into actual poverty reduction.

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1. Introduction

Governments in developing countries have been expanding social protection programs to alleviate extreme poverty and to enable individuals satisfying their most basic needs during financial hardship (e.g. Drèze and Khera, 2017). Most recently, the COVID-19 pandemic has highlighted the importance of such programs (Devereux, 2021; Gerard et al., 2020). While poverty reduction appears to be the primary motivation behind the expansion of social protection programs, it has also been shown that governments expand such programs to gain political support (Manacorda et al., 2011; Dodlova et al., 2017; Araújo, 2021).

As funding for such programs is limited, most social protection programs in developing countries continue targeting the poor and governments use various criteria to identify and select the beneficiaries in the absence of reliable tax, income, and wealth data (Baker and Grosh, 1995). These so-called proxy-means tests in combination with corrupt practices and/or lack of capacity either on the side of the selectors (supply side) or on the side of the potential applicants (demand side) can lead to misidentification of beneficiaries. The resulting targeting errors refer to either the share of eligible individuals not receiving the benefits (exclusion errors), or the share of beneficiaries being ineligible (inclusion errors) (Cornia and Stewart, 1993).

While the targeting challenge applies to many different types of social protection schemes in many countries around the world, this study focuses on social pensions for elderly poor in India. Social pensions, as a type of cash transfer, are increasingly important for India's growing elderly population that largely cannot rely on formal sector pensions or savings in old age (Bloom et al., 2010; James, 2011). Given the country's federal structure, India's old-age social pensions include the centrally provided Indira Gandhi National Old Age Pension Scheme (IGNOAPS) and various social pension schemes provided by state governments. These programs have different eligibility criteria that also changed in the late 2000s. Initially, these criteria were vaguely defined, leaving scope for corrupt practices or unintentional human errors in scrutinizing the applicants. Over time, both the central and state schemes have undergone reforms in the eligibility criteria making them fewer in number, more verifiable and overall simplified.

This variation across states and over time allows us to examine empirically whether and how simplifying eligibility criteria can reduce the targeting errors. By examining potential cost-effective avenues for improving social pension targeting, we build on the existing literature that has documented the mistargeting of social pensions (Asri, 2019). Exploiting the changes of state-level and national-level eligibility criteria in terms of their number and verifiability, we examine how simplifying eligibility criteria along these two dimensions can reduce mistargeting measured by exclusion and inclusion errors.

Methodologically, we combine the nationally representative India Human Development Survey (IHDS) from 2004-05 and 2011-12 with detailed administrative information from seven Indian states. As dependent variables, we focus on the exclusion and inclusion error operationalized at the individual level. Our independent variables of interest indicate the simplicity of eligibility criteria in terms of fewer criteria, more verifiable criteria, or a combination of the two at the state-level measured at two points in time. While fewer criteria refer to simply reducing the count of the eligibility conditions, more verifiable criteria indicate the ease of verifying a criterion as a selector, e.g. destitution being more difficult to verify than income, income being more difficult to verify than land, and land being more difficult to verify than holding a Below-Poverty-Line (BPL) card. The BPL card is a document that certifies that a household is poor according to a census and a score-based system with state-level cutoffs (Ram et al., 2009; Panda, 2015).

Most prominently, in 2007, the central government replaced the vague poverty-related criterion “destitution” (without any operational definition) by the easily observable requirement to hold a BPL card (Government of India, 1998; 2007). Several state governments followed this reform by including the BPL card as an eligibility criterion. Overall, while some states changed only the number of eligibility criteria (e.g. Madhya Pradesh), other states changed only the verifiability (e.g. West Bengal) and yet others did both (e.g. Uttar Pradesh).

The main results suggest that choosing more verifiable criteria is the primary driver of improving the targeting performance through a reduction of the exclusion error. Reducing the number of criteria used for targeting does not robustly predict lower exclusion errors. More generally, for both dimensions, namely, the number and verifiability of the eligibility criteria, we do not document any significant change in the inclusion error.

Our robustness checks address the main threat to our identification strategy. There could be state-level changes at the same time as the eligibility reforms that influence both the targeting performance as well as the simplicity of eligibility criteria. Our results are generally robust, but we find that the state-level ruling party's ideology is an important factor influencing the targeting performance. Further, we demonstrate that the eligibility criteria must sufficiently well reflect actual poverty incidence if the more accurate selection of beneficiaries according to formal criteria shall also translate into actual poverty reduction.

This study speaks to the literature that examines different interventions to improve targeting of social transfers in developing countries (e.g. Alatas et al., 2012; Premand and Schnitzer, 2021). Typically, the challenge to allocate scarce resources for social transfers to intended beneficiaries is considered as a principal-agent problem with the government as the principal and local government officials as implementing agents. The existing literature has therefore given most of the attention to approaches that aim to incentivize or monitor the agents or to enable citizens to hold agents in charge accountable (Björkman and Svensson, 2009; Francken et al., 2009; Olken, 2007; Peisakhin, 2012; Peisakhin and Pinto, 2010; Reinikka and Svensson, 2004; 2005; 2011). Shifting the focus towards the capacity of local agents, one could argue for the need of the interventions that either improve their capacity to handle the existing task or reform the eligibility criteria to facilitate their task. This paper addresses the latter and thereby speaks to the question on how to design proxy means tests and which criteria to include. This question continues to be a subject of ongoing debate (e.g. Brown et al., 2018).

There are two main directions in the recent discourse on how eligibility criteria could be changed corresponding to the two dimensions of simplification studied in this paper. On the one hand, one could reduce the number of eligibility rules; and on the other hand, one could select eligibility rules that are easier to verify. For the Indian context, Niehaus et al. (2013) show that it is better to have fewer rules; while Drèze and Khera (2010) argue that simpler inclusion and exclusion criteria are needed which can be more easily observed. Niehaus et al. (2013) analyze how a proxy means test should be designed and 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. In their work on targeting of BPL cards, Drèze and Khera (2010) show the importance of using eligibility criteria that are easy to verify. Instead of reducing the number of criteria as suggested by Niehaus et al. (2013), the authors suggest replacing complex eligibility rules 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). Drèze and Khera (2010) argue that this simplification also helps to facilitate participatory monitoring and to prevent fraud.

Overall, our findings, supporting the introduction of more verifiable eligibility criteria — as long as they actually capture poverty — are relevant for the implementation of welfare schemes in developing countries fraught with an ubiquity of corruption, lack of information and constrained state capacity. For instance, when poor people do not know or do not understand the eligibility criteria, they cannot claim their rights and hold agents responsible. Furthermore, corruption, lack of capacity and 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, encourages local government officials to select beneficiaries among those people they are personally acquainted with. This shows that our results that build on Niehaus et al. (2013) and Drèze and Khera (2010) are broadly applicable to the challenge of targeting of social transfers beyond the Indian context.

2. Old-age social pensions in India

Social pensions, i.e. cash transfers for elderly poor, are provided in India by the national government as well as state governments. State governments do not only complement the national social pension amount to the beneficiaries in the states but also further cover additional groups of beneficiaries following different eligibility criteria and selection procedures.

The national scheme IGNOAPS was introduced in 1995 with a central government contribution of 75 INR per person per month. 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 national social pension scheme but the state governments are responsible for the implementation through gram panchayats (village councils) and municipalities. As the 1998 guidelines of the National Social Assistance Programme (NSAP) state, panchayats and municipalities, representing the smallest local governance units in rural and urban India respectively, shall be actively involved in the identification of beneficiaries (Government of India, 1998, p. 4).

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), actually who did and who did not belong to this group was unobservable in practice. Moreover, 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, the minimum age was reduced to 60 years (Government of India, 2007).

Regarding the complementary state pensions, we also observe several reforms of eligibility criteria that either changed the number of eligibility criteria or the verifiability of eligibility criteria or both. 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. Yet, in other states such as Madhya Pradesh, state-run programs simply follow the IGNOAPS criteria. Finally, there are a few states such as West Bengal that fully abstain from running their own state-level programs. For the latter, the reform of IGNOAPS directly defines the indicators for the simplification of eligibility criteria in the state.

Overall, the state governments appear to follow the national government in the move from using the destitution criterion towards using the BPL card with some states continuing to use income and land holding as poverty indicators and making distinctions between rural and urban areas. The change at the national and state level towards the increased use of BPL cards for targeting social transfers appears to be closely linked to the efforts in identifying the poor and providing them BPL cards with the Socio-Economic Caste Census in 2002. This raised awareness of BPL card holding as an easily observable criterion for social transfer targeting. In sum, eligibility criteria seem to move in most states from the vague destitution criterion to the more verifiable BPL status of households. Hence, in 2011-12, the elderly living in BPL households were supposed to receive IGNOAPS and the rules for the state schemes followed partially, but with some variation across states including income-based criteria, landlessness and destitution.

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.

3. Theoretical expectations

Simplifying eligibility criteria influences the behavior of local government officials in charge of selecting beneficiaries (supply side) and local citizens applying for social benefits (demand side).

On the supply side, the simplification of eligibility rules leads to increased costs of preferential treatment as the likelihood of being detected is higher and therefore targeting errors are expected to be reduced. Moreover, simplifying eligibility criteria reduces the burden of selecting beneficiaries, reduces the likelihood of human error and overall the administrative costs of the social protection schemes. On the supply side, the simplification of eligibility rules may thus address challenges related to both capacity constraints and corruption. At least in theory, this should imply that the limited resources can be used for transfers to the poor which we expect to lead to lower targeting errors.

On the demand side, simplifying eligibility rules facilitates the application process for eligible individuals and makes 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 more complicated criteria and higher discretionary power for the local government officials. Simplified eligibility criteria moreover facilitate that people are aware of their entitlements and help individuals scrutinize the selection of beneficiaries in public meetings improving their influence in the beneficiary selection process.[1] Hence, overall, we would expect that simplifying eligibility facilitates the selection of beneficiaries with positive impacts on the demand and supply sides.

Testing the effect of simplified 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 present in India, focusing on social pensions may make it relatively more 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 active 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 extremely simplified 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 simplifying eligibility criteria, either in terms of number or in terms of verifiability, 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.

4. Data and methods

4.1. Generation of the data set

To test the hypothesis that simplifying eligibility criteria improves targeting, we examine the likelihood of individual-level mistargeting depending on (a) having fewer rules, (b) having more verifiable rules and (c) having a combination of the two accounting for a number of covariates measured at different levels.

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 various topics including demographics, economic well-being, public welfare programs, 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-

[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)).

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 mistargeting of social pensions for elderly poor, we construct our samples of analysis as follows. For the exclusion error, we exclude all individuals who are younger than the state specific eligibility age.[2] For the inclusion error, we focus on all social pension beneficiaries.

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, the sample for the analysis of the exclusion error consists of 6401 elderly surveyed in 2004-05 and 8823 elderly surveyed in 2011-12. The sample for the analysis of the inclusion error consists of 895 beneficiaries surveyed in 2004-05 and 2181 beneficiaries surveyed in 2011-12.

Since IHDS re-interviewed respondents in the second round, it is possible to apply panel data methods with individual fixed effects to account 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 and it would be unclear what this sample would represent. For this reason, we use a pooled cross-sectional analysis instead.

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 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 variables and interpretation of empirical results. We provide a list of interviews in Appendix F.

4.2. Operationalization

4.2.1. Dependent variables

Any possible improvement in targeting should find its reflection in reduced targeting errors by reducing the number of eligible individuals not receiving the transfer (exclusion error) and/or the number of ineligible individuals receiving the transfer (inclusion error).[4]

In aggregate terms, the exclusion error is defined as the ratio of the number of eligible individuals not receiving the social transfer, divided by the number of eligible individuals. Similarly, in aggregate terms, the inclusion error is definded as the ratio of the number of ineligible individuals receiving the social transfer, divided by the number of beneficiaries (see e.g. Cornia and Stewart, 1993; Coady et al., 2004).

We take this concept to the individual level for the two dependent variables in our regressions. We create one indicator variable for the individual-level exclusion error and one indicator variable for the individual-level inclusion error. The variable exclusion error is equal to 1 if a person i is ‘wrongly excluded’ meaning eligible to receive the pension in state s but not receiving the social pension, and 0 otherwise.[5] The variable inclusion error is equal to 1 if a beneficiary i is ‘wrongly included’ meaning receiving the social pension despite of not being eligible to receive the social pension in state s, and 0 otherwise.

In contrast to the previous literature (e.g. Asri, 2019) examining the changes in targeting errors with a focus on asset-based poverty among elderly poor, we refrain from 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 or wrongly included in one place (or one point of time), and rightly excluded or rightly included in another. Along with the age criterion, we hence need to consider a number of variables in this context, related to consumption expenditure, income, BPL, land holding, and/or residential status. The destitution criterion relevant primarily for the early implementation of IGNOAPS (and some state-level social pension schemes) is measured by per-capita consumption (net of social pension receipts) below the median consumption of the elderly poor, 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.[6] Qualifying for any existing scheme, should, in principle, lead to social pension receipt. When

[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 for the sample used in the exclusion error analysis and Appendix D for the sample used in the inclusion error analysis. Code and data used for the analysis can be found here: https://web.iitd.ac.in/~sbpaul/online_appendix/JEBO2022/

[4] In statistical analysis, the exclusion error is also called type I error and the inclusion error is also called type II error (Cornia and Stewart, 1993).

[5] It should be noted that the average for this individual-level variable in our sample does not correspond to the average of 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).

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. Similarly, any beneficiary who does not fulfill the criteria of either of the schemes, is therefore considered as wrongly included.

4.2.2. Explanatory variables of interest

Our explanatory variables describe to what extent eligibility criteria were simplified towards fewer rules, more verifiable rules and a combination of the two. We thereby distinguish between reducing the number of rules, selecting more verifiable rules or both as potential approaches to facilitate the selection of beneficiaries.

Making use of the detailed administrative information collected for each of the seven states for both periods under review, we develop three complementary state and time specific index variables that we call *fewer, more verifiable* and *overall simpler*. In general, each of the simplification indices is higher if eligibility criteria are fewer in number, easier to verify or a combination of the two.

We start by classifying eligibility criteria into four main categories, namely destitution, income, land holding, and BPL card holding. In some cases, there are also other additional 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 simplification indicators, as their existence (as opposed to their value) is uniform across states and over time. Following Niehaus et al. (2013), our first indicator, the variable *fewer* is based on counting 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 and to follow. The variable *fewer* is then computed by subtracting the number of relevant conditions from their empirical maximum (= 4) plus 1 to avoid zero numbers.

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

However, not all criteria are equally difficult to assess, and this may be even more relevant for simplifying targeting than the number of criteria itself. Building on Drèze and Khera (2010), we hence suggest the additional indicator *more verifiable* 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. 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 substantially more difficult to verify (4 points) and destitution as by far the most difficult to verify (8 points). We aggregate the numbers to the value for the variable *more verfiable* by subtracting the highest verifiability weight (W) for any criterion used in a specific pension scheme from the empirical maximum value across all observations (=8) plus 1, again to avoid zero numbers.

$$\text{more verfiable}_{jt} = 9 - \max_i \{W_i I_i\} \forall \text{ state } j \text{ and period } t \tag{2}$$

where $I_i = 1$ if criterion i is specified, 0 otherwise. *More verifiable* 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.

Finally, we compute a combined version called *overall simpler*, which combines both aspects within a single indicator (see Fig. 1). This indicator assigns higher scores to state-level regulations that use fewer eligibility criteria and the eligibility criteria that are more easily verifiable. To compute this indicator, we proceed in three steps. The first two steps generate a complexity score which we convert into a simplification score in the third step. Fig. 1 below visualizes the calculation step by step.

We first focus on the difficulty to verify eligibility criteria and apply the same geometric weights. 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 complexity, 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 indicate how criteria are described in government regulations. The overall complexity 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 complexity, the weighted sum is $2\sum_{i=1}^{4} W_i = 30$. Finally, to obtain the score for *more verifiable*, we subtract the complexity score from the empirical maximum value (29), and again add +1 to avoid zero values:

$$overall\ simpler = 30 - \sum_{i=1}^{4} W_i S_i. \tag{3}$$

Summary statistics of our explanatory variables of interest are provided in Appendix C and Appendix D. The scores for each state in 2004-05 and 2011-12 are listed in Appendix E.

4.2.3. Covariates

We further consider a number of covariates to account 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

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

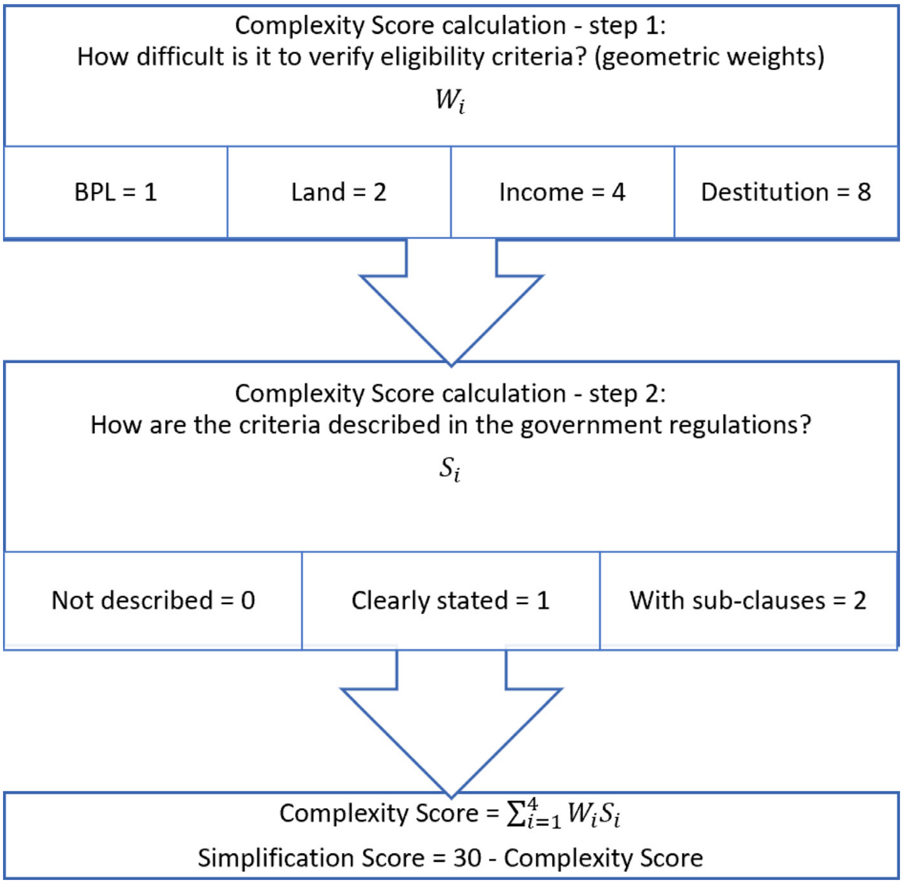

Fig. 1. Coding of the overall simplification score. Source: Authors' illustration.

appropriate control for the change in coverage, any change in exclusion error that we might attribute to the simplification of eligibility rules, 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, 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 simplification of the eligibility criteria (e.g. because a state that cares for the elderly poor will try to improve both, coverage and eligibility criteria), without a control for coverage, our estimator may be biased, and the effect of simplification of eligibility criteria itself may be much less pronounced than our initial regression outcomes would suggest.

At the same time, the number of eligible individuals, e.g., approximated by the share of elderly in the population, rises between the two periods, and again this increase is not uniform across states. The effect is exactly opposite to the one mentioned before 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 variables of interest.

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 are based on thresholds, the construction of which involves a number of possibly relevant controls, the latter may be endogenous. We thus distinguish between two sets of control variables - a first set, in which we exclude such potentially endogenous factors, and a second set in which we include them. The first set of exogenous covariates includes information on education, literacy, widowhood, gender, household's maximum education, whether any household member has a permanent job, 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 possibly endogenous covariates 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 the 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 simplification of eligibility criteria and the correct selection of beneficiaries. The summary statistics and definitions of all variables are displayed in Appendix C for the exclusion error sample and in Appendix D for the inclusion error sample.

4.3. Empirical strategy

As mentioned above, our main econometric analysis exploits the variation in the number, verifiability and overall simplification of eligibility criteria for the social pension for elderly poor and relates it to the individual level probability of being wrongly excluded and wrongly included. We opt for a linear probability model for ease of interpretation.[7] To avoid related heteroscedasticity problems, we use heteroskcedasticity-robust error terms clustered at the district level (Angrist and Pischke, 2008).

As a default, our regression models always include an indicator variable for the survey period, which is coded equal to 1 for the second round of the IHDS (2011/12) and equal to 0 for the first round (2004/05), state fixed effects and state level social pension coverage. The year and state fixed effects account for unobservable period- or state-specific heterogeneity. Our empirical model therefore becomes:

$$Y_{it} = \beta_0 + \beta_1 Year_{2012} + \beta_2 \mathrm{Score}_{st} + \mathbf{X}_{it}'\boldsymbol{\gamma} + a_s + u_{it} \tag{4}$$

where Y_{it} is a binary variable capturing whether individual i is wrongly excluded or wrongly included in period t, $Year_{2012}$ is the period dummy, $Score_{st}$ is the simplification score for state s in period t, a_s is the state fixed effect and $\mathbf{X}$ is a vector of control variables that we described in detail in Section 4.2.3. Our focus is on parameter β_2. In all regressions, observations are weighted using corresponding probability weights.

As we are using the same specification for the exclusion error and the inclusion error, one might expect a mechanical relationship between the effects of the two given the identity:

$$Recipients = (Eligibles - wrongly\,excluded) + wrongly\,included \tag{5}$$

However, changes in eligibility rules also change the number of eligibles and not only the numbers of wrongly excluded and wrongly included. While we control for state-level coverage in percent to capture the number of recipients, we can only roughly approximate the number of eligible individuals by controlling for the poverty rates and the share of elderly. Further, as described in Section 4.1, our analysis for the exclusion error and inclusion error needs to consider different samples — those who are age-wise eligible in a state and those who are social pension beneficiaries.

With this empirical approach, an important remaining consideration is the correct clustering of the standard errors. Clustering standard errors at the district level could lead us to be overly confident of the statistical significance of our results. Indeed, since our indicators of simplifying eligibility criteria 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). We therefore present the p-values of the estimates obtained from wild-cluster bootstrapping for the clusters at the state level in all regression tables. As a default, our interpretation of statistical significance will be based on these results since we consider the state-level as the appropriate level for clustering of the standard errors.

4.4. Threats to identification

Our empirical analysis needs to address various potential threats to our empirical identification strategy: First, and most importantly, there might be important factors or conditions related to governance and public policy performance that also change over time and simultaneously influence both the simplification of eligibility criteria and the targeting errors in particular state-level variables which could relate to both. Second, we need to be concerned about selection on unobservables as we will not be able to measure or include every factor or condition that potentially influences both, the dependent and the independent variables. Third, besides controlling for state coverage in a linear way, there could be also nonlinear relationships between pension coverage and the targeting performance that we need to take into account. Fourth, our results showing on average whether and to what extent targeting errors depend on the simplification of eligibility

[7] For readers preferring the use of non-linear probability models, we replicate the core analysis using a logistic specification in Appendix G.

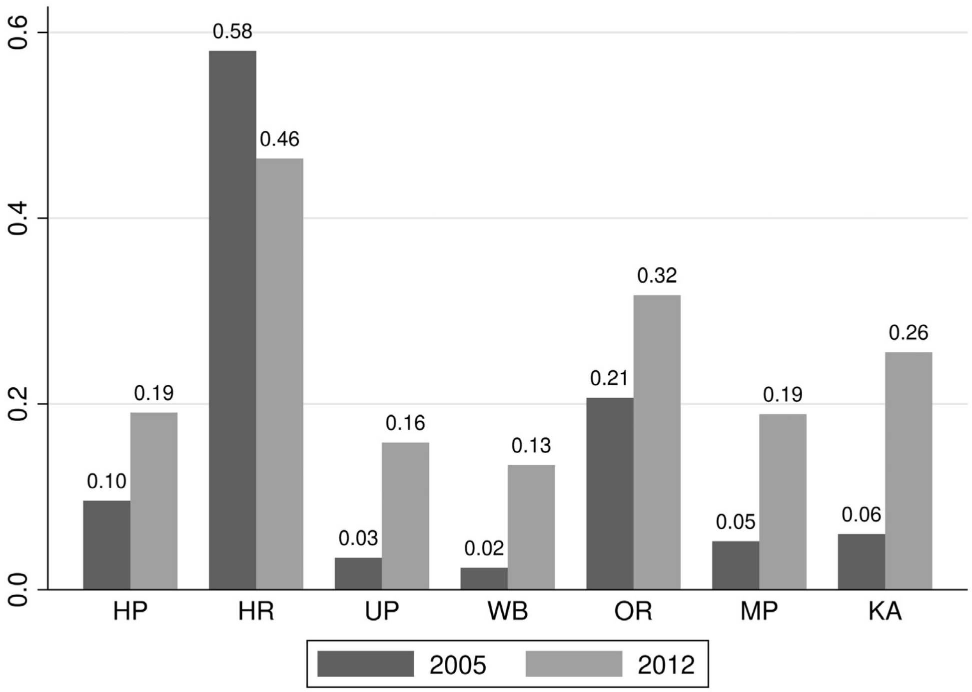

Fig. 2. Social pension coverage of elderly, by state and year. Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP), Karnataka (KA). Based on observations from pooled cross section. The elderly population includes all individuals who are at least as old as the local eligible age. Source: IHDS I for 2004-05 and IHDS II for 2011-12.

rules could be driven by individual states in our analysis. We will address these empirical challenges in our robustness checks.

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. Fig. 2 shows social pension coverage of the elderly, which reveals strong differences across states and over time. Overall, for all seven states in our analysis, the social pension coverage of the elderly increased from 9% in 2005 to 20% in 2012. Comparing across states, 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 58% in 2005 to 46% 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, Fig. 3 shows that this is not the case. As opposed to the previous figure, Fig. 3 only considers those elderly living in poor 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 Fig. 2. For all seven states considered in our analysis, social pension coverage among the elderly poor increased from 12% in 2005 to 33% in 2012. Compared to the earlier sample of elderly, 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.

Fig. 4 and Fig. 5 show the exclusion and inclusion error rates at the state level in 2005 and 2012. Considering all the seven states in the analysis, while the exclusion error reduced significantly over time from 90.2% in 2005 to 69.7% in 2012, the inclusion error reduced only slightly from 30.3% in 2005 to 27.1% in 2012. We observe that the exclusion error is extremely high, even close to 100% in 2005 in Uttar Pradesh and West Bengal. 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 number of them cannot be covered, even if no funding is diverted to ineligible people. The inclusion error measured at the state level shows a different pattern. It increased over time in Himachal Pradesh and West Bengal, but reduced over time in the other states to different extents.

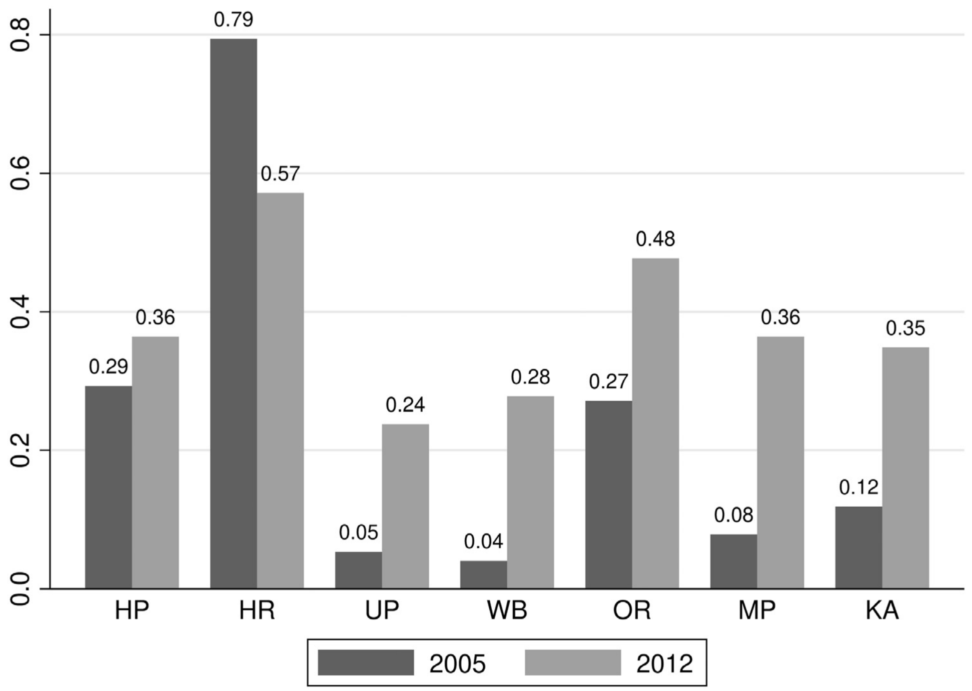

Fig. 3. Social pension coverage of elderly poor, by state and year. Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP), Karnataka (KA). Based on observations from pooled cross section. The elderly population includes all individuals who are at least as old as the local eligible age. Source: IHDS I for 2004-05 and IHDS II for 2011-12.

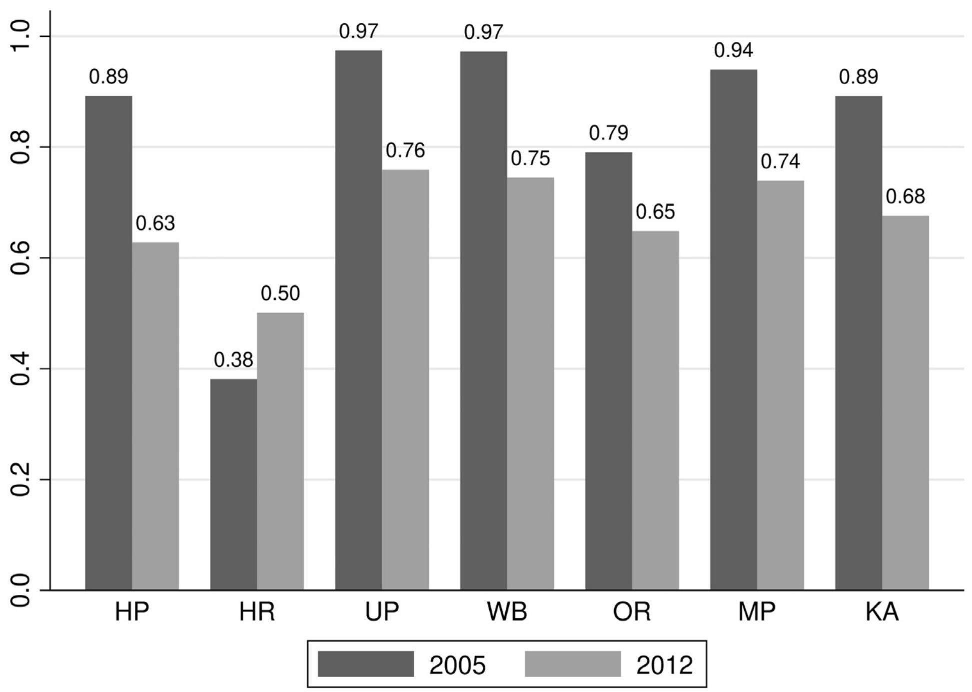

Fig. 4. Exclusion error by state. Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP), Karnataka (KA). Based on observations from pooled cross section. Source: IHDS I for 2004-05 and IHDS II for 2011-12.

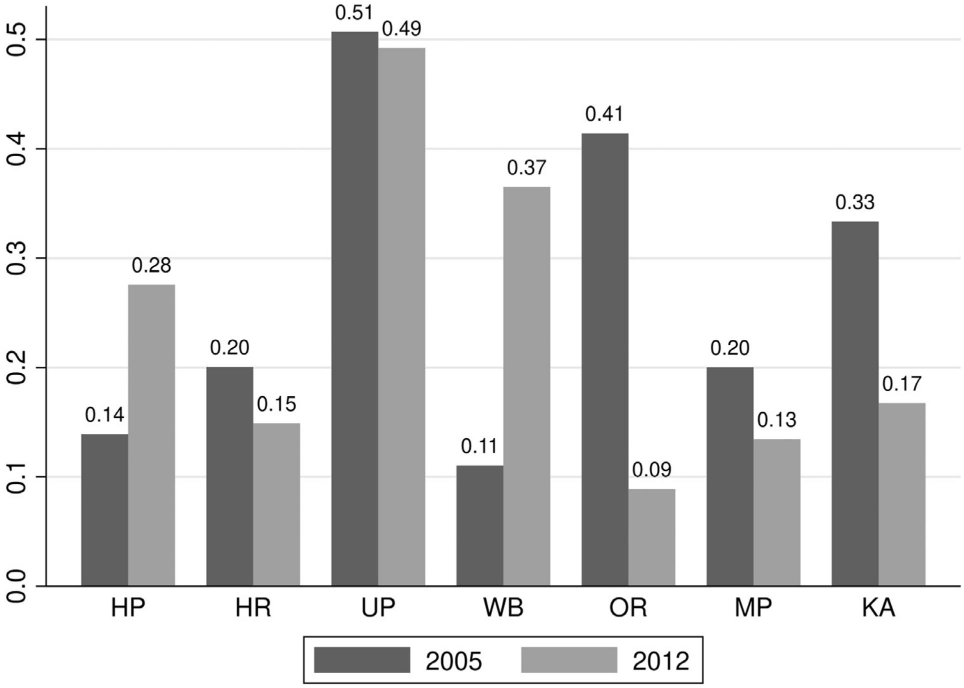

Fig. 5. Inclusion error by state. Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP), Karnataka (KA). Based on observations from pooled cross section. Source: IHDS I for 2004-05 and IHDS II for 2011-12.

5.2. Regression results

A priori, it is unclear whether policy-makers reforming eligibility rules for social transfers should focus on having fewer rules, more easily verifiable rules or a combination of the two to improve targeting of the limited resources to those who are eligible. By combining the detailed administrative information on the eligibility rules from state governments and individual-level survey data, we are able to assess the relationship between changing the eligibility rules in either of these dimensions and both targeting errors — exclusion and inclusion errors.

In Table 1, we regress the binary variables for wrong exclusion (Exclusion Error, EE) and wrong inclusion (Inclusion Error, IE) on the simplification indicators for *fewer, more verifiable* and *overall simpler* eligibility criteria coded at the state-level for both 2005 and 2012. As mentioned earlier, the sample for the exclusion error includes everyone who is age-wise eligible and the sample for the inclusion error includes all the beneficiaries from the seven states from both 2005 and 2012. We present three specifications for each of the two dependent variables. The first specification includes the period dummy, state fixed effects and state coverage. In the second specification, we add exogenous covariates and in the third specification the possibly endogenous covariates.

On the right side of the table, we see that changes in the criteria do not significantly affect the inclusion error when we consider the appropriate level of clustering standard errors at the state level with the wild-cluster p-value. Only very few of the point estimates reach any standard level of statistical significance when we consider the appropriate level of clustering standard errors at the state level with the wild-cluster p-value. However, in line with our theoretical expectations, we consistently observe that simplifying the eligibility criteria is associated with a significant reduction in the exclusion error. We find this effect for both reducing the number of criteria and for improving their verifiability, and then, not surprisingly, for the combined indicator of the overall simplification of rules. Substantively, the increase in the verifiability of rules has the strongest effect. Increasing verifiability by 1 unit is associated with a reduction of the likelihood of being wrongly excluded by 5.5.-5.8 percentage points. In relative terms, a 1 standard deviation change in the verifiability of rules is associated with a 14.7 percentage points lower probability of being wrongly excluded. Taking as an example the state of Uttar Pradesh where the verifiability of eligibility criteria changed from 1 to 8, by switching from the destitution criterion to the BPL card as main criterion, it is hence associated with a 38.5 percentage points lower probability of wrong exclusion which is economically significant. Hence, comparing these results to existing research, in the context of social pensions in India, our empirical results support rather the request for more verifiable eligibility rules by Drèze and Khera (2010) than by Niehaus et al. (2013) proposing a reduction in the number of eligibility criteria. As the effect for the inclusion error is generally insignificant, we do not document any direct cost of changing eligibility criteria in terms of the targeting performance.

Table 1
Targeting errors and simplification of eligibility criteria.

	EE	EE	EE	IE	IE	IE
Panel A: Number of rules						
Fewer	-0.068*	-0.078*	-0.148*	0.074	0.077	0.118**
	(0.000)	(0.000)	(0.000)	(0.020)	(0.022)	(0.002)
	(0.051)	(0.069)	(0.088)	(0.365)	(0.256)	(0.023)
Adj. R-squared	0.089	0.115	0.150	0.112	0.167	0.194
Between 0 and 1	1.000	1.000	1.000	1.000	0.936	0.900
Panel B: Verifiability of rules						
More verifiable	-0.057**	-0.058**	-0.055**	0.039	0.041	0.045
	(0.000)	(0.000)	(0.000)	(0.056)	(0.033)	(0.014)
	(0.029)	(0.029)	(0.033)	(0.107)	(0.146)	(0.113)
Adj. R-squared	0.114	0.138	0.152	0.111	0.167	0.189
Between 0 and 1	1.000	1.000	1.000	1.000	0.932	0.908
Panel C: Overall simplification of rules						
Overall simpler	-0.024**	-0.026**	-0.029**	0.019	0.020	0.025*
	(0.000)	(0.000)	(0.000)	(0.050)	(0.035)	(0.006)
	(0.033)	(0.031)	(0.029)	(0.173)	(0.173)	(0.098)
Adj. R-squared	0.103	0.129	0.153	0.112	0.168	0.192
Between 0 and 1	1.000	1.000	1.000	1.000	0.934	0.906
Avg. predicted value	0.469	0.469	0.469	0.278	0.278	0.278
Exogenous covariates	No	Yes	Yes	No	Yes	Yes
Endogenous covariates	No	No	Yes	No	No	Yes
Observations	15,224	15,222	15,222	3076	3076	3076

Dependent variable as indicated in column title. P-values are shown in parentheses with standard errors clustered at the district level. P-values below are from wild-cluster bootstrapping with clustering at the state level. Significance stars are shown according to the wild-cluster p-values.

In summary, our results suggest that simplifying eligibility criteria, and, in particular, increasing their verifiability, contributes to improving the targeting performance through a reduction of the exclusion error. However, simplified targeting rules in terms of fewer or more verifiable eligibility criteria (or a combination of the two) do not appear to influence the inclusion error.

5.3. Robustness checks and complementary analysis

To test the robustness of our results, we conduct a number of complementary analyses focused on our main result, i.e., the negative relationship between the verifiability of eligibility criteria and the exclusion error. We thereby aim to address the potential threats to identification described before in Section 4.4. In the following, we present our robustness checks in two categories - selection on observables and selection on unobservables. Further, we examine the important question whether the hitherto observed improvements in "formal targeting performance" also translate to improvements in "actual targeting performance" when we use poverty measures to determine wrong exclusion. Understanding this has important implications for policy-making and future reforms.

5.3.1. Selection on observables

We start by examining the possibility that not yet considered observable factors at the state level could drive our main results: First, there might be state-level political variables that influence both our dependent and independent variables. Second, our main results only account for a linear relationship of the targeting performance with state-level coverage. Third, our results might be driven by individual states.

While our main results already account for judicial speed and tax revenues, we constructed an additional data set to test the robustness of our results to the inclusion of further political and electoral variables that could be related to the effectiveness of policy making overall. After merging the survey data with these additional variables, we include them in the same regressions as presented for our main results. In Table 2, we insert one after the other the effective number of parties (according to the seat share), the chief minister's party share, the electoral margin of chief minister's party, voter turnout, closeness of next election and government ideology.[8]

Our results are robust to the inclusion of almost all of these political and electoral variables, namely, the effective number of parties, the chief minister's party share, the margin of chief minister's party, turnout and closeness of the next election, as shown below. The estimate of interest remains stable at around -0.06 and significant at the 5 percent level. However, the relationship between targeting errors and the verifiability of eligibility criteria becomes insignificant when we account for

[8] Electoral and political variables are based on online available Election Commission of India (ECI) reports (India, 2021) from each of the respective states for the relevant time period. The variable indicating timing in the electoral cycle follows (Franzese, 2000) and the ideology variable follows Dash and Raja (2013)

Table 2
Political and electoral covariates.

	EE	EE	EE	EE	EE	EE
More verifiable	-0.064**	-0.061**	-0.062**	-0.055**	-0.059**	-0.072
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	(0.035)	(0.026)	(0.026)	(0.035)	(0.045)	(0.206)
N parties (seat share)	-745.619					
	(0.000)					
	(0.334)					
Chief minister's party share		0.363				
		(0.000)				
		(0.337)				
Margin chief minister's party			0.234			
			(0.000)			
			(0.324)			
Turnout				0.033		
				(0.885)		
				(0.733)		
Electoral cycle					-0.144	
					(0.000)	
					(0.327)	
Ideology						0.313
						(0.001)
						(0.386)
Adj. R-squared	0.153	0.153	0.153	0.152	0.152	0.153
Between 0 and 1	1.000	1.000	1.000	1.000	1.000	1.000
Avg. predicted value	0.469	0.469	0.469	0.469	0.469	0.469
Observations	15,222	15,222	15,222	15,222	15,222	15,222

Dependent variable as indicated in column title. P-values are shown in parentheses with standard errors clustered at the district level. P-values below are from wild-cluster bootstrapping with clustering at the state level. Significance stars are shown according to the wild-cluster p-values.

Table 3
Sensitivity to polynomials of state coverage.

	EE	EE	EE
More verifiable	-0.048**	-0.049**	-0.034*
	(0.000)	(0.000)	(0.000)
	(0.033)	(0.029)	(0.073)
Adj. R-squared	0.134	0.136	0.143
Avg. predicted value	0.469	0.469	0.469
State coverage	Yes	Yes	Yes
State coverage^2	No	Yes	Yes
State coverage^3	No	No	Yes
Exogenous covariates	No	Yes	Yes
Endogenous covariates	No	No	Yes
Between 0 and 1	1.000	1.000	1.000
Observations	15,222	15,222	15,222

Dependent variable as indicated in column title. P-values are shown in parentheses with standard errors clustered at the district level. P-values below are from wild-cluster bootstrapping with clustering at the state level. Significance stars are shown according to the wild-cluster p-values.

the ideology of the state government. Interestingly, we also observe a high correlation between the verifiability score and the government having a more-egalitarian ideology, but with a value of just -0.07, the correlation between the exclusion error and having a government with a more egalitarian (more inclined towards the Left) ideology is negative as expected but not very strong. This makes the overall result somewhat difficult to interpret, as we cannot conclude that the effect of verifiability is actually an artifact of a redistributive government orientation more generally. This is also emphasized by the fact that the absolute value of the point estimate for the effect of verifiability actually increases rather than decreases when the ideology variable is included in the regression. Somehow, the inclusion of the ideology variable simply seems to increase the noise in the regression.

Second, 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 and state fixed effects. 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. Our main result, the significant relationship between having more easily verifiable criteria and the exclusion error is robust to the inclusion of polynomials of state coverage up to the third degree as shown in Table 3. The

Table 4
Accounting for increase in BPL card holding.

	EE	EE	EE
More verifiable	-0.057**	-0.058**	-0.059**
	(0.000)	(0.000)	(0.000)
	(0.029)	(0.029)	(0.023)
Adj. R-squared	0.114	0.138	0.153
Between 0 and 1	1.000	1.000	1.000
Avg. predicted value	0.469	0.469	0.469
Exogenous covariates	No	Yes	Yes
Endogenous covariates	No	No	Yes
Observations	15,224	15,222	15,222

Dependent variable as indicated in column title. P-values are shown in parentheses with standard errors clustered at the district level. P-values below are from wild-cluster bootstrapping with clustering at the state level. Significance stars are shown according to the wild-cluster p-values.

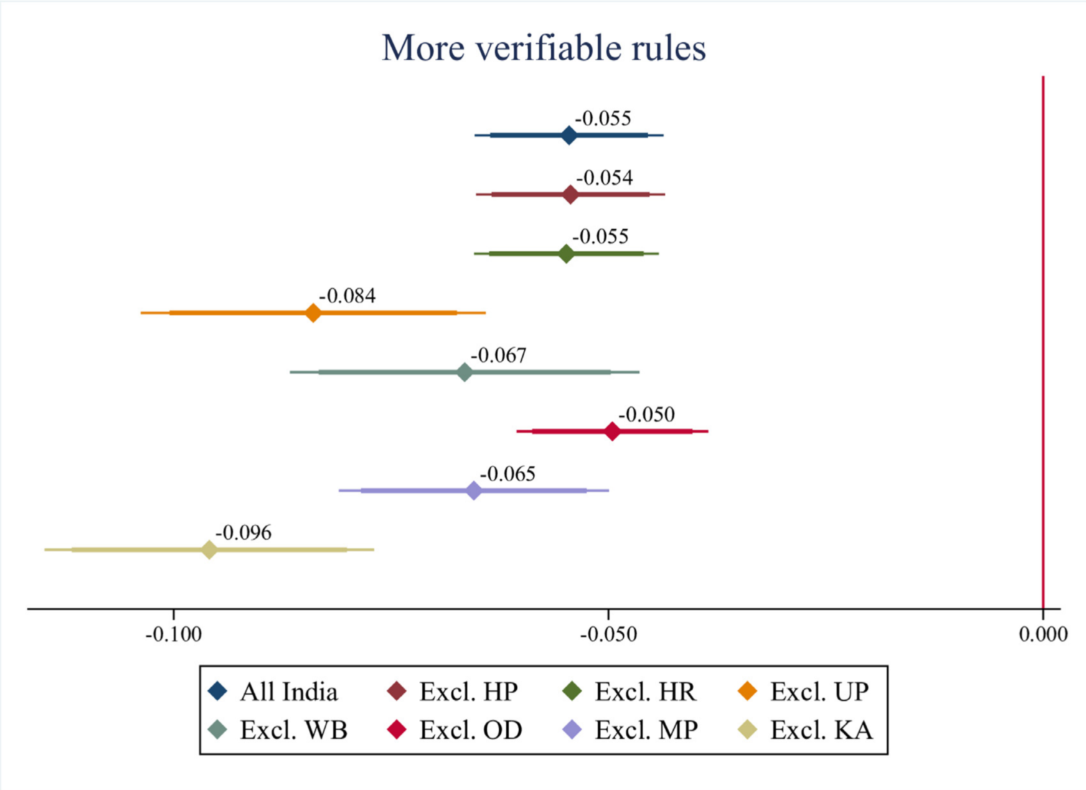

Fig. 6. Sensitivity of results to included states - exclusion error. Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP) .

empirical specifications presented 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. While adding the square term in specification (2) does not change the earlier results, the point estimate somewhat shrinks when adding the third polynomial, but remains economically significant with a 1-standard deviation change in the verifiability score being associated with a 9-percentage point lower probability of being wrongly excluded.

Third, the share of individuals holding BPL cards significanlty increased over time from 29.2% to 44.3% in the sample used for the regressions on the exclusion error. Given that this is one important aspect of eligibility, this could potentially affect our results. However, even theoretically speaking, a higher share of BPL card holding individuals would be associated with a higher exclusion error as more people are eligible and the omission of a variable such as the share of people in a state holding BPL cards would hence, if anything, lead to an underestimation of effect of simplifying the rules. In Table 4, we include state-level share of individuals holding BPL cards and the results confirm the robustness of our results.

Table 5
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	-0.043	-0.058	3.99
R1: Year FE	F2: Year FE, state FE, state coverage, exogenous controls, and endogenous controls	-0.043	-0.055	4.91
R2: Year FE and state FE	F1: Year FE, state FE, state coverage and exogenous controls	-0.059	-0.058	91.63
R2: Year FE and state FE	F2: Year FE, state FE, state coverage, exogenous controls, and endogenous controls	-0.059	-0.055	13.54

Fourth, the observed relationship between simplified eligibility rules and the targeting errors could potentially be driven by individual states and not representative of the seven states included in this analysis. For instance, Haryana was an outlier in the descriptive statistics and hence a possible candidate responsible for driving the results. However, this concern can easily be dispelled. The coefficient plot below shows that the main result for the verifiability of eligibility criteria and the exclusion error does not depend on any individual state. Regardless of which state is excluded, the coefficients are negative and significant.

5.3.2. Selection on unobservables

Beyond the potential identification threats falling under selection on observables addressed in the previous section, we also need to address concerns related to selection on unobservables. Despite our efforts to control for observable factors at state, district, village, household and individual level, the estimated effects can still be biased by unobservables. If these unobservable factors are correlated with the simplification 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:

$$\text{Selection Ratio} = \left| \frac{\hat{\beta}_F}{\hat{\beta}_R - \hat{\beta}_F} \right| \tag{6}$$

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.

Table 5 reports these regression coefficients now labeled $\hat{\beta}_R$ and $\hat{\beta}_F$, and the corresponding Selection Ratios. For the exclusion error, the ratio varies between 3.99 when we compare the coefficients for R2 and F1 (second row) and 91.63 when we compare the coefficients for R2 and F2 (third row). This implies that the effect of selection on unobservables would have to be at least 3.99 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 simplifying eligibility criteria on the likelihood of being wrongly excluded.

5.4. Formal vs. poverty-focused targeting performance

Our results suggest that improving the verifiability of eligibility criteria can help to improve the targeting performance of social pensions primarily through a reduction of the exclusion error. An important question that remains is whether these improvements of the formal targeting performance, i.e. the fulfillment of the eligibility criteria, also translate into improved targeting of social pension benefits to the poor among the elderly which shifts the focus to the poverty reduction objective of the scheme. This question is similar to Asri (2019) that studied how targeting improved from before to after the reform of the national pension system with a focus on asset-based poverty instead of checking the fulfillment of state-specific

Table 6
Poverty-based exclusion errors and simplification of eligibility criteria.

	EE	EE	EE
More verifiable	0.001	0.003	0.003
	(0.724)	(0.427)	(0.400)
	(0.693)	(0.476)	(0.157)
Adj. R-squared	0.022	0.227	0.231
Between 0 and 1	1.000	0.901	0.900
Avg. predicted value	0.328	0.328	0.328
Exogenous covariates	No	Yes	Yes
Endogenous covariates	No	No	Yes
Observations	15,224	15,222	15,222

Dependent variable as indicated in column title. P-values are shown in parentheses with standard errors clustered at the district level. P-values below are from wild-cluster bootstrapping with clustering at the state level. Significance stars are shown according to the wild-cluster p-values.

eligibility criteria and did not include an indicator for the simplification of eligibility criteria in her analysis. She finds that over time, much was achieved simply by expanding coverage, but rather little through the reform as such.

For this last step of the analysis, following Asri (2019), we focus on asset-based poverty to measure exclusion errors from a poverty-reduction perspective. Remember that so far, we focused on an exclusion error coded as 1 if an individual fulfilled all the eligibility criteria according to the survey data and did not receive the social pension and 0 otherwise. This shows the extent to which government officials satisfy government rules and regulations when selecting beneficiaries. While this is important from a policy and legitimacy perspective, the results in terms of actually targeting the poor will only improve if the criteria sufficiently reflect the potential recipients' level of poverty. While being poor could be captured in various ways and is generally hard to measure perfectly, we define it below in terms of asset ownership (but the results are qualitatively similar if we use per capita consumption expenditures instead).[9] Based on this measure of poverty, we now define all those as wrongly excluded who are older than the age cutoff and asset poor but do not receive the social pension benefits. As shown in Table 6, simplifying eligibility criteria does not influence the poverty-based targeting performance. In other words, while the more easily verifiable criteria lead to a formally more correct selection of beneficiaries, this does not translate into actual targeting towards the poor in the context at hand.

6. Discussion

The above results leave us with a puzzle. On the one hand, we do find a significantly positive and substantively important effect of a simplification of eligibility criteria on the correct choice of beneficiaries. Those people who do fulfill the requisite criteria then also have a better chance to receive the social pension. We obtain the strongest results for verifiability, suggesting that in settings, in which people can easily prove their rights, these rights cannot be easily denied. Hence, we find a clear effect on the exclusion error. As the inclusion error is not affected in a similar way, people who do not satisfy the criteria still get included in significant numbers. It might be that this side of the problem requires a credible monitoring system to be in place. As long as nobody asks any questions, even if clearly ineligible people are selected, the responsible officers will not be sanctioned. While verifiability should also facilitate the monitoring process, its effect on the inclusion error thus depends on whether such a process exists in the first place.

So far, so good. But then, why is the strong beneficial effect on the exclusion error not reflected in better access of the truly intended target group, namely the elderly poor? Why does poverty measured directly not become a stronger determinant of obtaining the benefits?

The answer lies in the substantively appropriate choice of the selection criteria. In our case, improved verifiability was achieved primarily through the shift from the destitution criterion to the Below Poverty Line card as the main selection criterion. Our results thus raise concerns with respect to the BPL card as an appropriate indicator of poverty.

Indeed, BPL card allocation is often criticised for bad targeting, and it is frequently held by non-poor households. The Indian government, too, 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.

[9] The correlation between the asset-based measure of poverty and the consumption-based measure of poverty is 0.275, the correlation between the asset-based measure of poverty and BPL card holding is 0.289, and the correlation between the consumption-based measure of poverty and BPL card holding is 0.203.

In summary, for social security programs to truly target the poor, criteria should be such that they are easy to verify, but simultaneously, they must be strongly correlated with poverty. If either of these complementary conditions fails to be met, the system will not work well. If the criteria do not reflect poverty, their enforcement will not lead to improvements for the poor. But if they reflect poverty, and they are not verifiable, they will not be enforced.

By focusing on “formal targeting errors”, our study focuses on the second part. This focus allows us to shed some light on the selection process, in a way that was not possible in prior studies such as Asri (2019). As a result, we obtain a much more differentiated picture on the conditions of improved targeting. Drawing all arguments together, our results suggest that, indeed, three elements need to be considered: (1) the substantive relevance of the criteria, (2) the verifiability of the criteria, and (3) the monitoring of their enforcement. The first two are complements and need to be satisfied simultaneously to reduce exclusion error in terms of actual poverty. The third appears to be relevant to also reduce the inclusion error.

Different conditions are thus intertwined when it comes to ensuring overall targeting performance. Our results suggest that selecting more verifiable eligibility criteria for the targeting of social transfers is a cost-effective and viable route to reduce the exclusion error, once the condition of substantial relevance of the criteria is equally satisfied. And it may induce further improvements regarding the inclusion error if a basic level of monitoring is equally ensured.

Hence, while our case study of social pensions in India ends with the disappointing conclusion that, despite the improvement in verifiability, no tangible substantive effects on poverty reduction have been achieved by the reform, it provides us with interesting clues on how targeting processes could be improved in the future.

Our results correspond to the view to regard exclusion errors as primary concern and inclusion errors as secondary concern — also revealed in many of our qualitative interviews with experts in the field. Nevertheless, inclusion errors can be substantial and may significantly constrain the poverty-reducing impact of social transfers when ineligible individuals receive the social transfer instead of eligible ones.

As in any study, there are a few limitations regarding our empirical analysis. First, the sample size used for the inclusion error analysis is by construction much smaller than the sample size for the exclusion error analysis and therefore statistically less powered. Second, there may be other behavioral reactions to the change in rules that we cannot study here, and that also affect the overall impact of social security programs. For instance, in our context, since eligibility criteria with respect to social support fromfamily members changed over time, this may have led to some behavioral reactions, notably lesser in-family care for the elderly. Even if the selection process clearly focused on the poor, such behavioral reactions of family members could reduce the positive effect on the target group. In India, the social norm concerning supporting elderly family members is very strong and it appears unlikely to us that family support reduce due to changes in social scheme eligibility. But such discussions clearly go beyond the scope of this paper and remain to be addressed in future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 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 ≤ Rs. 6000 and if the elderly has adult children their income should not exceed Rs. 11000	Age 60 years or above, individual does not have anyone to take care of him/her, individual annual income ≤ Rs. 9000 or total annual family income ≤ Rs. 15,000 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 ≤ 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'sincome ≤ 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 ≤ 3.25 acre for rural areas or individual income < Rs. 12,000 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)
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 ≤ 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 ≤ Rs 20000
Sources:		Rajasekhar et al. (2009), Chathukulam et al. (2012) Gov of KA (undated)	webindia123.com (2007)

A1. 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.

A2. Himachal Pradesh

A2.1. Himachal Pradesh 2004-05

Government of Himachal Pradesh (undated(a)) Evaluation Study of Beneficiaries under Old Age Widow and National Security Pension Scheme. Shimla: Evaluation Division, Planning Department. Available at https://web.archive.org/web/20160508190345/http://hpplanning.nic.in/beneficiaries%20under%20old%20age%20widow%20and%20national%20security%20pension%20scheme%20-%20himachal%20pradesh.pdf, accessed on 15 September 2020.

A2.2. Himachal Pradesh 2011-12

Government of Himachal Pradesh (undated(b)) Social Security Pension Schemes. Shimla: Directorate of Social Justice and Empowerment. Available at http://web.archive.org/web/20170222012249/http://admis.hp.nic.in/himachal/welfare/SocialSecurityPensionSchemesOct2013_A1b.pdf, accessed on 15 September 2020.

A3. Haryana

A3.1. Haryana 2004-05

Government of Haryana, (2006) Notification [regarding the Old Age Allowance Scheme] No. 1988-SW4(2006) dated 20 September 2006, extracted from Haryana Government Gazette, dated 7th November 2006, Social Welfare Department. Available at http://web.archive.org/web/20161020013151/http://socialjusticehry.gov.in/Website/oasa(1).pdf, accessed on 15 September 2020. Government of Haryana, (2011) Notification [regarding the Old Age Samman Allowance Scheme] No. 458-SW(4)2011 dated 10 June 2011, extracted from Haryana Government Gazette, dated 10 June 2011, Chandigarh: Social Justice & Empowerment Department. Available at http://web.archive.org/web/20160222055746/http://socialjusticehry.gov.in/SocialJusticeNotification.pdf, accessed on 15 September 2020. Government of Haryana, (undated(b)) Pension schemes. Chandigarh: Directorate of Social Justice & Empowerment. Available at https://web.archive.org/web/20160729233028/http://socialjusticehry.gov.in/pension11.aspx, accessed on 15 September 2020.

A3.2. Haryana 2011-12

Government of Haryana, (undated(a)) Social security schemes. Chandigarh: Directorate of Social Justice & Empowerment. Available at http://web.archive.org/web/20170215085709/http://socialjusticehry.gov.in/Website/SocialSecurity_PensionSchemes.pdf, accessed on 15 September 2020.

A4. Uttar pradesh

A4.1. Uttar pradesh 2004-05

Government of Uttar Pradesh (undated) Indira Gandhi National Old Age Pension Scheme. Department of Social Welfare: Lucknow. Available at https://web.archive.org/web/20160708031602/http://sspy-up.gov.in/pdf/oap_scm.pdf, for application format, https://web.archive.org/web/20160708152801/http://sspy-up.gov.in/AboutScheme/app_frmt_oap.pdf, accessed on 15 September 2020. Comptroller and Auditor General of India, (2009) Report on the audit of expenditure incurred by the Government of Uttar Pradesh. New Delhi: CAG, Government of India. Available at https://cag.gov.in/sites/default/files/audit_report_files/Uttar_Pradesh_Civil_2009.pdf, accessed on 15 September 2020.

A4.2. Uttar pradesh 2011-12

Government of Uttar Pradesh (2010a) Government Order on Mahamaya. GO No. 2359/26- 2–201 0- 3MS̃/10, dated 3 August 2010. Available at https://web.archive.org/web/20160607124742/http://swd.up.nic.in/pdf/GO03082010_final.pdf, for application format, No. 2359/26- 2–201 0- 3 MS/10. Lucknow: Social Welfare Commissioner. Available at https://web.archive.org/web/20160607123712/http://swd.up.nic.in/GO130920100001.pdf, accessed on 15 September 2020. Government of Uttar Pradesh (2010b) Government Order on Mahamaya. GO No. 2530/26-2-2010-3MS̃/2010, dated 10 August 2010. Lucknow: Social Welfare Commissioner. Available at https://web.archive.org/web/20160607123706/http://swd.up.nic.in/10082010.pdf, accessed on 15 September 2020. Government of Uttar Pradesh (2010c) Government Order on Mahamaya. GO No. 2400/26-2-2010-3MS̃/10, dated 3 August 2010. Lucknow: Social Welfare Commissioner. Available at https://web.archive.org/web/20160607124742/http://swd.up.nic.in/pdf/GO03082010_final.pdf, accessed on 15 September 2020.

A5. West bengal

Government of West Bengal (undated) Social Security Schemes. Kolkata: Department of Panchayats & Rural Development. Overview page available at http://web.archive.org/web/20160627182135/http://wbprd.gov.in/HtmlPage/SSECURITY.aspx, accessed on 15 September 2020, see PDF for more detailed information.

A6. Madhya pradesh

A6.1. Madhya pradesh 2004-05

Government of Madhya Pradesh (undated) (in Hindi) Samajik Sahayata ki Bistrut Jankari. Bhopal: Social Justice Department. Available at http://web.archive.org/web/20160513082657/http://socialjustice.mp.gov.in/Portal/Public/Scheme_Details.aspx?ID=1, accessed on 15 September 2020.

A6.2. Madhya pradesh 2011-12

Government of Madhya Pradesh (2012) (in Hindi) Samajik Suraksha Bruddhabastha Pension Yojana. Bhopal: Social Justice Department. Originally available at http://pensions.samagra.gov.in/SSPDetails.aspx, accessed on 13 July 2016, see PDF documentation online. Government of Madhya Pradesh (2013) (in Hindi) Samajik Suraksha Bruddhabastha Pension Yojana. Bhopal: Social Justice Department. Originally available at http://pensions.samagra.gov.in/IGNOAPDetails.aspx, accessed on 13 July 2016, see PDF documentation online.

A7. Odisha

A7.1. Odisha 2004-05

Government of Odisha (2008) The Odisha Gazette. Notification No. 11-I-SD-50/2007-WCD. Cuttack: Women and Child Development Department. January 4, 2016. Available at http://web.archive.org/web/20161130174447/http://odisha.gov.in/govtpress/pdf/2008/15.pdf, accessed on 15 September 2020.

A7.2. Odisha 2011-12

Government of Odisha (undated (a)) Indira Gandhi National Old Age Pension. Bhubaneswar: Women And Child Development Department. Available at http://web.archive.org/web/20160605093834/http://wcdodisha.gov.in/node/60, accessed on 15 September 2020. Government of Odisha (undated (b)) Madhu Babu Pension Yojana. Bhubaneswar: Women And Child Development Department. Available at http://web.archive.org/web/20160529181623/http://wcdodisha.gov.in/node/64, accessed on 15 September 2020.

A8. Karnataka

Rajasekhar, D., G. Sreedhar, N.L. Narasimha Reddy, R.R. Biradar, and R. Manjula, (2009) Delivery of Social Security and Pension Benefits in Karnataka. Institute for Social & Economic Change, Bengaluru. Report submitted to Directorate of Social Security and Pensions Department of Revenue, Government of Karnataka. Available at http://dssp.kar.nic.in/news.pdf, accessed on 15 September 2020. Chathukulam, Jos, Veerasekharappa, Rekha V., and C.V. Balamurali, (2012) Evaluation of Indira Gandhi National Old Age Pension Scheme (IGNOAPS) in Karnataka. Centre for Rural Management, Kottayam, Kerala. Report submitted to Ministry of Rural Development, Government of India, New Delhi. August 2012. Available at http://crmindia.org/files/KaIGNOAPS.pdf, accessed on 15 September 2020.

A8.1. Karnataka 2004-05

Government of Karnataka (undated) Sandhya Suraksha Yojana. Available at http://web.archive.org/web/20150522020009/http://dssp.kar.nic.in/sandhyasur.html, accessed on 15 September 2020.

A8.2. Karnataka 2011-12

webindia123.com (2007) K'taka Govt to launch 'Sandhya Suraksha Yojana' on July 29. Mysore, July 4, 2007. Available at http://news.webindia123.com/news/ar_showdetails.asp?id=707040701&cat=&n_date=20070704, accessed on 15 September 2020.

Appendix B. Age distribution

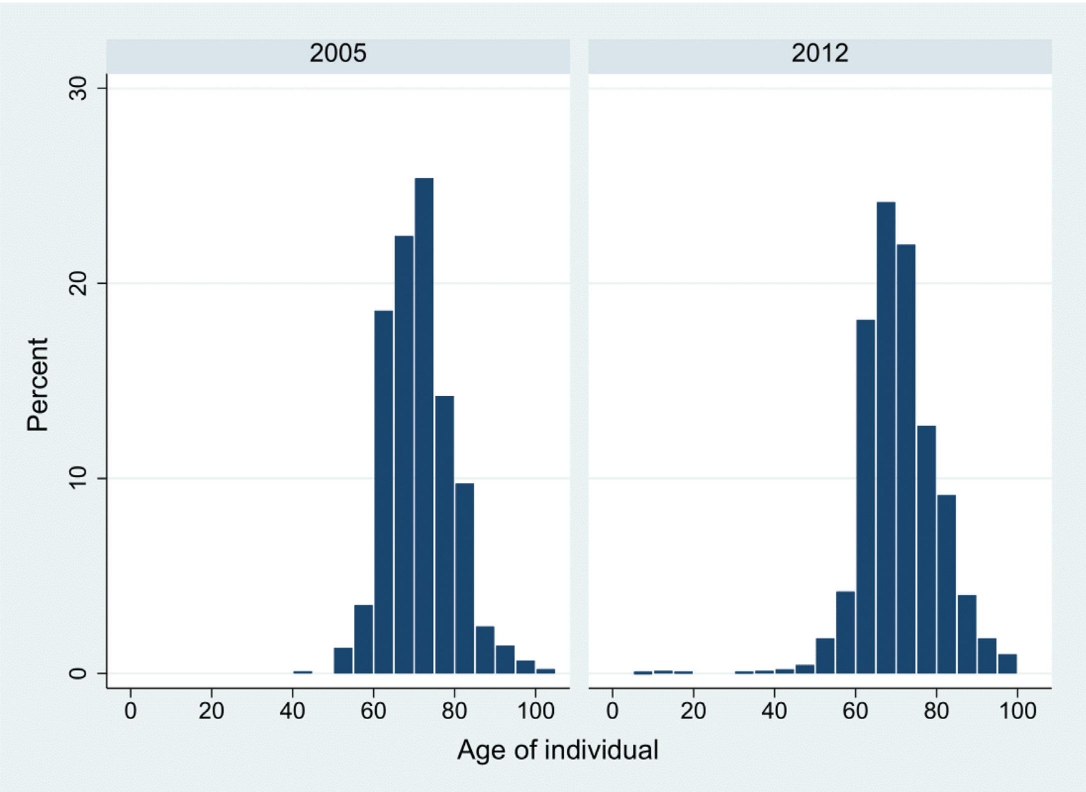

Fig. B1. Age distribution of social pension beneficiaries. Source: Authors' illustration, descriptive statistics based on IHDS-I for 2004-05 and IHDS-II for 2011-12.

Appendix C. Variable description and sources for exclusion error

VARIABLES	2004-05		2011-12		Measurement level	Definition	Data source
	mean	se	mean	se			
Error excluded	0.633	0.010	0.373	0.008	Individual	Dummy equal to 1 if individual does not receive social pension but fulfills the locally relevant eligibility criteria	IHDS & admin. info
Fewer	2.475	0.032	2.409	0.014	State	Fewer= 5 - number of eligibility criteria (clauses and sub-clauses). Range is 1–4.	Admin. info
More verifiable	1.656	0.021	5.751	0.044	State	More verifiable = Verifiability score of the least verifiable category of eligibility criteria applied. Range is 1–8.	Admin. info
Overall simpler	19.613	0.074	25.005	0.065	State	Overall simpler = Weighted sum of eligibility criteria whereby weights are based on verifiability score. Range is 17–29.	Admin. info
Pension recipient	0.090	0.005	0.204	0.006	Individual	Dummy equal to 1 if individual receives social pension	IHDS
Age	69.082	0.162	68.541	0.144	Individual	Age of the individual	IHDS
Female	0.483	0.011	0.503	0.008	Individual	Dummy equal to 1 if individual is female	IHDS
Literate	0.332	0.009	0.381	0.008	Individual	Dummy equal to 1 if individual can read and write	IHDS
Widowed	0.375	0.010	0.374	0.008	Individual	Dummy equal to 1 if individual is widowed	IHDS
Working	0.436	0.011	0.339	0.008	Individual	Dummy equal to 1 if individual is working at least 240 hours per year	IHDS
BPL card	0.292	0.010	0.443	0.008	Household	Dummy equal to 1 if household holds a BPL card	IHDS
Household assets	10.649	0.108	13.028	0.102	Household	Number of household assets owned	IHDS
Landless	0.366	0.010	0.407	0.008	Household	Dummy equal to 1 household is landless	IHDS
Permanent job	0.094	0.005	0.143	0.005	Household	Dummy equal to 1 if any household member has a permanent job	IHDS
Household max. education	7.496	0.112	8.074	0.090	Household	Education level of the most educated person in the household.	IHDS
Local government connection	0.098	0.006	0.335	0.008	Household	Dummy equal to 1 if household has a direct connection to the local government	IHDS
Household size	6.458	0.077	5.598	0.046	Household	Number of persons sharing one kitchen	IHDS
Urban	0.193	0.006	0.252	0.006	Household	Dummy equal to 1 if household lives in urban area	IHDS
Share state confidence	0.240	0.004	0.338	0.003	District	Share of households having confidence in the state government	IHDS
Share of elderly	0.088	0.001	0.111	0.000	District	Percentage of elderly population	IHDS
Share of SC, ST, OBC	0.721	0.004	0.717	0.003	District	Percentage of SC, ST, OBC population	IHDS
Share of Muslims	0.132	0.003	0.145	0.002	District	Percentage of Muslims	IHDS
Share of literate voters	0.569	0.003	0.635	0.002	District	Percentage of literate adults among adult population	IHDS
Gini coefficient	0.344	0.002	0.338	0.001	District	Gini coefficient based on consumption exp. adj. for social pension benefits	IHDS
Head count ratio	0.444	0.003	0.234	0.003	District	Head count ratio based on consumption exp. adj. for social pension benefits	IHDS
Political competition	0.669	0.001	0.664	0.001	District	Political competition in the Lok Sabha constituency based on the Hirschman-Herfindahl concentration index	Election Commission of India (ECI)
Participation in public meeting	0.292	0.003	0.251	0.002	District	Share of households participating in public meetings	IHDS

VARIABLES	2004-05		2011-12		Measurement level	Definition	Data source
	mean	se	mean	se			
Share electrified	0.586	0.005	0.735	0.005	District	Share of households having electricity	IHDS
Share bureaucratic difficulties	0.073	0.002	0.065	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	0.003	0.313	0.004	State	Disposal rate as indicator of judicial speed or institutional efficiency	Reserve Bank of India
Coverage	0.099	0.002	0.216	0.001	State	Social pension coverage of age-wise eligible elderly	Reserve Bank of India
Effective number of parties (seat share)	0.00033	0.00000	0.00025	0.00000	State	Measure of political competition following Laakso and Taagepara (1979)	Author's calculations based on ECI reports
Chief minister's party share (seat share)	0.466	0.003	0.576	0.001	State	Assembly seat share of Chief Minister's party	Author's calculations based on ECI reports
Political margin	0.237	0.003	0.342	0.002	State	(CM party seats - opposition seats) divided by total seats	Author's calculations based on ECI reports
Voter turnout	0.571	0.003	0.596	0.003	State	Voter turnout in the latest state assembly elections.	Author's calculations based on ECI reports
Electoral cycle	0.107	0.005	0.207	0.003	State	Indicator of electoral cycle following Franzese (2000)	Author's calculations based on ECI reports
Ideology	2.883	0.019	2.535	0.015	State	1–5 scale political ideology indicator, where 1 is extreme right, 5 extreme left.	Following Dash and Raja (2013)
Number of observations	6401		8823				

Appendix D. Variable description and sources for inclusion error

VARIABLES	2004-05		2011-12		Measure-ment level	Definition	Data source
	mean	se	mean	se			
Error included	0.303	0.026	0.271	0.016	Individual	Dummy equal to 1 if individual receives social pension but does not fulfill the locally relevant eligibility criteria	IHDS & admin. info
Fewer	2.662	0.069	2.248	0.029	State	Fewer= 5 - number of eligibility criteria (clauses and sub-clauses). Range is 1–4.	Admin. info
More verifiable	2.833	0.098	5.174	0.098	State	More verifiable = Verifiability score of the least verifiable category of eligibility criteria applied. Range is 1–8.	Admin. info
Overall simpler	21.135	0.173	23.918	0.152	State	Overall simpler = Weighted sum of eligibility criteria whereby weights are based on verifiability score. Range is 13–29.	Admin. info
Pension recipient	1.000	0.000	1.000	0.000	Individual	Dummy equal to 1 if individual receives social pension	IHDS
Age	69.226	0.367	68.807	0.327	Individual	Age of the individual	IHDS
Female	0.490	0.026	0.428	0.016	Individual	Dummy equal to 1 if individual is female	IHDS
Literate	0.140	0.017	0.286	0.015	Individual	Dummy equal to 1 if individual can read and write	IHDS
Widowed	0.411	0.024	0.363	0.015	Individual	Dummy equal to 1 if individual is widowed	IHDS
Working	0.376	0.026	0.355	0.016	Individual	Dummy equal to 1 if individual is working at least 240 hours per year	IHDS
BPL card	0.500	0.026	0.676	0.015	Household	Dummy equal to 1 if household holds a BPL card	IHDS
Household assets	9.370	0.265	10.725	0.170	Household	Number of household assets owned	IHDS
Landless	0.416	0.024	0.403	0.016	Household	Dummy equal to 1 household is landless	IHDS
Permanent job	0.053	0.007	0.080	0.007	Household	Dummy equal to 1 if any household member has a permanent job	IHDS
Household max. education	5.803	0.227	6.302	0.159	Household	Education level of the most educated person in the household.	IHDS
Local government connection	0.083	0.014	0.363	0.016	Household	Dummy equal to 1 if household has a direct connection to the local government	IHDS
Household size	5.992	0.232	5.290	0.083	Household	Number of persons sharing one kitchen	IHDS
Urban	0.096	0.011	0.144	0.009	Household	Dummy equal to 1 if household lives in urban area	IHDS
Share state confidence	0.235	0.008	0.332	0.006	District	Share of households having confidence in the state government	IHDS
Share of elderly	0.090	0.001	0.114	0.001	District	Percentage of elderly population	IHDS
Share of SC, ST, OBC	0.710	0.009	0.749	0.005	District	Percentage of SC, ST, OBC population	IHDS
Share of Muslims	0.079	0.006	0.117	0.004	District	Percentage of Muslims	IHDS
Share of literate voters	0.569	0.005	0.610	0.004	District	Percentage of literate adults among adult population	IHDS
Gini coefficient	0.348	0.004	0.333	0.003	District	Gini coefficient based on consumption exp. adj. for social pension benefits	IHDS
Head count ratio	0.408	0.010	0.273	0.007	District	Head count ratio based on consumption exp. adj. for social pension benefits	IHDS
Political competition	0.674	0.003	0.672	0.003	District	Political competition in the Lok Sabha constituency based on the Hirschman-Herfindahl concentration index	Election Commission of India (ECI)
Participation in public meeting	0.319	0.010	0.255	0.004	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	0.677	0.015	0.734	0.010	District	Share of households having electricity	IHDS
Share bureaucratic difficulties	0.068	0.004	0.064	0.002	District	Share of households having bureaucratic difficulties with ration card	IHDS
Share tax revenue	0.068	0.001	0.076	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	0.246	0.009	0.298	0.008	State	Disposal rate as indicator of judicial speed or institutional efficiency	Reserve Bank of India
Coverage	0.310	0.012	0.250	0.003	State	Social pension coverage of age-wise eligible elderly	Reserve Bank of India
Number of observations	895		2181				

Appendix E. Measuring changes in eligibility criteria

Table E1
Simplification scores by state and year.

	Fewer		More verifiable		Overall simpler	
	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	17
Karnataka	3	3	5	5	25	25

Appendix F. Qualitative research

Table F1
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

Appendix G. Logit regression model

Table G1
Logisitic regression model.

	EE	EE	EE
More verifiable	-0.245**	-0.259**	-0.249**
	(0.000)	(0.000)	(0.000)
	(0.022)	(0.018)	(0.028)
Pseudo R-squared	0.086	0.106	0.118
Avg. predicted value	0.469	0.469	0.469
Exogenous covariates	No	Yes	Yes
Endogenous covariates	No	No	Yes
Observations	15,224	15,222	15,222

Dependent variable as indicated in column title. P-values are shown in parentheses with standard errors clustered at the district level. P-values below are from wild-cluster bootstrapping with clustering at the state level. Significance stars are shown according to the wild-cluster p-values.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jebo.2022.06.003

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