An Effective "Targeting Shortcut"? An Assessment of the 2002 Below-Poverty Line Census Method[1]

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Abstract

Proxy means test methods are increasingly being used by governments as substitutes for the more expensive and administratively difficult means test methods to target poverty alleviation programs. In India as well, the 2002 Below Poverty Line (BPL) census replaced the previously used "exclusion" criteria method with a proxy means test in order to identify people living below the poverty line. In this paper, we use 1999-00 National Sample Survey data to analyze whether the BPL census methodology is effective at distinguishing the poor from the non-poor. Our results indicate large targeting losses in moving to a proxy means test method. However, even though the data reject the assumptions implicit in constructing a BPL score, overly stringent assumptions are not the main reason for the poor targeting performance. We use an augmented regression model that relies on additional indicators as an alternative that substantially reduces the targeting errors vis-à-vis the BPL method, particularly in the tails of the expenditure distribution. However, under-coverage is still high (34 percent), largely because even an augmented and flexible model performs poorly in sorting the poor from non-poor in the vicinity of the poverty line. With the high density of population with income close to the poverty line, arriving at an effective proxy means test is an inherently problematic and difficult exercise.

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1. Introduction

Proxy means test whereby each household is scored on the basis of easily observable indicators which is then used to determine its eligibility for receipt of program benefits, is increasingly being used by several governments worldwide. Programs in Colombia (subsidized health insurance programs), Mexico (cash transfers), Turkey (subsidized food rations) are a few examples of proxy means methods implemented around the globe.

In India too, in light of criticisms of the earlier (1992 and 1997) below poverty line (BPL) censuses, a proxy means method of identifying poor households was recommended by an Expert Group for the 2002 census. Accurate identification of poor through such censuses is becoming increasingly important because once identified as a BPL household, identity cards are issued to households that implicitly give them access to various anti-poverty programs (e.g., free or subsidized electricity, subsidized rations, preference under the Indira Awaas Yojana) that are implemented by the central and/or the state governments.

The BPL list based on the 2002 census has not been operationalized (until last month) due to a stay order passed by the Supreme Court on a writ petition filed by the People's Union for Civil Liberties which alleged that the new methodology would reduce the number of persons identified as BPL and a large number of the poor would lose their entitlements. Also, anecdotal evidence, field experiences relayed by NGOs, and field survey based studies (e.g., Mukherjee, 2003) suggest instances of both severe under-coverage of the most needy and coverage of the economically better-off population. As a result of the stay order, the current BPL list currently being followed for implementation of anti-poverty programs is based on the 1997 census.

Such anomalies could occur either due to deficiencies in the existing methodology to identify the poor or on account of manipulation of the BPL lists by local authorities.[2] In this paper, we assess the methodological construct of the 2002 BPL census. We analyze whether the BPL score instrument used to identify the BPL households is powerful enough to distinguish the poor from the non-poor. That is, whether the proxy-means "short-cut" method leads to disproportionate increase in targeting biases compared to a means test method.

The paper is organized as follows. Section 2 discusses the targeting design of the 2002 BPL census. In Section 3, we evaluate the BPL score index in identifying the poor. Our analysis shows that the BPL score index while good at distinguishing the bottom 10 percent from the top 20 percent of the population, it is unable to differentiate between extreme vulnerability and the not so poor. In Section 4, we examine the possible causes of the poor performance of the BPL index. Is it the underlying assumptions of the

[2] For example, in a case study of three villages in Uttar Pradesh, Srivastava (2004) documents that none of the villages had had BPL cards issued even though the BPL census had been completed. In practice, a list of BPL households had been drawn up by the Village Development Officer in consultation with the village chief and forwarded to the district level, where it was expected that some names would be deleted due to a ceiling on the total number of poor.

scoring methodology, or is it the choice of indicators that result in the poor targeting performance? Based on the results in Section 4, we propose different alternatives in Section 5. Conclusions and recommendations for further analysis are reported in Section 6.

2. *De Jure* Targeting Design of the BPL census

In 1992, the Ministry of Rural Development, Government of India, undertook the task of identifying "below poverty line" (BPL) households in rural India through periodic (approximately five-yearly) village censuses. The first such census used self-reported household incomes to identify BPL households. However, given the difficulties of measuring income, particularly when incomes come largely from self-employment in agriculture, the self-reported income approach was abandoned in the 1997 BPL census. In the modified format, a set of five questions — (i) whether operated size of land was more than two hectares; (ii) whether owned a 'pucca house' as defined in the Population Census; (iii) whether annual income was more than Rs. 20,000; (iv) whether owned any of the following consumer durables: television, refrigerator, ceiling fan, motor cycle/scooter and three wheelers; and, (v) whether owned farm equipment such as tractor, power-tiller, or combined thresher/harvesters -- were asked of each and every household in the village. If households answered in the affirmative to any one of the five questions, they were declared to be visibly non-poor. This was done to identify the "visibly poor" from the "visibly non-poor" households in the village relatively quickly and in an inexpensive manner. Visibly non-poor households were excluded from the more extensive BPL survey that collected information on consumption expenditures using an abridged budget-expenditure schedule based on a mixed reference recall period of 30/365 days.[3]

The 1997 BPL census methodology had several shortcomings as well, such as: (i) very stringent "exclusion" criterion whereby households are declared visibly non-poor even if they possessed a ceiling fan; (ii) non-availability of official poverty lines for all states/UTs; (iii) using uniform criteria without allowing for inter-state variations especially for hilly and remote areas; and (iv) not allowing new households to be declared poor in the interim period before the next survey is instituted (Sundaram, 2003). Prior to the next survey in 2002, an Expert Group was established to recommend changes in the 1997 BPL identification guidelines to overcome the criticisms.

The Expert Group recommended that rather than rely on welfare measures like incomes or expenditures to identify the poor, socio-economic indicators reflecting the quality of life of households in the village should be used to identify the BPL households. Each household would be given a score of one to four for each of thirteen "scorable" indicators and the scores would be summed to an aggregate index ranging between zero and fifty-

[3] The survey also gathered information on household demographics, housing conditions, land ownership, formal training for skill development and receipt of assistance from various programs but this information was not used for categorizing households as BPL.

two[4]. Households would be ranked based on the total score that they received and would be categorized as poor or non-poor based on a cut-off score. These cutoff scores could vary locally across districts, blocks or at times even villages, with one constraint that the number of BPL poor was to be the same (or not more than 10 percent) as the number of persons living below the poverty line in that state or union territory as estimated by the Planning Commission for the year 1999-2000.

Thus, according to the 2002 BPL census method, household *i* is considered to be BPL if:

$$S_i = \sum_{j=1}^{13} I_{ij} \le S^r_{cut-off} \quad (1)$$

S_i is its aggregate score and I_j is the household's score for indicator j and $S^r_{cut-off}$ is the area specific criterion to declare a household poor or not. Targeting on the basis of proxy means test like the BPL while operational in a couple of dozen countries as yet (Coady et. al.) is becoming fairly common in developing countries. Generally such methods are used for large benefits and/or for multiple programs. Currently it is used for cash transfers (Armenia, Colombia, Mexico), targeting food subsidies and rations (India, Indonesia, Turkey), rationing entry for subsidized health insurance schemes (Colombia) etc.

3. How well does the BPL indicator perform in targeting the poor?

As a starting point, we take per capita consumption expenditures as the "ideal" measure of poverty status. In the context of measuring welfare in developing countries, household consumption expenditure is considered to be the best measure of permanent income or persistent poverty (Ravallion, 1992; Deaton and Zaidi, 1999). However, collecting information on consumption through household surveys is time-consuming and expensive. Therefore, one is often forced to rely on "shortcuts" like the BPL score method – an imperfect proxy but one that can be more easily and cheaply collected. Targeting shortcuts will inevitably result in targeting errors because some poor are misclassified as non-poor (exclusion errors) or because some non-poor are misclassified as poor (inclusion errors). Our objective is to assess whether the targeting errors, and associated welfare losses, are large or small.

Our analysis is based on the household consumer expenditure ("Schedule 1") of the National Sample Survey (NSS) for 1999-00.[5] Schedule 1 contains a very detailed module

[4] The thirteen indicators included size of land holding, type of house, availability of clothing per person, food security, sanitation, possession of consumer durables, literacy, status of household in labor force, means of livelihood, status of children between 5-14 years, type of indebtedness, reasons for migration in case of a migrant household, and preference for assistance from among various schemes.

[5] At the time of writing, this is the most recent available "thick sample" NSS. The larger "thick" samples are surveyed every five years. Smaller ("thin") samples are surveyed annually but official poverty estimates are considered to be more reliable in the thick samples.

on consumption expenditures which is the basis of official Government of India (GOI) poverty estimates. In addition to the consumption module, the survey also includes data on household characteristics such as religion, caste, land ownership, demographics and education. We base our analysis on the sample of approximately 60,000 rural households from the 16 major states.[6] We classify households as being (actually) poor, using the "gold" standard of per capita monthly consumption expenditures and the official Planning Commission state-specific rural poverty lines. Alternative targeting methods, such as the BPL score index, are then compared to this classification to assess the extent of targeting errors.

3.1 Who are the BPL poor? Methodology to identify the BPL poor in the NSS

In order to evaluate the efficiency of the BPL method in identifying the poor as compared to the expenditure based poverty measure, we use information in the NSS survey to construct household scores that are as similar as possible to the BPL-based scores. The constructed BPL score indices are close, but not identical, to the administrative BPL scores because the survey instruments are not the same and there are some differences in the definitions of variables.[7]

Table 1 provides details of the mapping of the 13 BPL score-able indicators to the NSS data. Among the 13 BPL indicators are variables like type of house (whether permanent, semi-permanent or temporary), reasons for migration, indebtedness of the household, and sanitation facilities available to the household. Information on these variables (or on variables that are similar) is not available in the NSS. We include fuel used for cooking and for lighting to proxy for type of household. For some variables such as information on food security the responses in the NSS data do not match one-to-one with the BPL categorizations. We have approximated these variables as closely as possible. Table 2 reports the scores assigned to the different categories of the various socio-economic indicators. Since we are able to find a close match for only 11 of the 13 indicators, the minimum score that a household can get is 0 while the maximum score is 44.

Based on the distribution of BPL scores within each state, we define a state-specific BPL score cut-off such that the number of BPL poor (i.e., people with BPL scores below the cut-off) is exactly equivalent to the number of persons living below the poverty line in that state as estimated by the Planning Commission for the year 1999-2000.[8]

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[6] These comprise Andhra Pradesh, Assam, Bihar, Gujarat, Haryana, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal.

[7] We should note that while the score-based BPL indices were introduced in 2002, the data we use are from 1999-00. However, the predetermined number of BPL households at the state level set by GOI were based on the 1999-00 headcount rates, and therefore, the discrepancy, if any, should not be significant. We will also repeat this exercise when more recent data from the 61st NSS round become available to confirm the robustness of results.

[8] In our analysis, some households with an estimated score exactly equal to or slightly below the cut-off score may be declared non-poor. This is done to ensure that the poverty rates based on the BPL scores exactly matches up with the official poverty rates. We need this requirement to ensure a fixed budget for

3.2 Targeting Performance of the BPL: Evaluation indicators

As mentioned earlier, the BPL score method is viewed as an imperfect proxy for the "ideal" consumption expenditure. It is therefore important to estimate the trade-off in terms of welfare losses associated with using the BPL index. Two commonly used evaluation indicators are the extent of undercoverage and leakage associated with the program. Undercoverage is defined as the percentage of the actual or expenditure-based poor who are incorrectly classified as BPL non-poor. In our context, at the state-level, the extent of under-coverage is identical to leakage -- the percentage of BPL poor who are actually (expenditure-based) non-poor – because of the restriction that the total number of BPL poor is the same as the number of expenditure-based poor in a state.[9] Therefore, whenever we refer to state-level under-coverage estimates as a measure of targeting accuracy, it is useful to keep in mind that it implies the same extent of aggregate state-level leakage, by assumption.

A shortcoming of undercoverage and leakage measures is that they do not differentiate between exclusion (inclusion) of households who are just below (above) the poverty line and households that are far below (above) the poverty line. If most of the targeting errors (exclusion and inclusion) were concentrated around the poverty line, the welfare losses suggested by these measures would be considerably lower.

In order to examine the nature of the targeting errors, i.e., where in the consumption distribution these errors manifest themselves, we follow the approach developed by Skoufias and Coady (2002) to display the targeting errors graphically. We construct a variable that takes a value one when households that are classified as "poor" and "nonpoor" according to consumption are classified incorrectly as "nonpoor" and "poor", respectively, according to the BPL indicator. Otherwise this variable take the value zero. Using non-parametric methods described by Skoufias and Coady, we plot the mean of this variable against the log of reported per capita expenditures normalized by the poverty line. The value on the y-axis is the "predicted error probability" (PEP). The height of the curve captures the extent of targeting errors made at different points in the distribution. The shape captures where in the distribution these errors are being made. For example, a bell-shaped curved concentrated around 0 (where expenditures equal the poverty line) indicates that most of the misclassifications involve households that are just below and above the poverty line.

The impact of targeting losses can be summarized in a welfare index that places a greater "welfare weight" on income transfers to households that are lower income households

comparisons of welfare losses under alternative methods. However, the qualitative results of the paper do not change even without this restriction.

[9] In the remainder of the paper, expenditure-based poor or non-poor are simply referred to as poor or non-poor.

(Skoufias and Coady, 2002). Equation (2) derived from standard welfare theory defines an index λ_p for program *p*:

$$\lambda_p \equiv \frac{\sum_h \omega^h dy^h}{\sum_h dy^h} = \sum_h \theta^h \omega^h \qquad \text{where} \qquad \omega^h = \left(y^z / y^h\right)^\varepsilon, \;\; \theta^h = \frac{dy^h}{\sum_h dy^h} \tag{2}$$

h refers to households who receive transfers and dy^h is the level of transfers for household *h*, so that the denominator is the total budget to be allocated across households.[10] θ^h is each household's share in the total budget. ω^h is the weight assigned to household *h* and is the social valuation of income transfer to household *h*. y^z is the state-specific poverty line, y^h refers to consumption of household *h*, and ε is the inequality aversion parameter. For example, ε=0 implies no aversion to inequality and all welfare weights take a value of unity, i.e., transfers to all households are viewed equally. When ε=1, if household *h* has half (twice) the consumption of the poverty line, then its welfare weight is 2.0 (0.25), and so on.

3.3 Targeting Performance of the BPL: Empirical results

Table 3 reports the extent of under-coverage (and therefore, also leakage) in the BPL classification at the state-level. By these measures, the BPL score is a very poor shortcut for identifying the poor. The BPL score misclassifies *nearly half* (49 percent) of the poor as non-poor, and conversely, 49 percent of those identified as BPL poor are actually non-poor. Even in the "best" state, Orissa, 32 percent of the poor are misclassified while in the worst state, Andhra Pradesh, three out of every four poor people are misclassified as non-poor based on the BPL indicator. The problem of exclusion of the poor (and therefore, inclusion of non-poor in the BPL classification) tends to be greater in the richer states (Figure 1).

Figure 2 which plots the PEP curve associated with the BPL indicator shows that targeting errors decrease sharply with higher per capita incomes, above the poverty line. This implies that the BPL indicator works relatively well in excluding the more rich amongst those who are above the poverty line. Inclusion errors are largely concentrated amongst households that are only marginally above the poverty line. However, the BPL indicator is problematic below the poverty line. Even though targeting errors do tend to decrease with distance from the poverty line, the errors of exclusion are high even amongst very poor households. For example, over 20 percent of the population with per capita expenditures which are *half* the poverty line (x-axis value -0.7) are misclassified as *nonpoor*!

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[10] Strictly speaking, λ_p is a benefit-cost ratio but it is equivalent to a welfare index since we assume that the budget is fixed across simulations. For each program that we evaluate, we assume that the number of poor is equivalent to the number of poor determined by the official headcount rate.

This is also evident in Table 4 which reports poverty rates (expenditure based and BPL score based) and under-coverage and leakage rates by per capita expenditure classes.[11] In the neighborhood of the poverty line (in the third decile), the BPL indicator misclassifies 62 percent of the poor as BPL non-poor and 33 percent of the non-poor are classified as poor.[12] In the poorest decile, a large share of the population (40 percent) is incorrectly classified as being non-poor. Targeting errors in the richer expenditure classes are, by comparison, marginal.

Such a distribution of targeting errors is suggestive of potentially large welfare losses from using the BPL indicator as a targeting method. Following equation (2), we calculate and compare the welfare indices for an expenditure-based and a BPL based classification of the poor. Households classified as poor according to the indicator are assumed to receive a transfer of 1 unit each. Note that the budget is held fixed in both simulations since an equal percentage of the population is considered to be poor under both classifications. The welfare indices reported in Table 5 suggest extremely high welfare losses from the BPL classification, ranging between 18 percent and 45 percent, depending on the inequality aversion parameter. Losses are greater at higher levels of inequality aversion which reflects the pattern observed in Figure 2 which showed that targeting errors are high even amongst the poorest expenditure deciles.

To summarize, the BPL indicator does a relatively good job at classifying the rich correctly. However it performs significantly worse in the lower part of the expenditure distribution, and the errors are not just concentrated around the poverty line, indicative of large welfare losses.

4. Why does the BPL indicator perform poorly?

Sundaram (2003) makes several pertinent observations about why the 2002 BPL census methodology is likely to be problematic in terms of clearly identifying the poor. He highlights two broad sets of concerns. First, the assumptions underlying the scoring and aggregation method in the BPL indicator may not be valid, and second, the sub-indicators used to construct the overall BPL score may themselves be a poor description of poverty. We examine both reasons empirically in the sections that follow.[13]

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[11] Expenditure classes are constructed over the all-India distribution of per capita expenditures, normalized by the state-specific poverty line to correct for cost of living differences across states. Under-coverage and leakage rates differ across expenditure classes since the number of poor and BPL poor, while identical in the aggregate at the state-level, need not be the same in each expenditure class.

[12] The third decile of the per capita expenditure distribution corresponds to the range (-0.1 to 0.3) on the x-axis in Figure 2. The short range arises because of the large mass of people concentrated very close to the poverty line. By contrast values below and upto -0.26 on the x-axis correspond to the poorest 10 percent of the population, with the mass of the population towards the top end of that range.

[13] Sundaram (2003) also discusses other concerns with the BPL census, including absence of provision for addition to the BPL list in the period between two censuses, problem of absence of poverty lines for some states, and dropping of the exclusion criterion which expands the required coverage of the detailed survey

4.1 Testing the Assumptions underlying the BPL indicator

Equation (1) in Section 2 entails three key assumptions.[14] First, the scoring method transforms the data for each indicator to a uniform cardinal scale – scored as 0, 1, 2, 3, or 4, with zero representing extreme deprivation – such that the difference between 0 and 1 (for example, the difference between being illiterate and having some primary education) is the same as between 3 and 4 (for example, the difference between having secondary education versus having a graduate degree). Forcing cardinality can also result in some problematic rankings, as for instance in the case of the indicator on means of livelihood which presumes that an 'artisan' household is always better off than one engaged in 'subsistence cultivation'.

Second, each indicator enters the aggregate score with an equal weight, implicitly assuming that each indicator has the same impact on poverty status. Equal weights have the appeal of simplicity and apparent objectivity, but these qualities only mask the fact that the imposition of numeric equality is completely arbitrary. It can lead to absurd situations where having less than one square meal per day for much of the year can be treated the same as non-ownership of any of the listed consumer durables.

Third, the same aggregation procedure is used in every state, implying that the weights assigned to indicators are the same across all states. This implies, for example, that literacy status of the highest educated adult in the household has the same impact in differentiating poor versus non-poor in Bihar as it does in Kerala, an assumption that will clearly not hold for every indicator. As a another example, a household with an operational holding of 0.95 hectares of unirrigated land in a high rainfall state and another household, with the same size of unirrigated land in a desert state will be assigned the same score, even though the two situations are very different.

To test whether the assumption of equal weights to each indicator is true, we estimate a ordinary least squares model regressing monthly per capita expenditures (y_i) on the 11 BPL indicators on which we have data, and test for equality of coefficients of the different indicators (equation 3).

$$y = \alpha + \sum_{k=1}^{11} \beta_k score_k + \varepsilon : \quad \text{Equal weights: } H_0 : \beta_k = \beta_j \quad \forall k, j = 1,..,11 \ \& \ k \neq j \qquad (3)$$

manifold. These are valid and important concerns. In this paper, however, we focus on the construct of the BPL score itself, to empirically assess whether it is likely to an effective targeting short-cut.

[14] Another assumption is the set of indicators that are included in the aggregate score. These are chosen to reflect a household's "quality of life" and a ranking of households based on some combination of these indicators is expected to reflect the relative positioning (presumably in terms of poverty status, or long-term economic status) of each in household in a village. Later in the paper, we return to alternative sets of indicators for identifying the poor.

Note that the specification in equation (3) assumes that cardinality holds. To test for cardinality, we treat the indicator scores as if they were ordinal. We estimate a flexible specification in which each discrete level of an indicator is entered into the poverty regression as a dummy variable. The estimated coefficients $\left(\hat{\beta}_{pk}\right)$ in equation 4 are the impacts of different indicators implied by the data. This functional form imposes no *a priori* constraints on the effect of the various indicators and allows us to test (i) whether the impact of moving from one level of an indicator (e.g., from 1 to 2) to the next (2 to 3) is equal, for all indicators – a test of cardinality, (ii) whether the impact of all indicators are equal – a test of equal weights, and (iii) whether the assumption of equal weights within each category of an indicator are equal (i.e., whether a landless household should be given the same weight as another household that owns say, 2 hectares of irrigated land).

$$y = \alpha + \sum_{p=1}^{4}\sum_{k=1}^{11} \beta_{pk} score_{pk} + \varepsilon : \qquad (4)$$

Equal weights: $H_0 : \beta_{pk} = \beta_{lj} \ \forall k, j = 1,..,11 \ \& \ p, l = 0,..,4$

Cardinality: $H_0 : \left(\beta_{j+1p} - \beta_{jp}\right) = \left(\beta_{j+2p} - \beta_{j+1p}\right)$ for j=1,2 and p=1,…11

Equal weights on each category of individual score: $H_0 : \beta_{kp} = \beta_{jp} \forall k, j = 0,...4; k \neq j; p = 1,...,11$

Finally, we relax the constraint of equal weights across states in equation (4) to allow coefficients of each indicator to vary across states. We also test whether this unrestricted model is accepted in favor of the more restricted model where we impose cross-state common coefficients restrictions.

The results of the above tests, reported in Table 5, indicate that all the assumptions implicit in the construction of the BPL score – of cardinality and equal weights (across indicators, within each category of indicator, and across states) -- are rejected by the data. Overly restrictive assumptions are evidently to blame, at least in part, for high targeting errors and associated welfare losses of the BPL indicator. The question is how much? In section 5, we construct an alternative index that relaxes these assumptions (by assuming ordinality within each indicator and by allowing the data to generate state-specific weights for each category of every indicator) in order to assess the extent to which targeting losses could be reduced by allowing for a more flexible specification.

4.2 *Examining the set of indicators in the BPL score*

A second reason why the BPL score performs poorly may be the choice of indicators. As the purpose of the census is the identification of poor households, there should be a clear link between the indicators and the underlying concept of poverty. Figure 2 plots the distribution of scores for each indicator across per capita expenditure classes. As is evident from the figure, some of the indicators are clearly ineffective from sorting out rich from poor. For example, the scores of indicators such as the preferred form of assistance and food security do not vary significantly across expenditure classes. The indicator on the status of children 5-14 years does show some variance although the gradient is not the expected direction. A larger share of the richest 20 percent of the population has a score of zero as compared to the poorest 10 percent of the population. This relationship arises because households with no children in the 5-14 year age group are also assigned a score of zero, as are households with children who are working and illiterate. Assigning a score of zero to households with no children in the 5-14 year age group artificially pushes these households into the BPL set.

Other indicators show a shift in the distribution of scores in the expected direction, with the distribution shifting towards higher scores from poor to rich households. However, it is important to note that the change in distribution in the poorer half of the population (for example, across deciles in the poorest 40%) is not very strong. That is, the types of indicators that are included in the overall BPL score do not do particularly well in sorting out households into poor and less poor categories amongst the lower half of the expenditure distribution. For this fundamental reason, indexes based on these scores, regardless of the weighting and aggregation method used are unlikely to be effective targeting instruments.

Another issue is that the same set of indicators is used in all states. [*need to complete*]

Finally, what guides choice of indicators? Some strong correlates of poverty such as caste etc are not included [*need to complete*]

5. Ways forward – Alternatives to BPL scores

In this section, we experiment with four alternative models/methods for identifying the poor. We start by constructing two alternative indexes using the same sub-indicators but after relaxing the two assumptions of cardinality and equal weights. First, is a *regression-weights based index* (hedonic approach) that uses the estimated coefficients of our most flexible specification (equation 4 modified to allow different coefficients across states) to predict a household's monthly per capita expenditure. The linear regression coefficients implicitly produce weights for the linear index of these indicators that predicts expenditures most closely.

Second, we use principal components analysis to determine the weights for constructing an index of the same variables (i.e., the dummies for each indicator class as in equation 4). The first principal component of these indicators is the linear index of all the variables that captures the largest amount of information that is common to all of the variables (see Filmer and Pritchett, 2001) under the normality assumption.

Third, we expand the list of indicators in an augmented regression-based index that captures other household characteristics that may add explanatory power towards identifying the poor. To retain the maximum flexibility in the index and consistent with the evidence that equal weights for indicators across states is not validated by the data, we allow coefficients of all regressors to vary across states. Specifically, we regress monthly per capita expenditures on a set of demographic, occupational and educational variables in addition to select BPL score variables (including land, type of cooking fuel, lighting, assistance from public programs, ownership of durables, and clothing). A few BPL indicators are excluded since, as discussed in the previous section, they are not correlated strongly with per capita expenditures. Demographic variables include sex of the household head, household size (and its square), and the share of children in the household. Occupational variables include household type (self-employed in agriculture or non-agriculture, type of laborer, and other), sources of income (e.g., from cultivation, agricultural or non-agricultural enterprises etc.), and the principal industry of the main occupation in the household. We include variables on the educational status of the highest educated adult male and female to capture the effect of education.

Fourth, as a thought experiment, we *randomly* assign a share of the bottom 40 percent as BPL poor such the overall percentage of poor in each state equals to state-specific rural poverty rate. This experiment is motivated by the analysis in section 4 which suggests that the indicators included in a BPL index do reasonably well at sorting out the rich from poor but are largely ineffective at sorting out the poor from less poor in the lower expenditure deciles. Taking this as a starting point, we assume that it is possible to identify with reasonable confidence the bottom 40 percent of the population in each state, but further sorting of this group into poor versus non-poor is infeasible. We refer to this experiment as the “strawman” model in the sense that while the practical implementation of such a scheme is not politically feasible, it provides us with a benchmark with which to compare the results from other feasible alternatives.

Poverty and under-coverage rates, and the welfare losses under different risk aversion parameters for indices using alternative assumptions are reported in Tables 7 and 8. The first point of note is that relaxing the assumptions implicit in the BPL score indicator improves targeting but the gains are not substantial. The regression-based weighted index which discards the assumptions of cardinality and equal weights across indicators reduces under-coverage only marginally, from 49 percent to 45 percent, and welfare losses are lowered by between 1 to 13 percent depending on the inequality aversion parameter.

The big gains in improved targeting come from relaxing the assumptions *and* revising the list of indicators to discard some that are problematic (e.g., status of children 5-14 years) and add others that are strong correlates of poverty (e.g., sex of household head and caste). This index results in a 32 percent reduction in under-coverage compared to the BPL model. The main reason for the reduction in exclusion error stems from the fact that the model identifies 80 percent of the poor in the poorest 10 percent of the distribution compared to only 63 percent by the BPL index. Inclusion errors are also lower, although this is mainly because again the augmented regression model performs better at correctly assigning people in the top 40 percent as non-poor. Improvements in the neighborhood of the poverty line are very small (see also Figure 4).

Although the augmented regression based model performs better, it is important to note that it is still not as good as a random assignment of BPL status amongst the bottom 40 percent of the population. By construction, under-coverage in the random assignment are 33 percent (since two-thirds of the bottom 40 percent are eligible and the rest are not) and 12 percent, which is better than the most flexible regression-based model that we can construct from the data.

Why does even the most flexible regression model, with a long list of indicators perform worse than a random assignment amongst the bottom 40%? A comparison of poverty rates between the two models in Table 7 sheds some light. The augmented regression model is much better than random assignment at identifying the poorest among the poor. However, targeting errors are much higher in the vicinity of the poverty line (in the third and fourth expenditure deciles), and this is a problem evident in all other targeting models as well. With the high density of population with income close to the poverty line (see Figure 1 which shows the distribution of per capita expenditures), arriving at an effective proxy means test is an inherently problematic and difficult exercise.

6. Conclusions and Future Work

An Expert group set up prior to the 2002 BPL census, recommended the use of proxy means test based on thirteen score-able socio-economic indicators to identify the BPL households. Our analysis shows that the 2002 BPL census methodology is a poor shortcut for identifying and targeting the poor. The assumptions of cardinality and equal weights are not validated by the data. However, while relaxing the assumptions improves targeting performance, the reduction in targeting errors is not substantial (8 percent reduction in under-coverage in the regression-weighted non-cardinal index). Therefore, standard criticisms of the proxy means test targeting methods regarding the assumptions of equality of weights and cardinality are not the main reasons for the poor performance of the BPL scoring index in identifying the poor.

The main reason why the BPL indicator performs poorly is that the indicators used to construct the overall BPL indicator are poor correlates of poverty. Some indicators, while clearly linked with an underlying concept of poverty (e.g., food security) do not exhibit enough variation in the population. Others while effective at sorting rich from poor, do not exhibit enough variation in the bottom 40-50 percent of the population. There is a big reduction in targeting errors from augmenting the list of indicators and allowing the impact (or weights) of different indicators to vary across states.

Nevertheless, a sobering conclusion of the empirical work is that even for the augmented regression model, the exclusion errors are estimated to be around 34 percent. The augmented model does not do better than the “strawman” model of random assignment in the bottom 40 percent of the population. What the augmented regression model does is to improve identification at the tails of the distribution, so that a smaller share of very poor households (in the bottom 10 percent) are likely to be excluded as compared to the classification based on the BPL indicator.

Our conjecture is that one possible reason for not being able to correctly identify the poor based on a proxy-means test is that the high density of population in the vicinity of the poverty line makes it an inherently difficult problem. Because the cumulative distribution function of per capita expenditures is extremely steep in the neighborhood of the poverty line, any proxy to classify people near this line will naturally result in relatively large targeting errors. As long as targeting errors were concentrated close to the poverty line, welfare losses would be small and from that perspective the targeting errors would be tolerable.

Another conjecture is that there is little difference in the standard of living between poor and middle class (median) households, at least in the types of indicators that are measured by the NSS. Very few questions in the NSS have much variation in the bottom half of the income distribution, a finding also evident in other datasets. For example, using data from the two (1992-93 and 1998-99) National Family and Health Surveys, Chaudhary and Hammer (2005) find that the difference in standard of living at the dividing line of the first and second quintile and that between the third and fourth is very small in any realistic sense, which limits the ability to make distinctions near the official poverty line in India.

Questions for further work:
(a) Explore state-level variations further: why do the indicators work better in some states than others?
(b) other alternatives: apply exclusion criteria, and then try a regression-based model. Cheaper to implement but basic problem of not having much variation in indicators in the lower half of the expenditure distribution remains.
(c) de Jure BPL targeting is awful. But does it work better in practice, and why: For this, we could analyze data from the state of Uttar Pradesh and Jharkand to analyze *dejure* versus *defacto* targeting. Are the actual field level experiences different from what theory predicts? We could examine alternative indicators in the more detailed datasets that will more accurately identify the poor from the not so poor. Also, we could analyze some community variables (caste composition, inequality within village, quality of gram sabha participation etc.) to explain why *defacto* targeting works better, if it does, than *dejure* in some villages but not in others.

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Table 1: **Mapping of NSS variables to BPL score indicators**

BPL variable	Closest NSS variable (55th round)	Comments
Size group of operational land holding	(a) Land irrigated (b) Land cultivated	
Type of house : houseless, katcha, semi-pucca, pucca, urban type	(a) Cooking code (b) Lighting code	NSS thick rounds do not collect information on type of house. We can say use cooking code and lighting code
Average availability of normal wear clothing (per person in pieces): less than 2, 2-4, 4-6, 6-10,>=10	Consumption of clothing during last 365 days; Divide by household size to get approximation to BPL categories	Most items are in numbers, others like dhoti, sari, cloth for shirt pyjama, etc. convert into pieces of particular clothing
Food security: less than one square meal per day for major part of the year, normally one square meal per day but occasionally less than one square meal, one square meal throughout year, two square meals with occasional shortage, adequate food throughout year	Do all members of your household get enough food everyday? (yes: throughout the year, some months of the year, no)	
Sanitation	NO INFORMATION	
Ownership of consumer durables	Expenditure for purchase and/or repair and maintenance of durable goods for domestic use in the last 365 days	Any positive expenditure on the different durable goods will be assumed to mean possession
Literacy status of the highest literate adult : literate, upto primary, completed secondary, graduate/professional, post graduate	Personal history file of household members	
Status of household labor force	Personal history file of household members	
Means of livelihood	Household type categories	
Status of children	Personal history file	
Type of indebtedness	NO INFORMATION	
Reasons for migration from household	NO INFORMATION	
Preference of assistance: wage employment, TPDS, self-employment, training and skill upgradation, housing, loan/subsidy for more than Rs 1 lakh	Public works, IRDP, PDS	IRDP can be mapped into self-employment; No TPDS data but from the PDS module we can separate out households who purchase from PDS outlets. No information available on training and skill up-gradation and on loan/housing

Table 2: **Scores assigned to indicators in the NSS**

BPL variable	NSS variable details	Scoring Codes: Variable definition	Score
Size of operational land holding	Block 3: Land cultivated and irrigated	Landless	0
		1 ha. of un-irrigated or .5 ha of irrigated	1
		1-2 ha. of un-irrigated or .5-1 ha of irrigated	2
		2-5 ha. of un-irrigated or 1-2.5 ha of irrigated	3
		>5 ha. of un-irrigated or >2.5 ha of irrigated	4
Average availability of normal wear clothing	Block 6: Items 360-371 and Block 3: household size (Qs1) <u>*COMMENT*</u>: 360-363 divide by amount of cloth that will be needed to get one unit of clothing (convert to number rather than cloth size)	Less than 2 per person	0
		(2,4] per person	1
		(4,6] per person	2
		(6,10] per person	3
		>10 per person	4
Food security	Block 12: Question 1	Not enough food throughout year	0
		Not enough food for some months	1
		Enough food throughout year	4
Ownership of consumer durables	Block 9: 561, 562, 590, 596 (group 1) Block 8.2: 488, Block 9: 597, 598 600, 611, 612 (group 2) <u>*COMMENT*</u>: number in use at time of survey and/or whether made any purchases in last 365 days of the item	Nil	0
		Any 1 item of Group 1	1
		Any 2 items of Group 1	2
		Any 3 items of Group 1	3
		All items of Group1 and/or any one item of Group 2	4
Literacy status of the highest literate adult	Block 4: Age and general education code	Illiterate	0
		Non-formal education	1
		Primary education (incomplete & complete)	2
		Completed secondary education	3
		Graduate and above	4
Status of household labor force	Block 4: Age, sex, worker, income received <u>*COMMENT*</u>: To define bonded labor check whether adult members are workers and whether they receive any income from their work.	Bonded labor	0
		Adult female and child labor	1
		Adult females only	2
		Adult males only	3
		Adults (females & males)	4

Table 4 (cont.)

BPL variable	NSS variable details	Scoring Codes: Variable definition	Score
Means of livelihood	Block 3: Household type	Agricultural labor	0
		Other labor	1
		Self-employment in agriculture	2
		Self-employment in non-agriculture	3
		Others	4
Status of children 5-14 years	Block 4: Age, education and worker	Illiterate (working & not working)	0
		Literate through informal education & working	1
		Literate through formal education & working	2
		Informal education & not working	3
		Formal education and not working	4
Preferred forms of assistance	Block 3: IRDP, Public Works; Block 11: 1,2,3,4 <u>*COMMENT*</u>: Household if a PDS beneficiary if and only if he buys any of the listed items (rice, wheat, kerosene, sugar) from a PDS shop only	All 3 types of assistance received	0
		2 types of assistance received	1
		Any one type of assistance received	2
		No assistance received	4
Primary source of energy used for cooking [a]	Block 3: Cooking	Firewood	0
		Dungcake	1
		Coke, coal, , charcoal	2
		Kerosene, gobar gas	3
		LPG, Electricity, others	4
Primary source of energy used for lighting [a]	Block 3: Lighting	No lighting	0
		Candle	1
		Kerosene, other oil	2
		Gas, electricity and others	4

Notes:

- [a]: These two variables have been used as substitutes for type of house and sanitation.
- No proxy variables available for reasons for migration and indebtedness of the household

Table 3: Poverty Rate and Targeting Errors in the BPL Classification, by State

State	Rural Poverty Rate (%)	Under-coverage (%)
Andhra Pradesh	10.5	76.9
Assam	40.3	41.6
Bihar	44.0	40.6
Gujarat	12.4	64.9
Haryana	7.4	73.8
Himachal Pradesh	7.5	74.5
Karnataka	16.8	64.2
Kerala	9.4	72.6
Madhya Pradesh	37.2	43.8
Mahrashtra	23.2	54.4
Orissa	47.8	32.1
Punjab	6.0	72.4
Rajasthan	13.5	63.8
Tamil Nadu	20.0	64.5
Uttar Pradesh	31.1	51.9
West Bengal	31.7	46.3
All India	26.8	49.1

Notes:

- Under-coverage is the percentage of the poor population wrongly classified as BPL non-poor
- Rural poverty rates are estimated using the official Planning Commission state-specific rural poverty lines

Table 4: Poverty Rate and Targeting Errors in the BPL Classification, by Expenditure Class

Expenditure class	Poverty Rate		Targeting Errors	
	Expenditure based	BPL score Based	Under-coverage	Leakage
Poorest 10%	100.0	63.2	36.8	---
2nd decile	100.0	47.6	52.4	---
3rd decile	69.7	36.2	62.2	27.3
4th decile	0.0	31.9	---	100.0
3rd quintile	0.0	23.0	---	100.0
4th quintile	0.0	14.3	---	100.0
Richest 20%	0.0	8.0	---	100.0
Total	27.0	27.0	49.1	49.1

Notes*:*

- The poverty rate measures the percentage of population with per capita expenditures less than the official Planning Commission state-specific poverty lines
- Under-coverage is the percentage of the poor population wrongly classified as BPL non-poor
- Leakage is the percentage of the BPL poor that is actually (expenditure-based) non-poor

Table 5: Welfare losses arising from the use of BPL score index (expressed as percentage of expenditure based welfare levels)

State	High inequality aversion ($\varepsilon = 5$)	Moderate inequality aversion ($\varepsilon = 2$)	Low inequality aversion ($\varepsilon = 1$)
Andhra Pradesh	87.61	56.55	35.24
Assam	18.19	20.55	13.63
Bihar	36.32	20.84	13.34
Gujarat	53.82	38.41	24.41
Haryana	71.81	48.53	30.83
Himachal Pradesh	50.40	44.57	30.98
Karnataka	56.44	38.32	23.89
Kerala	42.13	40.40	27.53
Madhya Pradesh	16.36	23.65	16.00
Maharashtra	11.87	30.75	20.93
Orissa	25.76	17.41	11.24
Punjab	40.60	44.31	30.48
Rajasthan	12.81	34.37	23.37
Tamil Nadu	38.86	38.82	26.25
Uttar Pradesh	68.00	30.06	19.59
West Bengal	44.74	26.72	16.43
ALL INDIA	45.33	27.56	18.03

Note:

- The actual welfare values underlying the above table is available from the authors on request

TABLE 6: Test specifications to test the validity of the BPL score assumptions

Assumption	Model	H_0	Accept/Reject H_0	Test statistic
Equal weights	$y = \alpha + \sum_{k=1}^{11} \beta_k score_k + \varepsilon$	$H_0 : \beta_k = \beta_j \quad \forall k, j = 1,..,11 \,\&\, k \neq j$	Reject	F-test
Equal weights	$y = \alpha + \sum_{p=1}^{4}\sum_{k=1}^{11} \beta_{pk} score_{pk} + \varepsilon$	$H_0 : \beta_{pk} = \beta_{lj} \; \forall k, j = 1,..,11 \,\&\, p, l = 0,..,4$	Reject	F-test
Cardinality	$y = \alpha + \sum_{p=1}^{4}\sum_{k=1}^{11} \beta_{pk} score_{pk} + \varepsilon$	$H_0 : \beta_{j+1p} - \beta_{jp} = \beta_{j+2p} - \beta_{j+1p} \;\; for \;\; j = 1,2$ $p = 1,..,11$	Reject	Series of Wald tests
Equal weights on each category of individual score	$y = \alpha + \sum_{p=1}^{4}\sum_{k=1}^{11} \beta_{pk} score_{pk} + \varepsilon$	$H_0 : \beta_{kp} = \beta_{jp} \quad \forall k, j = 0,..,4 \,\&\, k \neq j$ $p = 1,..,11$	Reject	Series of Wald tests
Uniform weights across different states	$y = \alpha^j + \sum_{k=1}^{11} \beta_k^j score_k^j + \varepsilon$ $j = 1,..,16$	$H_0 : \beta_k^j = \beta_k^l \quad \forall l, j = 1,..,16 \;\&\, l \neq j$ $k = 1,..,11$	Reject	F-test

***Note*:**

- For the interested reader, the values of the test statistics are available from the authors

Table 7: Poverty rates by expenditure classes across different targeting methods

Expenditure Class	Principal components weights	Regression based weights	Augmented regression model	"Strawman" randomization model
Poorest 10 percent	63.87 (1.06)	65.95 (4.35)	80.30 (27.05)	68.10 (7.74)
2nd decile	48.94 (2.74)	51.38 (7.86)	62.12 (30.42)	67.37 (41.43)
3rd decile	37.89 (4.57)	41.56 (14.70)	45.58 (25.82)	66.08 (82.39)
4th decile	32.02 (.52)	32.15 (.93)	30.14 (-5.38)	64.08 (101.15)
3rd quintile	22.40 (-2.64)	22.73 (-1.18)	16.74 (-27.23)	0.00 (-100.00)
4th quintile	14.24 (-.47)	12.23 (-14.53)	7.07 (-50.58)	0.00 (-100.00)
Richest 20 percent	6.71 (-15.96)	4.25 (-46.70)	1.83 (-77.09)	0.00 (-100.00)
Total		26.95		

***Notes*:**
Assumptions underlying the alternative models are given in Table 8
Figures in parentheses are the percent change from the BPL model

Table 8: Targeting evaluation indicators for alternative models

	Model 1	**Model 2**	**Model 3**	**"Strawman" model**
Assumptions	**Principal components weighed index; no cardinality; BPL variables; uniform weights across states**	**Regression based weighted index; no cardinality; BPL variables; uniform weights across states**	**Regression based poverty model; no cardinality; additional regressors*; non-uniform weights across states**	**27 percent of households in the bottom 40 percent of the expenditure distribution randomly declared to be poor**
Classification errors:				
Under-coverage	48.12 (-6.02)	45.43 (-11.28)	34.54 (-32.54)	32.91 (-35.73)
Welfare losses:				
High inequality aversion (ε=5)	43.89 (-3.18)	44.74 (-1.32)	27.34 (-39.69)	24.37 (-46.25)
Moderate inequality aversion (ε=2)	26.40 (-4.22)	24.40 (-11.48)	15.49 (-43.80)	16.81 (-39.00)
Low inequality aversion (ε=1)	17.27 (-4.21)	18.49 (-13.45)	10.03 (-44.38)	9.76 (-45.90)

***Notes*:**
- Numbers in parentheses are percentage reduction in errors/welfare losses as compared to errors/losses arising in the BPL score index
- *Additional regressors: sex of head, social group, highest education level of adult household members (by gender), household size, proportion of kids in the household, whether household receives income from different activities (cultivation, wages etc.), classification of household according to 2-digit NIC code, NSS regional dummies

Figure 1: Under-coverage Rate and Rural Poverty across states

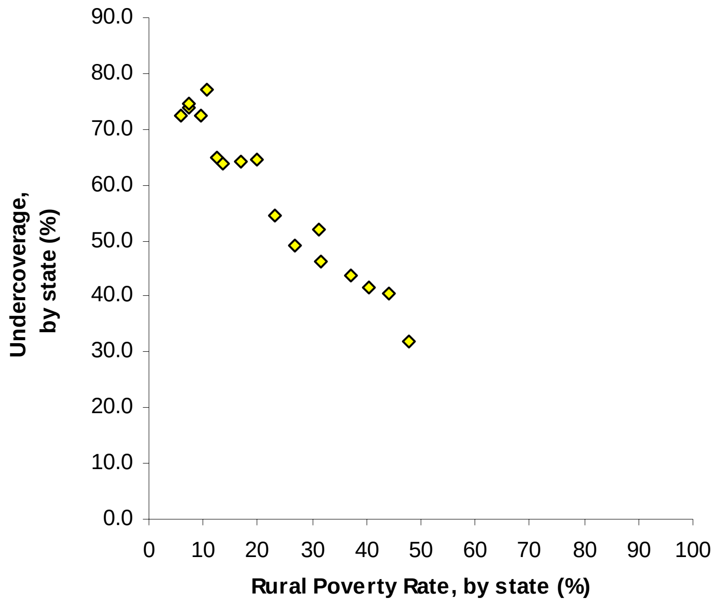


Figure 2: Predicted targeting errors in the BPL classification

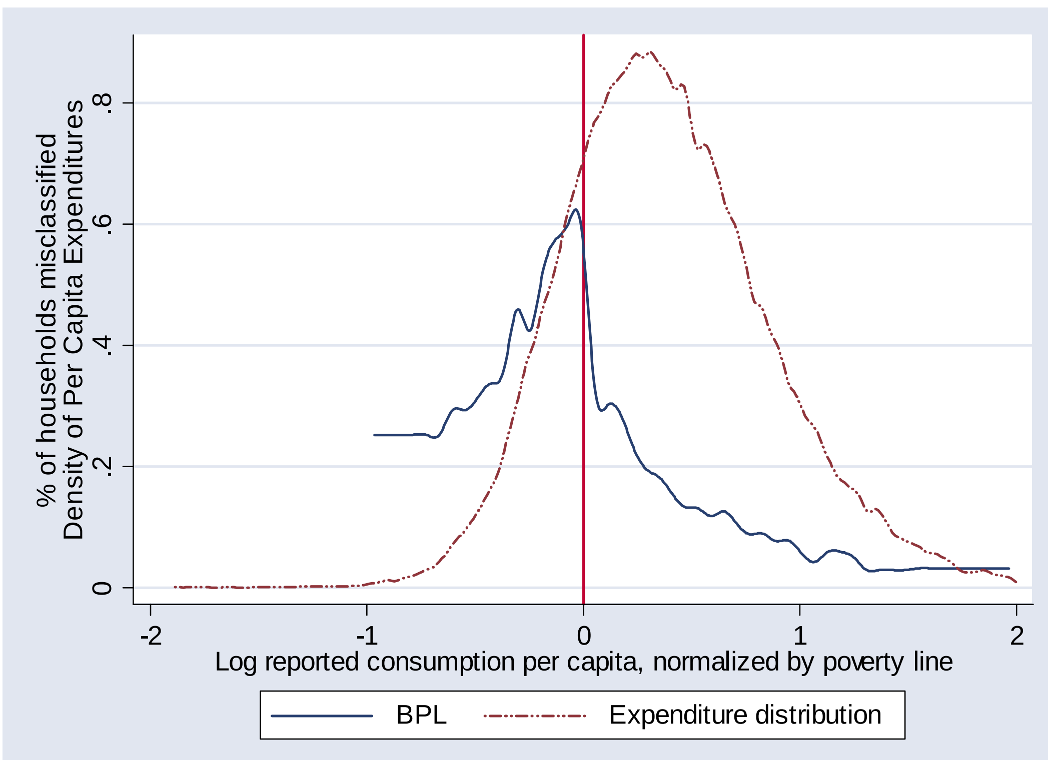


Figure 3: Distribution of individual indicator scores across expenditure classes

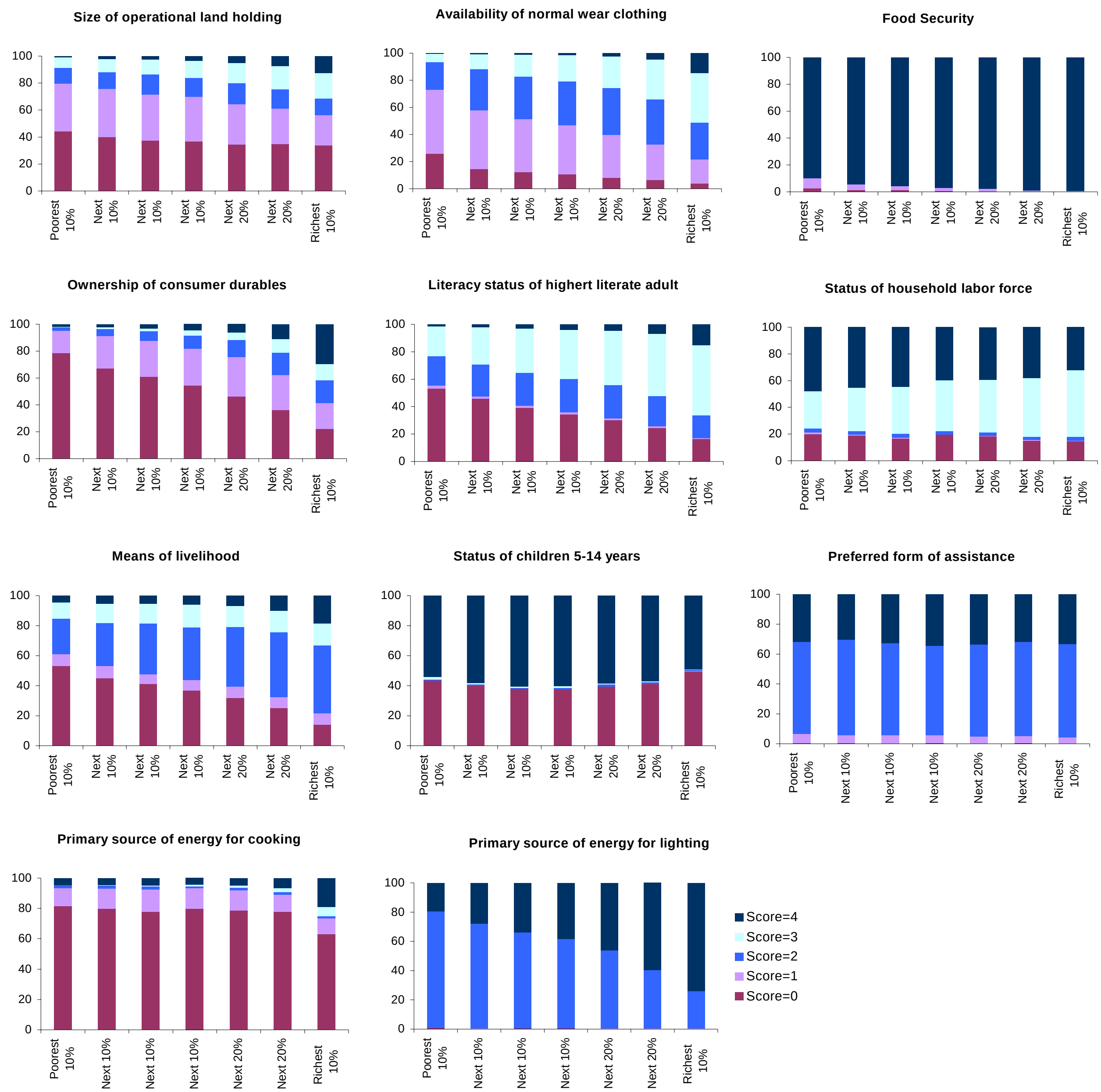
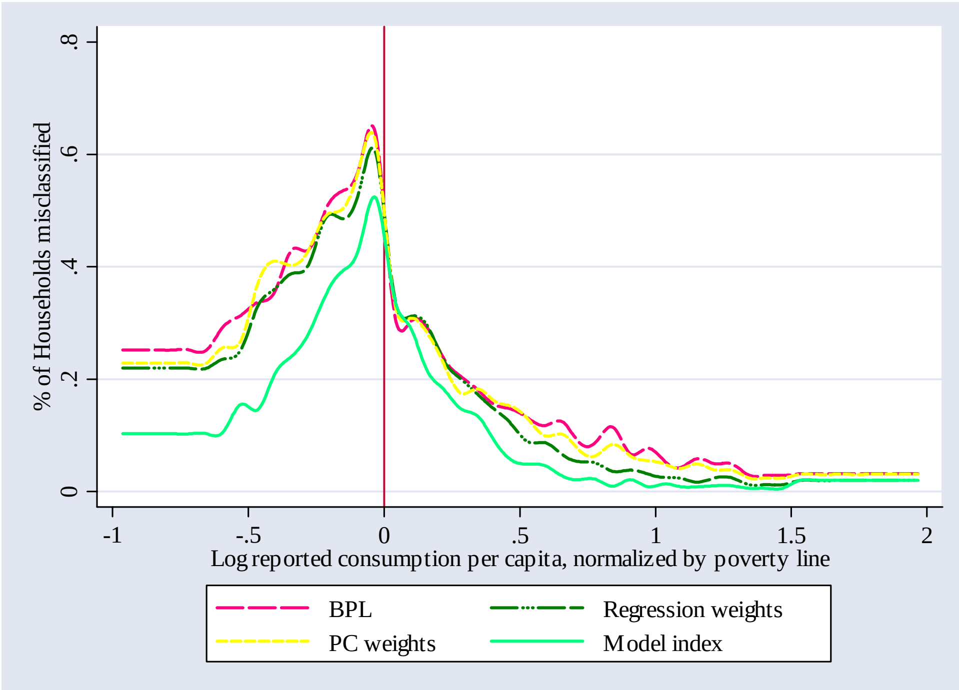


Figure 4: Predicted targeting errors under different alternatives



ANNEX TABLES

Table A1: BPL Targeting errors across NSS regions

Regions	Type 1	Type 2
Andhra Pradesh: Coastal & Inland(South)	74.71	11.24
Andhra Pradesh: Inland(North) & Southwest	79.15	6.27
Assam: Eastern Plains	51.57	26.29
Assam: Western Plains & Hills	36.51	29.22
Bihar: South	38.47	29.96
Bihar: North	34.78	36.62
Bihar: Central	50.08	25.54
Gujarat: Eastern Plains & Saurashtra	61.80	7.59
Gujarat: Northern & Southern Plains & Drylands	67.86	10.29
Haryana: East & West	73.75	5.67
Himachal Pradesh	74.51	6.16
Karnataka: Inland(East), South, Coastal	69.27	10.43
Karnataka: Inland(North)	62.79	16.05
Kerala: North & South	72.58	7.46
Madhya Pradesh: Chhatisgarh	38.45	32.04
Madhya Pradesh: Vindhyas, Southwest, South	45.83	28.91
Madhya Pradesh P: Central, Malwa, North	47.95	20.05
Maharashtra: Inland(North), Coastal	33.06	19.77
Maharashtra: Inland(West)	52.86	12.98
Maharashtra: Inland(Central)	78.57	12.16
Maharashtra: Inland(Eastern), Eastern	57.36	22.56
Orissa: Coastal	41.84	24.85
Orissa: South	19.32	53.94
Orissa: North	35.33	34.79
Punjab: North & South	72.39	4.67
Rajasthan: West	56.66	10.27
Rajasthan: North-east, South-east, South	65.96	9.73
Tamil Nadu: Coastal & Coastal(North)	64.31	16.80
Tamil Nadu: South & Inland	64.72	15.67
Uttar Pradesh: Uttaranchal & West	51.91	25.62
Uttar Pradesh: Central & South	41.74	24.10
Uttar Pradesh: East	57.26	21.21
West Bengal: Himalayan & Eastern Plains	39.11	30.17
West Bengal: Central & Western Plains	53.73	15.17
Total	49.14	18.13