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Poverty and Social Protection in Urban India

Targeting Efficiency and Poverty Impacts of the Targeted Public Distribution System

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I. INTRODUCTION

With the steady pace of urbanization in recent years, development concerns in urban areas across the developing world have assumed greater significance. Rapid population growth in the cities has placed higher demands on housing, civic infrastructure and employment opportunities and influenced welfare outcomes. High incidence of informal employment, unequal access to public services and social utilities often permeate socioeconomic vulnerabilities, which calls for adequate social safety nets to safeguard living standards of the urban poor. Social protection mechanisms involving insurance schemes, pensions, targeted subsidies and income transfers have emerged as alternative policy instruments stemming out of the need to insure vulnerable population groups against multiple deprivations and insecurities.

For a fast-growing economy like India's, rapid urbanization has ushered new policy challenges to offer adequate social protection coverage for the poor. In the recent years a number of programs have been introduced or re-oriented to protect the urban poor against shocks such as loss of employment and income, illness, and disability and to ensure improved living standards. However, there is scarce empirical evidence on understanding the efficiency of these social protection measures in terms of targeting the intended beneficiaries, and possible welfare impacts. A few recent evaluations provide some information on the functioning of the programs and identify loopholes in the design and implementation issues, but fall short in answering key questions relevant to improving program performance and impacts. Again, since vulnerabilities and multiple deprivations of the poor encompass different, and often unique dimensions in urban areas, assessments of the social protection programs need to accommodate these aspects as well while accounting for program functioning and impacts. At the core of the success of social protection programs, applying equally to urban as well as rural areas, is the need to identify well the intended beneficiaries and cut down leakages for improving benefit incidence. For programs with a narrow targeting design, such as providing subsidized illness cover or food-grains to a particular interest group (the poor, or workers in the unorganized sector for example), the need to accurately identify the target group assumes greater importance. Since some of these programs do not have any self-targeting mechanisms in the form of explicit incentives or disincentives to discourage access to these programs by non-targeted populations, proper identification is a key to ensure both cost-effectiveness as well as maximum impact of the programs.

Drawing on a recent household survey in two Indian cities and considering one of the earliest and largest social protection schemes in India involving a targeted food-grains distribution programme, this paper aims to provide broad indications on how effectiveness of social protection measures is closely linked with targeting efficiency. We argue that empirical assessments of targeting efficiency can be improved by employing alternative, and broad-based welfare indicators to identify the poor, and not on the basis of income (or expenditure) alone. We also provide estimates on possible poverty impacts through implicit income transfers arising out of participating in or accessing the program and how such effects vary according to economic status.

The rest of the paper is organized as follows: Section II presents a brief overview of the food-grains distribution program – the Targeted Public Distribution System (TPDS) – and reviews some related work. Section III describes the data and the methods and analytical approaches followed, while Section IV discusses the results. Section V highlights the policy aspects in the light of the findings and concludes the discussion.

II. THE TARGETED PUBLIC DISTRIBUTION SYSTEM IN INDIA

The Public Distribution System (PDS) is one of the earliest and most important elements in India's safety net system. It originally evolved as a key instrument of the government policy for management of food scarcity and for distribution of food-grains at affordable prices. Historically, the objectives of the PDS have been to maintain price stability, achieve food security at the household level, rationing during situations of scarcity and keep a check on private trade. The system primarily operates through direct procurement of food-grains from farmers by agencies of the Central government, which stock and supply these food-grains to state governments on the basis of 'quotas'. The Central government controls the pricing – both procurement rates and 'issue' prices to the states – with the states adding a margin on the central prices (for transaction and distribution costs) and distributing the food-grains through a network of fair- price shops (FPS)[1]. During its long existence, the PDS program has witnessed a number of changes in the scale, scope and orientation of the program. A range of commodities apart from the principal food-grains (rice and wheat) like sugar, edible oil, kerosene, coarse cloth, notebooks, coking coal etc., are distributed by the Central government under the PDS currently.

Since 1997, the PDS program was re-oriented as a targeted food subsidy program and renamed as the Targeted Public Distribution System (TPDS). The essence of TPDS lies in classifying the beneficiary families into below poverty line (BPL), above poverty line (APL) and the poorest of the poor (*Antyodaya Anna Yojana* or AAY) families, and distributing fixed (maximum) quantities of food-grains at differential prices to these family-groups. After few revisions, BPL and AAY families were entitled to 35 kgs. of food-grains per month at the Central government 'issue' prices of rice at Rs. 5.65/kg and wheat at Rs. 4.14/kg for BPL and Rs. 3 and Rs. 2 for AAY households. The issue prices for APL households were fixed at Rs. 8.30 and Rs. 6.10 for rice and wheat respectively. The states were given the responsibility to classify the households into AAY, BPL and APL categories. This list was to be prepared on the basis of a BPL Census (the latest being in 2002, with a fresh exercise currently ongoing), which listed each household on the basis of 13 criteria (including housing type, employment, landownership, assets, basic living standards etc.) and derived an aggregate score. The total number of households that could be identified as poor, or BPL in other words, was however fixed by the Central government on the basis of state-specific poverty lines determined by the Planning Commission[2]. With this cap on the number of BPL households that would be entitled to receive the subsidized food-grains under the TPDS, BPL households were identified by the state governments as those who fell below a cut-off score consistent with the cap. However, states may consider a higher cut-off and hence classify a higher number of households as poor, but must bear the subsidy for the excess number of households themselves. While this scheme of identifying the target (i.e. BPL) households who are to receive higher subsidies is arithmetically cognizable, the actual identification is fraught with high risks of errors. We discuss this in greater details in the review that follows.

As for most other similar programs of food subsidies, aiming at a degree of income transfer as an instrument for poverty alleviation and social protection, the Indian experience with TPDS has been considerably reviewed and criticized by observers. The only official national evaluation of the TPDS (PEO 2005) admits that owing to significant targeting errors, leakages and diversions during the distribution process, a fraction of intended benefits actually reach the poor. For example, the report estimates that only about 57% of the BPL households are covered under the TPDS and only about 43% of the budgetary subsidies reach the BPL families. It asserts in the light of above that the cost of income transfers to the poor through the PDS is much higher than other alternatives. A related report also identifies similar leakages and problems in properly targeting the poor under the TPDS, and citing reasons of fiscal and distributional inefficiencies, suggests a roll-back to the universal system (Planning Commission 2005). A series of papers, (e.g., Ahluwalia 1993, Dutta and Ramaswami 2001, Jha and Ramaswami 2010) mostly based on analysis of different rounds of the National Sample Survey data from the consumption expenditure surveys, also highlight inequalities in participation in the PDS program between the poor and non-poor families, significant regional variations in the utilization of PDS and 'offtake' of food-grains, skewed share of the food subsidies accruing mostly to the non-poor and low cost- effectiveness of the program due to inefficient targeting and wastages. In a recent work, Svedberg (2010) revisits the Planning Commission's (2005, *ibid.*) estimates on targeting errors and finds them to be of a larger scale. He suggests introducing direct cash-transfers instead, based on smart-cards which, he opines, can eliminate most of the targeting errors. On the other hand, Khera (2011), based on a primary survey across nine states, suggests a 'revival' of the TPDS: she finds more than 80% of the respondents received their full entitlements, and calculates the implicit subsidy for BPL households from TPDS to be equivalent to about a week's wages under the 'self-targeted' national employment generation program. Jha and colleagues (2011) using primary survey data from three states also identify improper targeting and find that real income transfers due to the program are often influenced significantly by local prices and consumption patterns, land and asset ownership and other household demographic variables. However, they too echo Khera (2011) on the need to reform the TPDS through better identification mechanisms of the target groups (BPL families) and to cut down other leakages through better monitoring and supply-side interventions instead of switching towards either a universal food-subsidy system or direct cash transfers.

The literature provides two clear and related sets of issues that are of significance in assessing the role of the TPDS program as a social protection measure and hence, dictate the focus of this paper. Firstly, this involves the contentious issue of targeting and identifying the target, vulnerable group(s) that is unarguably in need of a larger concentration of the program benefits. Clearly, the current system of identifying the poor (both BPL and AAY households) is error-prone, with analysts providing differing estimates of the scale of the targeting errors. In this paper, we too provide similar estimates of different types of such errors using alternative welfare indicators. While we attempt through this to comment on the targeting efficiency of TPDS, we also consider the possible factors that may influence TPDS targeting and welfare impacts (losses) arising out of improper targeting. The second aspect is that of net impacts on poverty, or household welfare that could be attributed to the implicit income transfers from 'participating' in the TPDS. This, is essentially an upper bound of the possible poverty impacts, since, primarily due to data limitations, we are unable to adjust these estimates for the cost (to the government) for providing the income transfers.

III. DATA AND METHODS

The data for this paper is from a primary survey conducted in the cities of Delhi and Ranchi during July- November, 2010, jointly by the Institute of Rural Management, Anand (IRMA) and the Institute for Human Development (IHD), New Delhi. Details of the sampling design and other aspects of the study can be found elsewhere (Unni & Naik 2011). The survey covered 2998 households from these two cities, with 2020 households from Delhi and 978 from Ranchi. For this study we consider the urban areas of the Delhi state, within the National Capital Region (NCR) and Ranchi, which is the capital of the state of Jharkhand in eastern India. In the survey, detailed information was collected on employment types, primary/secondary occupation, duration of residence in the city, migration status, wages/ income earned, household expenditure, ownership of assets, housing conditions and living standards. A section on social protection measures canvassed questions on the TPDS, which included types of 'ration cards' possessed by the households (denoting whether the household is officially classified as AAY, BPL or APL household) and quantities of food-grains (rice and wheat), sugar and kerosene purchased under TPDS. The survey, however, did not collect any information on local open-market retail prices for commodities purchased under the TPDS, or the prices at which the quantities of above commodities were actually purchased from the FPSs. To compensate for this shortcoming, we have used secondary information on both TPDS and open-market prices. While for the former, we have relied on information provided by the respective state government departments for food and civil supplies (that are responsible for the TPDS), open-market price information is used from the city-level monthly price data maintained by the Price Monitoring Cell, Department of Consumer Affairs, for the concerned commodities. To account for the fluctuations in the price-levels, average prices for the entire period of 2009-10 were used.

Table 1 presents summary statistics on certain key parameters for the study population, according to the respective cities. The household sample in Delhi is significantly better-off, both in terms of consumption expenditure as well as income, than the sample in Ranchi. Almost an equal proportion of workers in both the cities are engaged in informal employment (~86%), but based on the sectoral classification of the National Commission for Enterprises in the Unorganized Sector (NCEUS), a higher proportion of the workers in Ranchi (66%) are engaged in the informal sector than in Delhi (58%) (Unni & Naik 2011). Nearly 15% of the surveyed households in Delhi and 12% in Ranchi have at least one adult household member migrating into the city during the last 10 years. Proportion of working women, expressed as a fraction of the total household members, is higher in Ranchi than in Delhi. Surveyed households in Ranchi also tend to have lower educational levels on an average, and are of a larger size.

In terms of other indicators of living standards, nearly a third of the households suffer deprivations in terms of basic urban infrastructural facilities such as drinking water, sanitation and toilet facilities. Asset poverty is much higher in Delhi (34%) than in Ranchi (19%), while housing facilities tend to be poorer on an average in the latter. As for the TPDS coverage, more than 63% of the households in Ranchi and about 42% in Delhi have no access to TPDS provisions, as they do not have cards of any type. Both BPL and APL cardholders are significantly higher in Delhi, partly due to the higher proportionate coverage.

Identifying Poverty: Alternative Approaches

An important empirical concern in this study, akin to that faced by similar exercises to evaluate targeting performance of anti-poverty or social protection programs, is to decide on the appropriate welfare indicator that, in principle, would approximate the target group in line with the program's orientation, and serve accordingly as the reference scale against which actual targeting performance is to be adjudged. In essence, this involves identifying the indicator(s) which could most distinctively segregate the target group from the general population, unless some automatic inclusion criteria measured objectively forms the basis of the program targeting. As mentioned above, the discrimination in subsidized prices of the commodities distributed under the TPDS is on the basis of BPL-non BPL classification of households identified by the state agencies from independent assessments, unobserved by the researcher. A common practice, as an alternative, has been to use the official poverty lines to classify households into poor-non poor, and observe the TPDS classification (on the basis of type of ration cards possessed) of these households. However, such an approach is fundamentally incorrect as the poverty line, based on consumption expenditure, is only a valid indicator to estimate the size of (relative) poverty and not as an indicator for *identifying* the poor. A better approach is to involve a kind of proxy-means test, similar in spirit and content to the actual exercise followed under the 'BPL Census'. We adopt a similar approach to derive a 'summary' welfare indicator with which we examine targeting performance of the program. In doing so, we recognize recent work on multidimensional poverty indicators (Alkire & Seth 2008) involving indicators of deprivations in multiple dimensions. Alkire & Seth (2008) have calculated 'deprivation' indicators from the Indian National Family Health Survey (NFHS), matching them with indicators used in the BPL Census 2002. They have shown that the multidimensional indicator overcomes several shortcomings of the scoring-approach adopted in the BPL Census. In a related work, but employing regression-based weighting schemes, Jalan and Murgai (2006) have also criticized the scoring methodology which they found to lead to significant targeting errors (again, however, using consumption expenditure as the comparing 'standard' for identifying the poor).

Multidimensional indicator of poverty

Table 2 summarizes the variables or dimensional indicators that we have considered as components of the multidimensional poverty indicator. As a reference, similar variables that have been used in the latest BPL Census are provided in the first column. Following Alkire & Seth (2008), cut-offs or deprivation thresholds were considered for each of the individual indicators as mentioned in column 2. For certain indicators, the decision on fixing the cut-off categories was relatively straightforward. These included indicators for housing type, drinking water and sanitation, electricity and air quality. The education deprivation indicator is computed as a dichotomous indicator, denoting households where no adult member has completed more than five years of formal schooling as educationally deprived.

For livelihood deprivation a two-step procedure was followed. Firstly, all households having no adult workers with regular salaried/wage income were identified. To this, in the next step, households with self-employed or own account workers, but with incomes less than the household equivalent (total household consumption expenditure) to the consumption poverty line were added, to indicate households with vulnerable livelihood means, or having livelihood deprivation.

For asset deprivation, the earlier approach (Alkire & Seth 2008), has adopted a largely subjective approach to identify asset-deprived households on the basis of possessing certain pro-poor assets. Departing from this, we define asset deprivation as an outcome of three distinct classification approaches. First, two asset-classes, that can be conceived to lead to a sort of asset-poor and non-poor segregation was done on the basis of a principal component analysis of the asset ownership variables, and splitting them accordingly on the basis of the scoring matrix from the first component. Second, we observed the distribution of ownership of each individual asset, and then set an operational indicator of identifying more 'discriminating' assets, i.e., those owned by less than a third of the households. Households possessing none of these assets were identified as a second (intermediate) group of asset-poor. Third, we weighted possession of each asset by the inverse of the relative 'prevalence' in the population, i.e., by the proportion of households not possessing the assets. The aggregate score was split at its mean value to denote a third such group of asset-poor. Finally, we identify households that fall within the asset-poor typology, for each of the three approaches described above. These households we term and use as the asset-deprived households.

While using such individual deprivation indicators for different dimensions of living standards, the multidimensional poverty requires some form of aggregation of these component indicators[3]. The Alkire-Foster methodology argues for a threshold based on the number of deprivation/ dimensional indicators, but uses a rather arbitrary cut-off. Forexample, in the work cited above (Alkire & Seth 2008), households suffering deprivations on more than four dimensions (out of a total of 13 considered) were classified as multi-dimensionally poor. We review this in a related work (see footnote), but for our present analysis we prefer a relatively straightforward approach. Akin to the Planning Commission approach mentioned earlier to identify the poor households from the BPL census, we also put a cap on the number of poor households, as found by applying the official poverty lines on the consumption expenditure estimates on our household sample. The number of dimensions that corresponds most closely to the headcount rate thus obtained is set as the cut-off for identifying the multi- dimensionally poor. In this approach, the incidence of multidimensional poverty is pegged at the level of 'consumption' poverty, but allows identifying a different set of households as multi-dimensionally poor, irrespective of its location with respect to the consumption-based poverty line. In Appendix Table 1 and 2, we present a brief profile of the multidimensional poverty classification showing distribution of households for the number and type of the deprivation-dimensions considered, and as a rough comparison with the consumption indicator, average monthly per capita consumption expenditure for these individual deprivation classes. In the following section, the indicator of multidimensional poverty is employed in the analysis of targeting errors.

IV. RESULTS

A. Targeting Efficiency

1. Errors of Targeting

The literature on targeting errors of anti-poverty programs, including the family of targeted food subsidies is much due to Cornia and Stewart (1993), and elaborated considerably by the discussions in van De Walle (1998) and Coady et al. (2004). The common strand in these works, and also in the extensive body of empirical work (for a review see Coady et al. 2004) is to identify errors of inclusion and exclusion, referred as Type I and Type II errors. Inclusion errors (or Type I errors) refer to targeting errors of including non-target groups (e.g. non-BPL households) into the target group of beneficiaries (e.g. the BPL card-holders).

Some researchers refer to this error as leakage or diversions. Exclusion (Type II) errors occur when eligible beneficiaries are not included in the target group. A broader definition may include, particularly in the case of receiving entitlements of some form such as targeted food subsidies, individuals who have been 'excluded' due to not being classified in either groups: In our case this involves the poor households who do not have a 'ration card' at all. Both the errors denote weak targeting; however, it is believed that exclusion errors are of a greater concern, as often some amount of inclusion errors persist due to higher marginal (administrative) costs of removing non-target groups or due to political compulsions.

Before examining the errors in targeting, it is useful to observe the pattern of distribution of the TPDS cards across the households. As seen from Figures 1a-1c, nearly half the households do not possess any cards, with a higher proportion of no-card households in Ranchi (63%) than in Delhi (42%). Ranchi also has a lower coverage for the targeted groups (14% BPL and 7% AAY households) as compared to Delhi (30% and 4% respectively). Lastly, the profile of the different types of households (Table 3) in the two cities indicate that households with no cards tend predominantly to have a higher proportion of recent-migrating (within last 10 years) members, which probably explains lower coverage due to domiciliary requirements by the official agencies. However, in Delhi, the average consumption expenditure levels of these households are higher even than the APL households, which suggest that the no-card households in Delhi are not essentially of lower-economic status. BPL/AAY households in both the cities have a significantly higher proportion of household (working-age) members in informal employment and a significantly lower proportion in formal employment. Household size and demographic composition are found not to vary between the different groups of beneficiary and non-beneficiary households.

Analyzing the targeting efficiency involves observing how correct targeting of the 'coverage' under the TPDS is, i.e. what proportion of the target households (i.e. the multi-dimensionally poor in our approach) are covered under the BPL and AAY types of the entitlement cards; or how mistaken the coverage is through inclusion of the non-target group under these card types. Being a broader concept of targeting, the above schema also includes households that do not have any types of entitlement cards at all. We also include a subset of these errors – which we may term as classification errors nested within the targeting – limited to households having any entitlement cards, and examine how the cards held conform to their poverty classification in terms of the multidimensional indicator used. Tables 3a and 3b summarize the results.

Overall, the extent of targeting errors is substantial; 27% of inclusion errors and 56% of exclusion errors. Exclusion errors are also found to be much higher in Ranchi (65%) than in Delhi (47%), while a higher proportion of non-poor are incorrectly included in the TPDS program in Delhi (31%) than in Ranchi (17%). Limiting the size of targeting errors among the TPDS card-holders – the classification errors – leads to 19% of incorrect exclusion (poor households not having BPL/AAY cards) and 54% of incorrect inclusion. Again, the level of incorrectly identifying the non-poor households as BPL/AAY card entitlements is much higher in Delhi (54%). It thus appears that the system on which the identification of eligible target groups are based, is more biased towards a relatively disproportionate inclusion of the non- poor as the target group in Delhi, while in Ranchi it is more about leaving out the poor households. This is in line with the distribution of the TPDS cards across the different classes of beneficiary families; More than 63% of the households in Ranchi and 41% in Delhi do not have any of these cards. About a quarter of these 'no-card' households in Ranchi (22%) can be identified as poor in terms of the multidimensional indicator used. However, it does not seem that distribution of PDS cards (irrespective of the categories) in Delhi is biased against the poor, as a substantial majority of the households (91%) who do not have any type of PDS card are found to be non-poor.

In Figure 2, we plot the pattern of TPDS card-holding across the monthly per capita consumption expenditure (MPCE) deciles to see the progressivity in card-holding. For a well-targeted program, the curves would represent a step-function, with a prominent kink that denotes roughly the distinction mark between the poor and the non-poor, or the target group and the rest of the population. Contrarily, a weakly-targeted program will have a long, inelastic range which denotes that the identification of beneficiaries is rather independent of the welfare indicator chosen. As evident from the figure, TPDS is broadly progressive as proportion of households holding BPL or AAY cards falls steadily along with income (proxied through the MPCE deciles), and that for APL cards (and to a certain extent, for households with no cards) rises. However, no distinct break is noticed in any of the curves, which also indicates poor targeting.

An alternative way to assess targeting performance of distribution of TPDS cards is to examine the pattern of relative shares (and normalized shares) of different card types, once the population is segregated on some welfare criterion (Ravallion 2009)[4]. Ravallion (2009) suggests using some broad comparison groups, such as the poorest 40% against the rest of the population, and seeing how the share of entitlements conforms to the respective population share. For example in the case of the TPDS program, one may compare the relative share of the different TPDS card types with the population share. This measure we term as S. A related measure involves normalizing the share of entitlements with the population share, which we term as NS. Table 4 provides estimates of these two measures, where the households have been classified as MPCE terciles. Ideally, strong targeting through distribution of TPDS cards among households is indicated by a disproportionate share of BPL/AAY cards by the lowest one-third, or, a similar disproportionate share of APL cards by the highest one-third of the population. To an extent, that is evident as the lowest one-third of the population has 51% of the BPL/AAY cards (leading to a population-normalized share, NS, of 1.5). However, both S and NS for the highest tercile suggest that the concentration of APL cards is less-pronounced. In other words, judging by the NS values, and considering that the 1st and the 3rd terciles represent normatively the relevant target groups for BPL/AAY and APL type of cards respectively, it appears that the extent of exclusion errors (0.63) of the 'classification-type' (i.e., ignoring no-card holders) is higher than the inclusion errors (0.44). However, when adjusted for the population having no-cards across the terciles, the differential disappears. Nevertheless, the relative population-share approach highlights that the coverage of the existing system of TPDS through its scheme of differential targeting tends to be performing worse in terms of covering the poor as compared to preventing incorrect inclusion of the non-target groups.

2. Determinants of Targeting Efficiency

A simple starting point to consider incidence of targeting errors could be to consider these errors as purely random, or as administrative errors in identifying the beneficiaries which do not vary systematically with background attributes of the beneficiaries. These, however, are exogenous forms of influence on targeting errors; of greater interest is to look for any evidence on clustering of these errors based on observable socioeconomic, demographic or geographical characteristics. Before we attempt to decompose the targeting errors to identify the possible causes, it may be intuitive to examine how such errors vary according to these characteristics. In doing so, let us first consider the different deprivation dimensions that were considered while computing the multidimensional indicator which was used as a basis for estimating the errors. As seen from Table 6, exclusion errors are expectedly of greater magnitude for almost all the dimensional indicators. Put differently, households that suffer from deprivations in these attributes are more likely to be incorrectly excluded from being extended due coverage meant for the targeted groups – the poor households – under the TPDS. Naturally, as evident from the last two columns of the table, the size of the errors increases when the 'deprived' households having no cards at all are included. Again, certain dimensions, such as educational deprivation, livelihood deprivation, air quality or household environmental deprivation apparently exhibit a higher differential between the inclusion and exclusion error, which suggests that households suffering deprivation in these aspects of living standards are more likely to be left out while the entitlements under the TPDS are formalized through the distribution of cards. It may be noted, however, that these indicators are less conspicuous, or readily associated with household poverty in official assessments as compared to other more 'direct' indicators like household assets or housing conditions.

To further test such conjectures, while controlling for other potential confounders, we model the probability of targeting errors as a function of a vector of household attributes using three different specifications. In the first model, we allow for difference in the types of targeting errors (inclusion or exclusion errors) and employ a multinomial logit framework, where effects of the predictor variables on both inclusion and exclusion errors are separately and simultaneously observed. Here following the typology used above, we consider the errors of the 'classification' type, i.e. limiting the analysis to households possessing any type of TPDS cards. In the second specification, we additionally allow for targeting errors among those who do not possess TPDS cards – the broader form of targeting errors – and examine whether the parameter estimates vary significantly from those of the second model. In both the models, correct targeting (i.e. no targeting errors) serves as the reference category. As for the predictor variables, we employ a set of deprivation indicators, education and demographic variables (proportion of household members belonging to different age-sex groups; proportion of household members having formal, informal and self-employment; proportion of migrants etc.). All the models control for household consumption expenditure classes and city-fixed effects. Table 5 presents the results.

Households with a higher proportion of workers with informal employment as well as into self- employment have a higher likelihood of being incorrectly included – non-poor under BPL/AAY cards – in the TPDS program. On the other hand, inclusion errors are less likely among better educated households, those having a larger household size and with a higher proportion of elders. From the parameter estimates of Model 2, it also appears that inclusion errors are more likely among households with a higher proportion of children as well as those with a higher proportion of migrants. Considering the individual component indicators of the different dimensions of welfare considered in the multidimensional measure explained earlier, the estimates support the conjectures from the descriptive analysis of targeting errors above. Except for the dimensions of electricity and type of dwelling to an extent, households found to be deprived in terms of these individual attributes are significantly more likely to face exclusion errors, once direct welfare measures (consumption expenditure) are controlled for. When the broader notion of exclusion errors is considered, the pattern remains largely similar with an intensification of the effect of the deprivations in the case of household assets and drainage, and a reduction in the strength of the association for educational and livelihood deprivation. Again, due to the high majority of migrant households without any cards, exclusion errors when broadly defined are higher in households with more migrant members. The significance of the association for the independent variables was confirmed by likelihood-ratio tests.

The findings suggest that risk of imperfect targeting resulting in targeting inefficiency can be much explained by failure to capture the multiple deprivations in living standards faced by a household. Particularly for the exclusion errors, more than educational levels, duration of stay in the city or employment patterns of household members, deprivations in living conditions emerge as significant explanatory factors of such errors.

3. Differentials in Utilization of TPDS

While in the previous sections, the errors in targeting – failure to identify the targeted beneficiaries while distributing the TPDS cards – are discussed, it is in order to examine how the utilization patterns vary according to the TPDS card types possessed by the households and by basic welfare indicators independent of the card types. A third approach could be to compare the utilization of the TPDS, combining the other two classifying approaches, which may yield further understanding on whether the errors in targeting get reinforced through disproportionate utilization, or, stand corrected.

We start by examining the degree of utilization across different card-holder groups. The errors in targeting may be minimized if the imperfectly identified households, e.g. non-poor households with BPL cards, are found not to exercise their cards by purchasing the commodities at the subsidized and differential prices. From Figure 3 it can be seen that nearly two-thirds of the households with APL cards did not use their cards to make any purchases of food-grains. For Ranchi, only about 4% of these households purchased food-grains from the fair-price shops. 90% of the BPL card-holder households made some purchases during the previous month, and a marginally lower extent (about 85%) of the AAY households did so. Based on the multidimensional poverty indicator, it is seen that a significantly higher proportion of the poor households actually made purchases of food-grains under TPDS, as compared to the non-poor families. In general, utilization rates were much higher in Delhi than in Ranchi which indicates a better implementation of the program in Delhi, involving aspects like regularity in opening hours of fair- price shops.

Figure 4 plots the levels of utilization, or quantities purchased of different commodities (rice, wheat, sugar and kerosene) provided under the TPDS by different card-holder groups. The quantities are based on purchases made by the households in the last month preceding the survey. It is evident that despite the targeting errors, utilization of TPDS is progressive. APL households purchase significantly less of all the commodities as compared to the BPL and AAY households. Between the two target-group categories of BPL and AAY households, utilization differs as well. BPL households are found to purchase less rice, but more wheat, sugar and kerosene than AAY households[5]. Between the cities, significantly different utilization patterns could be noticed across the three categories of card-holders. Purchase of both wheat (8 kgs.) and rice (3 kgs.) by APL households in Delhi was much higher than their counterparts' in Ranchi (with less than one kilogram of both wheat and rice purchased by an average APL household). While a possible explanation could be the considerable difference in economic ability of the APL households in these two cities – MPCE for APL households in Delhi is about 70% more than that in Ranchi – it is also observed that economically weaker APL households in Delhi (by both MPCE and the multidimensional poverty indicators) purchase significantly more than the better-off APL households, given the substantial difference between the open-market price and subsidized TPDS price of food-grains.

The utilization figures for both wheat and rice follow a similar progressive pattern when we consider the levels of purchased quantities by the households ranked according to MPCE deciles, irrespective of the TPDS groups they fall (Figure 5). For both the cities, the inflexion points in the utilization curves are visible from about the median point of the consumption expenditure distribution. A similar pattern of a significantly higher utilization among the poor households, based on the multidimensional index, is also seen (results not reported) for both wheat and rice, and in both the cities.

To what extent do the targeting errors influence variance in utilization of TPDS by different household-groups? The welfare impacts of targeting errors, through differential utilization or purchases of food-grains under the TPDS, can be substantial if incorrectly identifying target households in the non-target category leads to lower utilization. On the other hand, particularly in the case of inclusion errors, the welfare loss in terms of imperfect targeting can be offset, if the non-poor households mistakenly classified under the BPL/ AAY category access the TPDS provisions to a lesser extent as compared to the 'correctly targeted' – the poor-BPL/AAY households – group. As evident from Table 6, imperfect targeting does not seem to be much of a concern so far as relative utilization levels are concerned. The shaded columns represent the targeting errors; Col B and Col F denote the exclusion errors and Col C and Col G denote inclusion errors. For the welfare-loss offsetting condition, the 'inclusion-error group' must have lower purchases than the BPL/AAY households. Additionally, it is desirable that the 'exclusion-error group' also purchases more than the APL households. Such a pattern is indicative of self-targeting. Irrespective of the TPDS classification, targeted BPL/AAY households purchase significantly more than the APL households. In both the cities, such a phenomenon is clearly identified. From Panel A of the Table, it can be seen that utilization rates are significantly higher among the poor households, and also among the 'targeting-error' groups; the utilization rates are about half among the 'inclusion-error' households and double among the 'exclusion-error' groups, as compared to the correctly identified groups in the BPL/AAY and APL groups respectively. The figures for average purchases made (Panel B), reiterate similar differentials, with the non-poor households having BPL cards actually purchasing much less and poor households with APL cards purchasing significantly more than their respective comparison groups constituting the correctly classified, or 'non-targeting error' households. Taken together with the utilization pattern across economic classes, this indicates that targeting inefficiencies through improper targeting do not significantly affect utilization of the TPDS, both in the extent or levels; rather a self-targeting mechanism has a higher influence on TPDS purchases.

4. Implicit Income Transfers due to TPDS

Following Radhakrishna et al (1997), we may define the implicit income/subsidy transfer or the income gain to a household from TPDS as the difference between the expenditure that the household would have incurred in the absence of TPDS and the actual expenditure under TPDS. It can be simply calculated by multiplying the quantity of purchases from TPDS with the difference in the open-market and TPDS prices. Hence income gain, can be expressed as

$$\Delta y_{ij}^{c} = q_{ij}^{c}(p_{m}^{c} - p_{rij}^{c})$$

Where is the quantity of commodity c consumed by the ith household having the TPDS card-type j (i.e. AAY, BPL and APL cards) at price p_{rij}^{c}. The open-market price for the commodity c, p_{m}^{c}, is the same across all card-type households. The total gain or size of the income transfers is obtained by summing 'y' for all commodities. The absolute value of the income gain would be high if:

i. the relative price – the difference between open-market and TPDS prices – is high, and/or
ii. quantity consumed is high.

The household survey data provides us information on only the quantity consumed. We compensated for this using TPDS pricing information available from the Food and Civil Supplies Departments for the state governments of Delhi and Jharkhand. For the open-market prices, we used price data maintained by the Price Monitoring Cell, Dept. of Consumer Affairs, Ministry of Consumer Affairs, Food and Public Distribution[6] for the study-cities, taking the average of the annual prices in 2009 and 2010. The implicit income transfer estimates thus computed is presented in per capita terms. For the calculations we consider wheat, rice and sugar, and present separate estimates for food-grains. To examine how the extent of income transfers vary according to economic status, card-holding patterns and household poverty, average subsidy for the relevant comparison groups are computed. Results are presented in Table 7.

On an average, an amount of Rs 52 per household member per month could be made available to the household through the TPDS. Considering only the food-grains, the amount works out to be about Rs 45. The difference in the implicit income transfer due to food-grains is not substantial between the two cities (Rs 46 and Rs 41 in Delhi and Ranchi respectively). If we consider the income transfer due to TPDS purchases of food-grains by the household and express it as a proportion of per capita household consumption expenditure on food (last column of table 7), it can be seen that TPDS income transfers could account for about 10% of the food expenditures of the average household, which can be viewed as an approximation of the net consumer subsidy accruing to the households participating in the TPDS.

The aggregate figures, however, mask important variations when the group-differentials are observed. Much due to higher proportional utilization, the size of both the income transfer for food-grains as well as the 'net subsidy' is significantly higher among the AAY and BPL households, as compared to the APL households. The income transfer gap is also significant, and pro-poor, when the multidimensional deprivation-based poverty indicator is considered. Such a definite gradient is not identifiable when we consider the MPCE decile classes. Up to the 8th decile, the size of the income transfer varies irregularly; for net subsidy there is a gradual decline while moving towards higher deciles, but with a flatter slope. Nevertheless, much along the similar lines of inference possible after considering the levels and patterns of TPDS utilization, the distribution of implicit income transfers across welfare classes indicates a degree of progressivity. However, even for the poorest or the most-deprived groups, the income transfer is found to account for less than a quarter of the household's food expenses, which is suggestive of an impact of low or moderate intensity.

An alternative way of analyzing the incidence of the consumer subsidies[7], or commenting on their relative impact, is to consider the targeting errors and estimate the hypothetical welfare gains possible if such errors are eliminated. Accordingly, we observe the variation in the levels of the subsidy or the standardized income transfers after cross-classifying households from the point of the targeting errors. As evident from Table 8, there are definite losses due to imperfect targeting. Correctly classified AAY and BPL households receive a fairly higher amount of subsidy income (18%), than those who were incorrectly classified as APL households (the exclusion error group - 4%). On the other hand, (non-poor) households who were mistakenly classified as APL gain much more (14%) than the correctly classified APL families (3%). Clearly, through a better targeting efficiency, the incidence and impact of the subsidy incomes on the target-group i.e. the poor households can be improved upon.

Additionally, it can reduce the 'leakages' where due to inclusion errors, non-poor households receive an undue proportion of the subsidy income.

To illustrate the hypothetical scenario of possible welfare gains arising from such improvement in targeting efficiency, we suppose that the targeting errors are somehow eliminated. Under naïve assumptions, we ignore the costs associated with better targeting. We further assume that households continue to purchase the same quantities of food-grains, even though their TPDS card-class types changes, and accordingly, the prices. The results are in the Panel B of Table 8. A direct fallout of improving targeting efficiency is that the subsidy difference – difference between the subsidy income accruing to the target groups (with or without targeting errors) and non-target group – increases from about 5% to 8%. However, the size of the implicit income transfer reduces for the 'new' BPL/AAY card-holders and increases for the 'new' APLs[8]. To correct this apparent anomaly requires separate assumptions on the other determinant of the subsidy income size, the quantity of purchases. A straightforward correction may involve allowing the imperfectly targeted households – both among the poor and non-poor – to have similar purchasing levels like their peer-households, i.e. the non-poor households wrongly allocated as AAY/BPL households are assumed to have the purchasing levels of the non-poor households who have been correctly assigned under TPDS to the APL group and vice-versa. The price-correction applied in the previous scenario is kept unchanged. As seen from Panel C, the results are dramatic. As a result of the combined effect of both price and quantity corrections through the simulations, subsidy income, both in absolute size as well as the standardized proportional figures are significantly revised. The standardized subsidy increases to 17% for the 'new' AAY/BPL families, with the size of the income transfer pushing up to Rs 64 per month; for the 'new' APL households the corresponding figures are 3% and Rs 17 respectively, both being desirable changes from the base (present) or the 'price-correction' scenario.

5. Poverty-reducing Impacts of TPDS

The poverty reducing impact of the TPDS follows from the notion of implicit income transfers made available to the households purchasing commodities under the TPDS. The impact is essentially a counterfactual scenario, where the subsidy incomes increase the income/consumption expenditure of the household relative to the poverty line, thereby leading to a fall in the headcount rate. Additionally, if one considers the distributional measures of poverty in terms of the conventional Foster-Greer-Thorbecke FGT class of poverty measures, subsidy income transfers also have the potential to influence both the depth and severity of poverty, if the utilization or purchasing patterns of the poor households are not uniform. To examine the magnitude of the reduction in the poverty rates, the subsidy incomes are added to the household consumption expenditure to calculate post-transfer expenditure levels, but keeping the poverty lines intact. Table 9 provides the estimates of both pre and post-transfer poverty rates for Delhi and Jharkhand.

separately, as the poverty lines for these two cities are different. To minimize coverage problems and measurement errors, the subsidy income transfers are limited to food-grains, and hence, can be considered to provide a lower-bound of the poverty impact due to TPDS.

Primarily due to higher coverage and levels of utilization of TPDS, poverty reduction due to TPDS subsidy income transfers are sharper in Delhi than in Jharkhand. The relative fall of the headcount rate is about 21% in Delhi - from about 15% to 12% - and by 17% in Ranchi (11% to 9%). Comparing other FGT class measures with pre and post-transfer levels also provide interesting information. The FGT(1) indicator, better known as the poverty gap index adds up the extent to which individuals on average fall below the poverty line, and expresses it as a percentage of the poverty line. As an indicator of the 'depth' of poverty, this indicator suggests that an average household below the poverty line in Delhi has 'moved up' by about 25% (24% and 25% in Delhi and Ranchi respectively), with a marginally better performance in Ranchi. From an alternative explanation, a fall in the poverty gap index can also be thought of as reducing the poverty gap – average shortfall or the minimum income required to push a poor household to the poverty line threshold – via the subsidy income transfer. From this viewpoint, the TPDS transfers are found to have a moderate poverty impact, as they almost pull up an average poor household by a quarter of its shortfall from the poverty line. The last indicator from the FGT family, the squared poverty gap index (F (2)) provides the magnitude of the severity of poverty, or in other words, inequality among the poor. A reduction in the severity measure suggests that the poorest of the poor gain disproportionately more from the income transfer relative to other 'better-off' households below the poverty line. As seen from the table, severity of poverty is found to reduce by 27% in Delhi and 24% in Ranchi which augurs well for the subsidy income transfers due to TPDS having a higher relative incidence among the households lying farther from the poverty line.

As we have found in the preceding section on subsidy income transfers due to TPDS purchases, that since both the size of the transfer as well as the standardized subsidy transfer over household food expenses vary according to household economic status, understanding poverty impacts of the subsidy transfers requires further analysis to comment on other household attributes that influence 'participation' behaviour in the TPDS program, and in turn, the impact on household poverty status through the implicit subsidy income transfers. Again, given the coverage of the TPDS program is much skewed with a considerable proportion of the households below the poverty line failing to be covered under the program, assessing the poverty impact of the program requires specifically controlling simultaneously for both participating in the program as well as the quantum of purchases made[9].

A few alternative identification and empirical specification strategies are available for the above problem. Recent literature on program impact evaluation suggests avoiding this predominantly 'missing- data' problem through statistically matching program participants and non-participants to construct relevant counterfactuals, and then comparing outcome indicators (such as net income gains) among these comparable groups. However, this approach relies on certain assumptions, most important among them being the condition of 'selection of observables' i.e. to identify a vector of attributes that explains both program participation and outcomes, to construct 'propensity scores' for all households; and to conduct matching among the participant and non-participant households using these propensity scores. A conceptually similar, but with fewer restrictions on the specifying form is the two-part selectivity model due to Heckman (Woolridge 2009, Cameron and Trivedi 2009). In practice this involves estimation of a selection equation – determinants of program participation – and, in the next step, regressing the outcome (subsidy income transfers in our case) on the factors associated with them. If one fails to reject the null hypothesis that the two estimating equations are non-correlated, or in other words the Inverse Mills Ratio is non-significant, it may be concluded that sample selection is not a problem and proceed estimating the equations through other estimation strategies. Once selectivity concerns are eliminated, for a problem similar to that we face, with a large number of 'missing' observations due to low coverage of the program, censored regression models are considered appropriate (Woolridge 2009). These models are also less restrictive in their assumptions and can be accounted for during the estimation.

Accordingly, we begin with the two-part Heckman selection models. Our principal variable of interest is the subsidy income transfer (we consider the food-grains component for reasons stated earlier) received by each household. Clearly, due to non-participation in TPDS, this variable has missing information for 49% of the observations. Further, another 15% of the households although technically 'participating' in the program (i.e. having TPDS cards) do not make any purchases, and thus, need to be distinguished empirically from the non-participant households in our identification strategy. For the set of predictors, the choice of variables is much guided from the earlier specification for the determinants of targeting errors, with a few amendments. Foremost, as we have seen significant differentials in food-grains purchasing behaviour across the different TPDS card-class of households, the card-type possessed by the household needs to be included as an explanatory variable. Demand for the TPDS-provided food-grains, through the quantity purchased is of direct bearing on the size of the transfers received. If we think of the price factor as controlled through the card-type possessed by the household, the consumption patterns and preferences of the households need to be accounted for. This may be achieved through including the proportion of food expenses out of total household consumption expenditure as a predictor, with the underlying premise that following Engel's Law, poorer households will have a higher proportional expenditure on food-grains and in turn, be hypothesized to have a higher reliance on subsidized provision of food-grains through the TPDS. Naturally, a significant positive relation with this variable is expected with the outcome variable. To assess the relative incidence of the subsidy transfers across certain other background attributes of the households, particularly the deprivation indicators discussed earlier, inclusion of these variables and examining the pattern of influence is needed. Lastly, allowing for distinctive utilization patterns across the two cities, we estimate separate models on the individual city-samples. To minimize the skewness of the subsidy transfer distribution, we employ a logarithmic transformation of the dependent variable. For both the city-samples, the results indicate the inverse Mill's Ratio λ to be non- significant, which suggests that there is no sample-selection problem.

Once selectivity issues are ruled out, we require applying adequate corrections in the estimation model for the nature of distribution of the dependent variable. Given the extent of lower-censoring of observations for non-participants at zero, a Tobit specification is considered appropriate (Woolridge 2009). However, to distinguish between the non-participants and non-purchasing TPDS card-holders in the lognormal outcome variable, the observations pertaining to the latter group are set to zero, while those of the non-participants at the censoring limit, γ. To control for violation of the homoscedasticity condition we report heteroscedasticity-adjusted robust standard errors as suggested by Woolridge (2009). Table 10 presents the parameter estimates of the models. For each of the city-equations the Ordinary Least Squares (OLS) coefficients are also reported, which highlights the added gains from using the censored-regression framework instead of treating the zeros as observations from the same underlying data-generation process like the other positive outcomes.

Certain broad inferences follow from the parameter estimates in the city-sample models. Demand-side factors, standardized for need through the 'food expenses as a proportion of MPCE' variable are significant for the Delhi sample, which suggests that in Delhi, poorer households gain more from the subsidy transfers. A similar pattern could not be observed in Ranchi. However, for both the cities, a strong positive association is established with the card-type possessed by the households; those with BPL or AAY cards receive nearly four times higher transfer incomes through TPDS purchases, as opposed to households with APL cards. Again, highlighting the poor coverage of TPDS among the migrant households, these households are found to receive significantly less subsidy transfers (by about 16% in Ranchi and 33% in Delhi). Among the demographic variables, larger-sized households in Ranchi receive marginally less, while those with a higher proportion of elders receive higher transfer incomes. A similar association with demographic parameters could not be established for Delhi. As seen from the results above, livelihood and employment patterns have a significant influence on the subsidy transfers a household receives from TPDS. For example in Delhi, households with a higher proportion of women in income-earning activities receive higher income transfers, while those with more members in formal employment receive considerably less. The latter group of households is more likely to be better-off due to higher and regular wages in the formal sector and the results reiterate the possibility of a self-targeting mechanism in operation which discourages these households from purchasing more from the TPDS, and thereby standing to receive higher income transfers. A slightly surprising result however is the non-significant coefficients on the livelihood deprivation indicator variable.

The coefficients of the multidimensional indicators, however, provide a cautionary note on the indicative inferences so far that the TPDS is possibly faring well by directing a proportionately larger share of the implicit subsidy transfers towards the poor, or the target groups. Considering the Delhi sample, which has a higher number of uncensored observations and is more likely to yield robust associations, households suffering deprivations in terms of assets, drinking water and drainage indicators are found to receive a lower extent of the subsidy transfers. This is most likely an indication of imperfect targeting and suggests the potential losses due to leakages and under-coverage of the target groups. However, households with lower educational levels can be seen to receive higher transfer incomes, possibly due to a higher association of this dimension of human development with the section of the target-groups of poor households that were correctly classified and hence, were enabled to benefit from the subsidized and differential prices.

Broadly, the results of the Tobit model suggest that the proportional incidence of the subsidy transfers is moderately progressive. Nevertheless, due to the inclusion and exclusion errors explained largely by the failure of the targeting system to adequately account for the multidimensional deprivations, the income transfers and consequently their impact on poverty reduction is less than the extent possible.

V. Summary and Conclusions

This paper, from the perspective of the need for provisioning adequate social protection coverage to the vulnerable sections of population in urban India, assesses the role of the TPDS in reaching out to the deprived groups and, through implicit income transfers, influencing positive welfare outcomes. By providing food-grains to identified target-group of households at subsidized prices, the TPDS has the potential to divert the 'surplus' household income to other non-food domains such as education and health, having direct impacts on improving living standards. From a precautionary motive, the income thus saved can be also thought of as potential insurance against idiosyncratic shocks befalling the household. Further, in a scenario of volatile food-prices, TPDS acts as an additional safeguard protecting vulnerable households against the price-shocks through highly subsidized prices. Much however, rests on how efficiently the program is targeted towards the households in the greatest need of such social protection mechanisms. The present research, drawing on recent household survey data, adds to the growing literature on the effectiveness of targeted social protection mechanisms in the developing world by providing evidence on how well the TPDS is targeted towards the poor in selected Indian cities and quantitative estimates on the possible poverty-reducing impacts arising out of such implicit income transfers.

Quite a few studies have documented the extent of targeting errors plaguing the TPDS in India, and suggested the leakages and under-coverage arising out of the imperfect targeting system as an impediment in realizing the desired objectives of the program. Following a different identifying strategy based on multidimensional deprivations suffered by vulnerable households, distinct from income or consumption-based measures alone, we too find substantial errors in targeting. On considering the broader notion of coverage across the entire population, exclusion errors are substantial (nearly half the poor households), partly owing to the low coverage rates of TPDS in the two cities studied. Only about half of the surveyed households on an average were found to possess any of the TPDS cards, with a much higher extent of under-coverage in Ranchi. Limiting to the targeting errors of a mis-classification nature, i.e. incorrect identification of the priority household-groups within those that have been provided with these cards, leads to the finding that a disproportionate number of non-poor households (54%) were incorrectly classified under the AAY or BPL categories, with a lower proportion of poor households (19%) incorrectly provided with APL cards. However, once the magnitude of the errors are adjusted for the relative population share of the poor and non-poor households, the existing system of TPDS appears to be performing worse in terms of preventing incorrect exclusion of the poor households from the targeted card-classes (AAY/BPL cards), rather than preventing leakages through mistakenly including non-poor households into these card-class types.

However, actual utilization levels and patterns across the households covered under TPDS suggest a better, progressive pattern. With indications of a form of self-targeting mechanism, presumably through provision of poorer quality of food-grains or placing higher indirect costs through waiting-time and other transaction costs, purchasing patterns of food-grains and sugar under TPDS by the households have a distinct pro-poor gradient. The poor households, irrespective of the card-types they possess, are found to use their cards to make purchases more often, and in higher quantities than the non-poor. Incorporating the targeting errors in the analysis of the utilization patterns provides encouraging results: targeting inefficiencies in distributing the TPDS cards amongst the households does not much affect the purchasing patterns between the poor and non-poor households; contrarily, the results support the premise that due to the possible self-targeting component, much of the potential welfare-loss due to incorrect targeting is offset through a differential utilization pattern across the households.

Since the magnitude of the subsidy incident on the users, through the implicit income transfers, depends considerably on the quantities purchased under the TPDS, apart from the open-market and subsidized TPDS price-differentials, a pro-poor purchasing pattern can be expected to translate to a higher relative incidence of the subsidy transfers on the poor households. As we found earlier, the subsidy differential between the poor and non-poor households is modest, but rather low in absolute terms. Leakages to non-poor households lead to a transfer of about Rs 43 per capita per month due to food-grains purchases to these households as against Rs 56 to a poor household; clearly the gains could be much more if targeting is improved. From the precautionary perspective of TPDS as a social protection measure, its adequacy is also found to be a shortcoming: even for the poorest of the households, subsidy transfers due to TPDS only accounts for less than 20% of the average food expenses of the household.

Adjusting for the targeting errors, we find the net subsidy difference standardized for consumption patterns between the target and non-target household groups to be about 5%. However, results of our simulations indicate that there can be substantial welfare gains once the errors are eliminated, through the combined effects of price-differentials and changes in the demand-patterns. Under conservative assumptions, such changes can lead to a net subsidy difference of about 14%, with a much higher proportionate incidence of the subsidy transfers on the target group of AAY/BPL households. With clear policy-implications, the simulation results promise significant welfare gains through better targeting efficiency of the current TPDS program. Although it is tempting to extend the simulations to possible scenarios of higher coverage among the households (say with 80% coverage as against the ~50% mark for the study cities presently), it involves wider assumptions on the demand functions of the households. A related, and much debated issue of universalization – dismantling the identification of target-groups and differential price system in the favour of a single, uniformly subsidized price system – also could not be commented upon on similar grounds of required assumptions and data. Particularly in the absence of adequate supply-side data on the costs involved – either in terms of reducing the errors, or increasing coverage, or both – it is not possible to comment on the gains from reforming the present program, an exercise that goes beyond the scope of the present paper.

The subsidy transfers can be thought of as a counterfactual income, and hence having an impact on the incidence of relative poverty. Accordingly, we find moderate levels of poverty reductions attributable to the TPDS income transfers. In both the cities poverty headcount rates fall; 21% in Delhi and 17% in Ranchi. In terms of the depth of poverty, TPDS transfers are found to be able to pull up an average poor household about the quarter-mark towards the poverty line. Lastly, the implicit income transfers also contribute towards reducing the inequality in the income-distribution among the poor households, with clear benefits to the poorest of the poor. In the multivariate analysis that followed, we account for the skewed coverage of the program while assessing the relative degree of the income transfers received by the households, to again find evidence of a moderate degree of pro-poor orientation of the program. However, the results provide a caution that identifying the target group has a crucial bearing on the scale of the program impacts – both in terms of reducing poverty as well as acting as a safety-net – and ignoring the multidimensional nature of the deprivations may compromise the potential welfare gains of the program.

Being one of the largest targeted food-based subsidized social protection schemes globally, much of the success of TPDS hinges on its targeting efficiency and coverage extended to the vulnerable groups of the society. In an urban setting, the challenges of livelihood and urban living introduce newer vulnerabilities and deprivations to the poor. Proper identification and targeting through the TPDS can act as an effective social protection mechanism, as the discussion above suggests, and lead to maximum gains to the poor.

Notes

1 In principle, the prices of subsidized food-grains are fixed with reference to the Central government's 'economic cost' – cost incurred by Central agencies in procuring and storing the grains. The state premiums are mostly 'transaction costs' – involving transportation and distribution of the allotted food-grains through the FPSs. Under the TPDS, the subsidized (retail selling) prices for the BPL families are typically at half the economic costs, while the APL households are supplied at the economic costs.

2 The poverty lines determined by the Planning Commission are on the basis of national sample surveys on consumption expenditure. For details on the methodology of computing poverty lines in India see Planning Commission (2009).

3 Observing the individual deprivation indicators and examining their association with other more common and direct indicators of welfare such as consumption and income is interesting and reveals how these

indicators highlight deprivation that surpasses the income or consumption based poverty thresholds. We consider these aspects and present a detailed analysis in a separate exercise.

4 Although Ravallion (2009) has used these indicators of targeting performance in terms of the share of actual transfers or subsidies going to the poor (or the target group), we consider it informative to apply the concepts in assessing the distribution of entitlement-eligibility norms or identifiers, since, the nature of TPDS and evaluating targeting performance of the actual income transfers or subsidies is strongly contingent on the types of entitlement identifiers, the TPDS cards in this case, a household possesses.

A similar exercise using the income transfers as the dependent variable is carried out in the analysis that follows subsequently.

5 Notably the price differentials between BPL and AAY households are in place only for wheat and rice (see Appendix Table 1 for details on process for each commodity for different card groups), and so we restrict the analysis only to these two food-grain commodities.

6 http://fcainfoweb.nic.in/pms/average1_web.aspx

7 A distinction may be made here of the sense in which we use the concept of subsidy, or the net consumer subsidy due to TPDS, from the general notion of subsidy which involves adjusting the estimates for supply-side costs (procurement, distribution etc.) incurred by the governments. In the present exercise we use the term net consumer subsidy which is conceptually closer to the implicit income transfers adjusted for differences in food expenses across households or more correctly, the counterfactual income earned due to the difference in the open-market and subsidized TPDS prices for the commodities purchased.

8 This is primarily due to the fact that removal of targeting errors also reduces the absolute size of the different card- class households; from about 58% of the card-owning households possessing either AAY or BPL cards, removal of inclusion error brings it down to about 15% (which is, by definition, almost equal to the size of headcount poverty rate). Since this meant that a considerable number of households, under the hypothetical scenario were made to face higher prices than the base (present) scenario, only a few households faced lower prices.

9 It may be noted in this regard that given the considerable under-coverage of the TPDS program (roughly covering about half of the sample households), income gains through the implicit subsidy transfer are limited to a narrow range of the income (or consumption expenditure) distribution. Hence, the Cumulative Density Functions (CDFs) of the pre- and post-transfer expenditure curves overlap for a long range of the distribution, in turn influencing dominance properties of the post-transfer expenditure. Limiting the above exercise only among participating households runs the risk of ignoring any selectivity patterns in the program coverage and leading to biased estimates of the poverty impact.

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Table 1: Summary Statistics of Key Indicators

Attributes	**Delhi**	**Ranchi**
Proportion of female-headed households	7.8%	7.1%
Head illiterate	16.7%	18.6%
Head with no formal schooling	4.5%	1.7%
Head with primary educ.	12.0%	12.8%
Head with middle-school educ.	17.3%	16.8%
Head with secondary educ.	21.4%	26.3%
Head with sr. secondary educ.	14.4%	10.3%
Head with graduate/PG educ.	13.6%	13.5%
Household size	4.7	5.4
% of household members in Informal Employment	19.3%	19.0%
% of household members in Formal Employment	4.7%	3.3%
Consumption-Poverty Line (Planning Commission 2009)	642.47	531.35
Monthly per capita consumption expenditure (MPCE) (Rs)	1685.138	1014.256
% of household members in Self-Employment	3.7%	1.9%
Monthly per capita Household Income (All sources) (Rs)	2909.484	1678.911
% of Children	27.2%	5.7%
% of Elders	4.6%	31.3%
% of Working women	29.7%	44.1%
% of Migrants (expressed as a % of household members)	39.9%	47.5%
% of households with any member migrating during last 10 years	15.4%	11.8%
Food expenditure as a prop. of MPCE	54.2%	21.6%
Asset deprivation indicator	34.4%	19.0%
Air quality deprivation indicator	21.8%	40.0%
Drinking Water source deprivation indicator	28.5%	67.5%
Household drainage deprivation indicator	28.5%	33.9%
Electricity deprivation indicator	8.0%	13.7%
Household type deprivation indicator	3.7%	25.6%
Education deprivation indicator	48.0%	58.3%
Livelihood deprivation indicator	38.0%	50.8%
Child deprivation indicator	10.1%	11.6%
Household has AAY card	3.7%	7.2%
Household has BPL card	30.2%	14.4%
Household has APL card	24.4%	15.2%
Household has no card	41.7%	63.2%
Number of households (N)	**2020**	**978**

Table 2: Component Indicators and Cut-offs for Multidimensional Poverty Indicator

SECC-2012	IRMA-IHD Survey	Dimension	% Deprived
1. Educational status	1. Education deprivation (If max. years of education completed by any member is less than 5 years)	Education	51.3
2. Main source of income/earnings/regular wage earnings by household members	2. Livelihood vulnerability (If any adult working-age member is employed as either unpaid family worker or casual wage labour or as an own account worker with wage income less than 'household' consumption poverty-line level).	Livelihood	42.2
3. Disability	Not available		
4. Caste/tribe status	Not considered		
5. Housing condition (wall/roof material)	3. Housing deprivation (if lives in kutcha house)	Living standard-Housing	10.8
6. Number of rooms	Not considered		
7. Ownership status of house (owned/rented/shared/ employer provided)	Not considered		
8. Source of drinking water	4. Deprivation of access to safe drinking water (not piped water – unprotected well/spring, river, dam, lake, ponds, stream, tanker truck, bottled water)	Drinking water	41.2
9. Source of drainage	5. Deprivation if household does not have any drainage facility	Sanitation - drainage	30.3
10. Type of toilet (whether water-closet type)	6. Deprivation in sanitation dimension if household uses any one of -pit-latrine (no slab), no facility (uses bush, fields), composting toilet, dry toilet.	Sanitation- toilet	68.2
11. Source of lighting	7. Deprivation in terms of electricity connection	Living standard-Electricity	9.8
12. Whether has separate kitchen	8. Deprivation in air quality if household has no separate kitchen and uses any one of coal, lignite, charcoal, wood, agri-crop, animal dung etc. as fuel source	Air Quality	27.7
13. Asset ownership	9. Asset deprivation	Asset	29.4
14. Chronic illness	Not included		
	10. Child deprivation (any incidence of child labour and at least one child aged 5-14 who doesn't attend school)	Child status	10.6

Table 3: Inclusion and Exclusion Errors (%)

Card Types	Delhi			Ranchi			Overall		
	Non-poor	**Poor**	**Total**	**Non-poor**	**Poor**	**Total**	**Non-poor**	**Poor**	**Total**
Antyodaya	3.58	4.46	3.66	5.66	11.86	7.16	4.18	8.45	4.8
card BPL card	28.16	48.51	30.2	11.73	22.88	14.42	23.4	34.7	25.05
APL card	25.8	11.88	24.41	17.12	9.32	15.24	23.28	10.5	21.41
No card	42.46	35.15	41.73	65.5	55.93	63.19	49.14	46.35	48.73

Classification errors	**Non-poor**	**Poor**	**Non-poor**	**Poor**	**Non-poor**	**Poor**
Antyodaya card	6.21	6.87	16.41	26.92	8.22	15.74
BPL card	48.95	74.81	33.98	51.92	46.01	64.68
APL card	44.84	18.32	49.61	21.15	45.78	19.57

Table 4: Relative Shares and Normalized Population Shares of TPDS Card-classes across MPCE Deciles

Expenditure (MPCE) classes	Share of different TPDS cards across expenditure classes (S)			Share of different TPDS cards across expenditure classes normalized by population share (NS)		
	AAY/BPL Cards	***APL card***	***No card***	**AAY/BPL Cards**	***APL card***	***No card***
Lowest third (1st tercile)	51.51	21.03	27.65	1.544	0.630	0.829
Middle third (2nd tercile)	33.97	34.11	32.58	1.020	1.024	0.978
Highest third (3rd tercile)	14.53	44.86	39.77	0.436	1.346	1.194

Table 5: Results of Multinomial Logit Model for Determinants of Targeting Errors

	Model 1		Model 2	
	Inclusion Error	**Exclusion Error**	**Inclusion Error**	**Exclusion Error**
Female-headed household	1.129	0.704	1.140	1.300
	(0.270)	(0.491)	(0.221)	(0.492)
Head with no formal schooling	1.002	0.077**	0.805	0.324**
	(0.304)	(0.089)	(0.218)	(0.153)
Head with primary educ.	1.010	0.288**	0.908	0.751
	(0.219)	(0.160)	(0.168)	(0.223)
Head with middle-school educ.	1.020	0.529	0.949	0.800
	(0.211)	(0.304)	(0.166)	(0.250)
Head with secondary educ.	0.654**	0.555	0.742*	0.867
	(0.140)	(0.304)	(0.130)	(0.275)
Head with sr. secondary educ.	0.376***	0.526	0.551***	0.520
	(0.103)	(0.501)	(0.113)	(0.301)
Head with graduate/PG educ.	0.246***	1.071	0.547***	0.558
	(0.080)	(1.288)	(0.119)	(0.484)
Household size	0.873***	0.927	0.859***	0.842***
	(0.035)	(0.110)	(0.025)	(0.054)
% of Informal wage-labour	3.187***	0.159	1.990**	1.615
	(1.194)	(0.194)	(0.542)	(0.957)
% of Formal wage-labour	2.474	6.591	1.791	3.875
	(1.909)	(26.411)	(0.858)	(8.571)
% of Self-employed	3.652*	0.128	1.316	0.306
	(2.415)	(0.304)	(0.628)	(0.401)
% of Children	1.130	5.987	2.009**	7.808***
	(0.424)	(7.474)	(0.562)	(4.824)
% of Elders	0.133***	7.828	0.160***	0.473
	(0.082)	(12.481)	(0.068)	(0.418)
% of Working women	0.810	6.442	0.509*	0.530
	(0.401)	(10.987)	(0.187)	(0.451)
% of Migrants	1.065	1.130	1.490***	1.736***
	(0.093)	(0.334)	(0.099)	(0.161)
Asset deprivation indicator	0.916	2.373**	0.971	5.900***
	(0.133)	(0.960)	(0.116)	(1.410)
Air quality deprivation indicator	0.819	5.530***	0.699***	5.322***
	(0.123)	(2.611)	(0.086)	(1.296)
Drinking Water source deprivation indicator	0.692***	3.079***	0.878	3.306***
	(0.095)	(1.285)	(0.087)	(0.748)
Household drainage deprivation indicator	1.200	2.108*	1.115	4.547***

	(0.170)	(0.813)	(0.125)	(0.950)
Electricity deprivation indicator	0.279***	0.970	0.347***	1.826**
	(0.064)	(0.433)	(0.059)	(0.439)
Household type deprivation indicator	0.395***	2.547**	0.296***	1.444
	(0.091)	(1.192)	(0.052)	(0.361)
Education deprivation indicator	1.021	5.103**	0.881	4.670***
	(0.164)	(3.538)	(0.109)	(1.501)
Livelihood deprivation indicator	0.689***	3.008**	0.656***	2.586***
	(0.090)	(1.482)	(0.066)	(0.577)
Child deprivation indicator	0.269***	2.249*	0.411***	2.128***
	(0.057)	(1.024)	(0.065)	(0.546)

Note: denotes statistical significance, p = *** .01, ** .05, * .1

Table 6: Targeting Errors and Utilization Patterns

	Wheat				Rice			
	Poor		Non-Poor		Poor		Non-Poor	
	Col A	*Col B*	*Col C*	*Col D*	*Col E*	*Col F*	*Col G*	*Col H*
	Panel A: Utilization Rate (% making any amount of purchases)							
Cities	**BPL/ AAY**	**APL**	**BPL/ AAY**	**APL**	**BPL/ AAY**	**APL**	**BPL/ AAY**	**APL**
Delhi	97.2%	83.3%	91.9%	47.5%	94.4%	79.2%	89.3%	41.2%
Ranchi	98.8%	9.1%	89.9%	3.1%	100.0%	9.1%	93.0%	3.1%
All sample	97.9%	47.8%	91.5%	38.1%	96.8%	45.7%	89.9%	33.1%
	Panel B: Utilization Levels (amount of purchases made)							
Cities	**BPL/ AAY**	**APL**	**BPL/ AAY**	**APL**	**BPL/ AAY**	**APL**	**BPL/ AAY**	**APL**
Delhi	18.4	14.2	17.2	7.9	7.9	5.9	8.1	2.8
Ranchi	10.4	0.9	9.7	0.3	21.3	2.1	20.3	0.5
All sample	14.9	7.9	15.8	6.3	13.7	4.1	10.3	2.4

Table 7: Subsidy Income Transfers due to TPDS

Attributes	Implicit income transfers					Income transfer as a % of monthly CE (per capita) on food
	Rice	Wheat	Sugar	Food-grains	All commodities	
MPCE deciles						
1	28.73	21.01	9.97	49.74	57.94	18.3%
2	30.41	20.40	9.81	50.81	58.53	14.5%
3	28.48	20.88	10.70	49.36	57.19	12.6%
4	28.21	22.60	12.85	50.81	59.43	11.6%
5	30.01	24.21	12.45	54.22	62.93	11.5%
6	22.48	21.95	16.53	44.44	52.24	7.5%
7	24.90	25.39	18.41	50.29	59.94	7.3%
8	22.16	22.56	21.36	44.72	53.23	5.3%
9	9.73	12.47	8.27	22.20	24.31	2.1%
10	6.37	7.55	13.10	13.91	15.75	1.0%
TPDS cards						
AAY	46.21	31.65	6.63	77.85	84.48	20.9%
BPL	34.87	27.47	13.84	62.34	76.18	13.8%
APL	6.90	9.74	.	16.65	16.65	2.9%
Poverty status#						
Non-poor	22.55	20.18	13.47	42.73	50.03	8.9%
Poor	33.70	21.99	9.75	55.69	63.53	15.5%
Income Transfer Gap (Poor – Non-poor)	11.15***	1.8	3.7***	12.9***	13.5***	6.6%***
Total	**24.25**	**20.46**	**12.68**	**44.71**	**52.09**	**9.9%**

denotes statistical significance, p = *** .01, ** .05, * .1

Table 8: Welfare Implications of Targeting Errors: Simulation Results

TPDS classes/ targeting Errors	Income Transfer for Food-grains (Rs)	Income transfer as a % of monthly CE (per capita) on food
PANEL A		
No-targeting errors		
AAY/BPL	64.5	18.4%
APL	16.42	2.8%
Targeting errors		
Inclusion error	64.93	14.0%
Exclusion error	19.62	3.8%
Subsidy difference adjusting for targeting errors		**5.4%**
PANEL B		
Hypothetical Scenario I: Post-removal of targeting errors (Price-effect)		
New AAY/BPL	56.54	15.7%
New APL	37.33	7.8%
Subsidy difference under no targeting errors (Price-Effect Only)		**7.9%**
PANEL C		
Hypothetical Scenario II: Post-removal of targeting errors (Price & Quantity-effect)		
New AAY/BPL	64.36	17.5%
New APL	17.32	3.3%
Subsidy difference under no targeting errors (Both Price & Quantity Effects)		**14.2%**

Table 9: Poverty Impacts of TPDS: Comparison of Poverty Rates and Indices

Cities	Poverty rates	FGT(0)	FGT(1)	FGT (2)
Delhi	P_0	15.2%	0.030	0.009
	P_1	12.0%	0.023	0.007
	$\Delta P = (P_1 - P_0)/ P_0$	**21.2%**	**23.5%**	**26.9%**
Ranchi	P_0	10.8%	0.014	0.0033
	P_1	9.0%	0.011	0.0025
	$\Delta P = (P_1 - P_0)/ P_0$	**17.1%**	**24.5%**	**24.2%**

Table 10: Parameter Estimates of Tobit Models for Subsidy Transfer

	Ranchi		Delhi	
	Tobit	OLS	Tobit	OLS
Female-headed household	0.003	-0.015	0.066	0.100
	(0.184)	(0.112)	(0.186)	(0.120)
Head with no formal schooling	-0.113	-0.119**	0.105	0.112
	(0.171)	(0.059)	(0.187)	(0.125)
Head with primary educ.	0.019	-0.032	-0.046	-0.017
	(0.134)	(0.066)	(0.171)	(0.113)
Head with middle-school educ.	-0.060	-0.031	0.200	0.144
	(0.104)	(0.048)	(0.166)	(0.113)
Head with secondary educ.	-0.058	-0.069	0.077	0.023
	(0.113)	(0.058)	(0.185)	(0.124)
Head with sr. secondary educ.	-0.197	-0.171	-0.015	-0.064
	(0.214)	(0.106)	(0.213)	(0.136)
Head with graduate/PG educ.	0.112	-0.077	-0.650***	-0.409***
	(0.164)	(0.077)	(0.237)	(0.142)
Household size	-0.039*	-0.041***	0.018	-0.034*
	(0.023)	(0.009)	(0.030)	(0.020)
% of Informal wage-labour	-0.165	0.016	-0.429	-0.103
	(0.233)	(0.116)	(0.269)	(0.160)
% of Formal wage-labour	-0.222	-0.126	-1.093**	-0.455
	(0.945)	(0.440)	(0.553)	(0.293)
% of Self-employed	0.833	0.109	0.029	0.140
	(0.509)	(0.290)	(0.467)	(0.299)
% of Children	-0.749***	-0.211*	0.020	0.197
	(0.274)	(0.127)	(0.273)	(0.165)
% of Elders	0.690**	0.259	0.620	0.079
	(0.328)	(0.199)	(0.505)	(0.355)
% of Working women	-0.251	-0.232	0.980***	0.511**
	(0.333)	(0.184)	(0.363)	(0.217)
% of Migrants	-0.165***	-0.009	-0.332***	-0.100***
	(0.056)	(0.010)	(0.057)	(0.021)
Food expenditure as a prop. of MPCE	0.249	-0.009	1.932***	1.240***
	(0.363)	(0.176)	(0.381)	(0.234)
Whether has an AAY or BPL card	4.792***	3.902***	3.762***	2.822***
	(0.074)	(0.080)	(0.101)	(0.076)
Asset deprivation indicator	-0.102	-0.015	-0.278**	-0.120*
	(0.098)	(0.042)	(0.111)	(0.071)
Air quality deprivation indicator	-0.063	0.035	0.246**	0.200**
	(0.087)	(0.041)	(0.116)	(0.078)

Drinking Water source deprivation indicator	0.019	-0.006	-0.176*	-0.019
	(0.086)	(0.039)	(0.104)	(0.063)
Household drainage deprivation indicator	-0.104	-0.032	-0.380***	-0.184***
	(0.083)	(0.039)	(0.110)	(0.069)
Electricity deprivation indicator	-0.118	-0.026	-0.270	-0.195*
	(0.089)	(0.036)	(0.169)	(0.107)
Household type deprivation indicator	0.252**	0.104**	0.055	0.040
	(0.102)	(0.050)	(0.230)	(0.159)
Education deprivation indicator	0.092	0.054	0.460***	0.367***
	(0.113)	(0.051)	(0.131)	(0.086)
Livelihood deprivation indicator	0.072	0.011	-0.050	-0.011
	(0.081)	(0.035)	(0.099)	(0.064)
Child deprivation indicator	0.149	-0.019	-0.244	-0.146
	(0.106)	(0.049)	(0.157)	(0.094)
Constant	-0.528*	0.402***	-1.389***	0.063
	(0.280)	(0.145)	(0.360)	(0.222)
σ	0.876***		1.817***	
	(0.095)		(0.044)	
No. of observations	957	957	1974	1974
Prob > F	0.00	0.00	0.00	0.00
Pseudo R^2/ R^2	0.51	0.90	0.22	0.61
Left censored observations	602		827	
Uncensored observations	355		1147	

Note: . denotes statistical significance; p = * .01, ** .05, * .1**

Figure 1a-1c: Distribution of TPDS card-types: City and All Sample

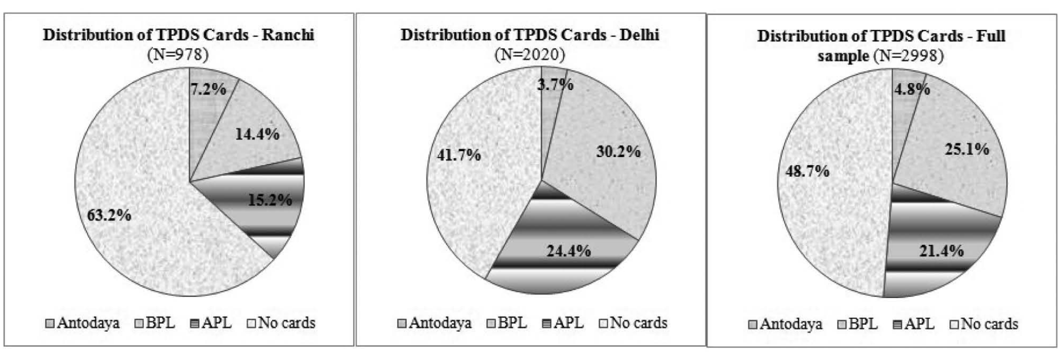


Figure 2: Pattern of TPDS Card-Holding across MPCE deciles

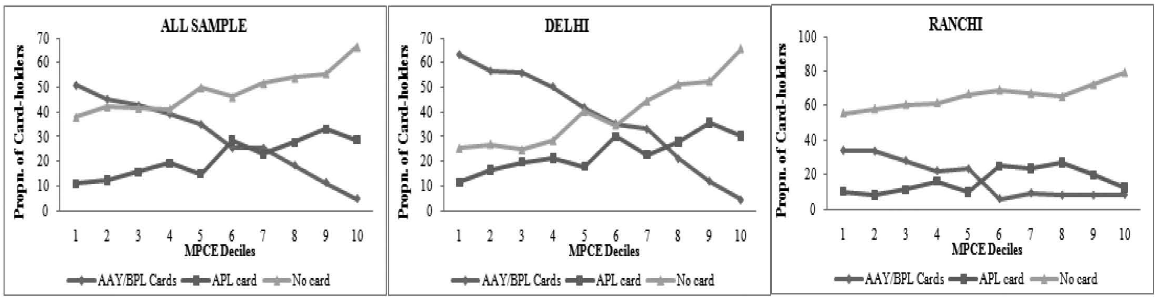


Figure 3: Utilization Rates by different TPDS Card-types for Food-grains

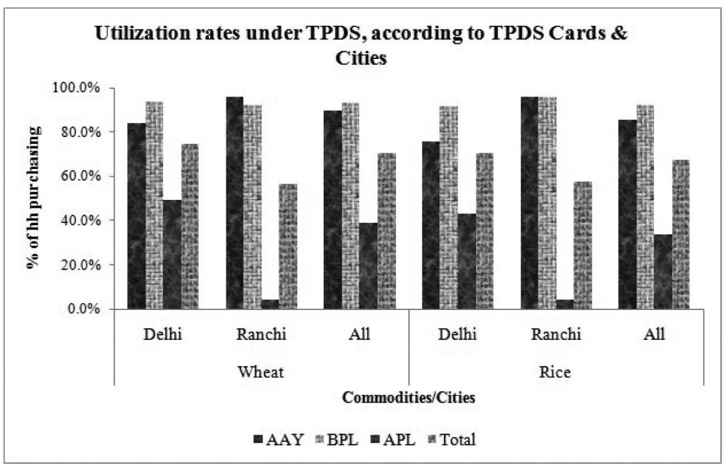


Figure 4: Average household consumption of commodities, by TPDS groups

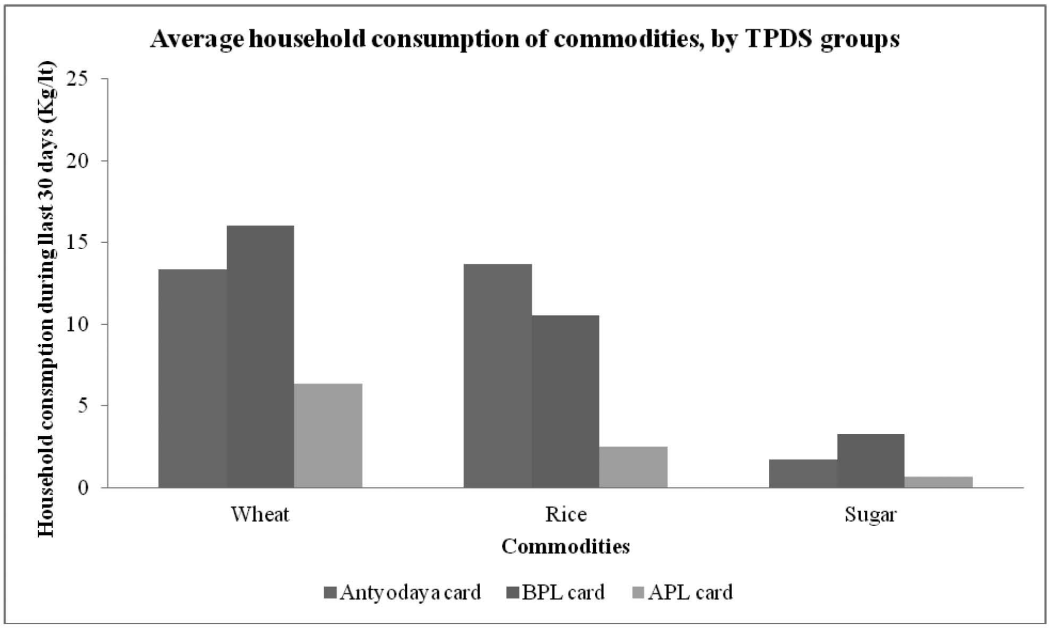
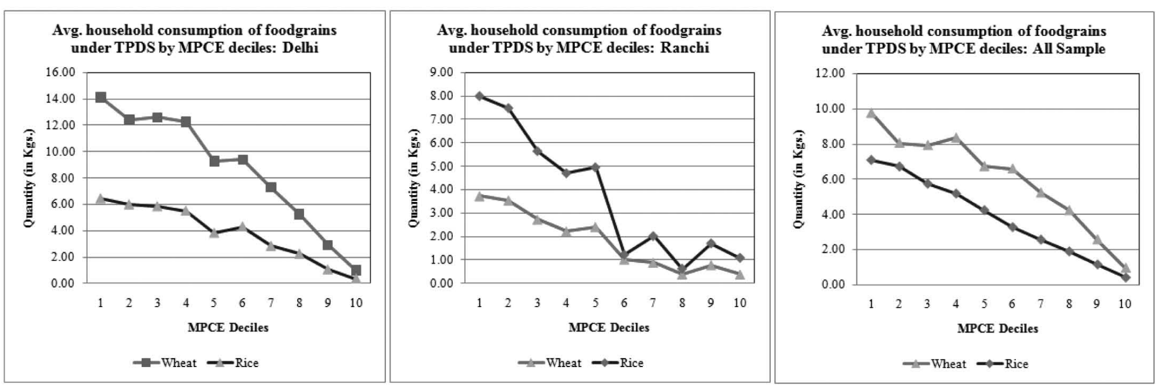


Figure 5: Levels of Utilization/Quantities purchased of Food-grains according to MPCE deciles



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