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Can Proxy Means Testing Improve the Targeting Performance of Social Safety Nets in Bangladesh?

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This paper develops and discusses a Proxy Means Test (PMT) based household targeting system for Bangladesh. The PMT model derived from household survey data includes observable and verifiable characteristics on (i) household demographics and characteristics of household head; (ii) ownership of assets; (iii) housing quality, and access to facilities and remittances; and (iv) location variables in a formal algorithm to proxy household welfare. Simulations of the model suggest that the proposed PMT formula is able to improve the targeting efficiency by a considerable amount when compared with existing targeted safety net programmes. However, numerous implementation challenges remain which include but are not limited to a cost-efficient data collection process, effective management of information and a feasible and cost-efficient monitoring and verification system to minimise fraud and leakage.

Keywords: Targeting, Proxy Means Test, Safety Nets, Bangladesh
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I. INTRODUCTION

Despite impressive gains in poverty reduction in recent years, the number of extreme poor in Bangladesh still remained at a staggering 35 million in 2005.

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Chronically underfed and highly vulnerable, this segment of the population have little to call their own that would enable them to fight hunger during lean seasons, treat debilitating disease and illness, and overcome losses associated with regular flooding and other calamities. Further, the sheer size of the population living around the poverty line[1] implies that a small shock can push a large number of individuals into poverty, and many who are already poor, into extreme poverty. The rise in global prices of rice in 2007-08 for instance offset the decrease in the incidence of poverty between 2005 and 2008 by an estimated 3 percentage points.[2]

In response to its extreme poverty levels and to mitigate the risk of households falling into (or further into) poverty as a result of shocks, Bangladesh implements a wide range of targeted safety net programmes operated by various government agencies.[3] Nevertheless, the number of people covered under these safety net programmes represents only 22 per cent of households in the bottom expenditure quintile and 4 per cent of the households in the top expenditure quintile (World Bank 2008b). The low coverage of the target group and the inclusion errors found in some programmes appear to be in part due to weaknesses in targeting mechanisms. Identification of the poor is often faulty as many public safety net programmes rely on selection criteria that are neither observable nor verifiable (Ahmed 2007). Targeting the poor in general is very difficult not least due to weaknesses in targeting instruments. Implementation details matter enormously to distributive outcomes, as is evidenced by the remarkable success of Bangladeshi non-government organisations (NGOs) and (Microfinance Institutions (MFIs) in their ability to reach the poor with services that combine safety net type interventions with microfinance products. Much of their success in targeting the poor has to do with their local level presence and knowledge as well as efficient management information systems funded by donors (World Bank 2007). These NGO driven targeting strategies which are often labour-intensive and community based are not always possible for large government bureaucracies to adopt let alone implement. Designing an effective household targeting system that can serve multiple safety net programmes run by

[1]As reflected by the distribution of consumption in HIES 2005. For detailed analysis, see Bangladesh 2008 Poverty Assessment (World Bank 2008b).

[2] World Bank (2008b).

[3]There are non-government institutions as well that operate many anti-poverty programmes such as microfinance institutions (MFIs) that act as safety nets that protect the consumption of households, especially during shocks. Although limited in scale, MFIs have becoming increasingly active in experimenting with a number of initiatives to address chronic poverty and vulnerability caused by seasonality.

the Government, especially those that target the extreme poor, remains an important part of the discourse on vulnerability and poverty reduction in Bangladesh.

The purpose of this paper is to present and discuss a household targeting system for Bangladesh that tries to identify the extreme poor based on a formula derived from household survey data. Known as Proxy Means Tests (PMT), this method of targeting involves using observable and verifiable household or individual characteristics in a formal algorithm to proxy household welfare. These variables are selected based on their ability to predict welfare as measured by, for instance, consumption expenditure of households. Such a system is often preferred for its transparent process and objective criteria, cost efficiency and its potential ability to minimise, to some extent, elite capture. The administrative difficulties associated with sophisticated means tests used by most public safety net programmes in Bangladesh and the inaccuracy of the results due to the problems with measuring income also provide a strong rationale for employing proxy means tests. Like means tests, proxy means tests can be costly relative to other forms of household level targeting (e.g. community-based targeting methods). However, they tend to produce the lowest errors of inclusions and thus are considered good investments.[4]

There is both academic evidence and practical experience that suggest using proxies for consumption expenditure can identify the poor with a reasonable level of accuracy. For example, Haddad, Sullivan and Kennedy (1991) use household level data to show that proxy variables can be used as good measures of caloric adequacy rather than using the memory of individuals which can be unreliable in many instances. Other studies use regression analysis to point to a set of variables that are able to proxy for welfare levels (Glewwe and Kanaan, 1989, Grosh and Baker 1995, Narayan *et al.* 2006, Ahmed and Bouis 2002). There is also encouraging practical experience from Latin American countries like Chile which have been using a PMT based targeting system since the 1980s, and from other countries, such as Colombia, Costa Rica and Mexico, which have adopted this targeting system more recently in the late 1990s. In all of these cases, the PMT based targeting system managed to perform well in terms of targeting incidence outcomes (Castenada and Lindert 2005). For example, between 80 and 90 per cent of the benefits of proxy-means tested programmes in Chile and Mexico are received by the poorest 40 per cent of the households in

[4] See World Bank (2008) for a comparison of the various types of targeting methods, including categorical and self-targeting mechanisms. See also Castenada and Lindert (2005) for a discussion of PMT-based targeting systems adopted by some Latin American countries.

those countries. The efficacy of proxy means testing has also been documented in an earlier comparative study which found that among all targeting mechanisms proxy means tests tend to produce the best incidence outcomes in developing countries (Grosh 1994). Proxy means tests are known to especially distinguish chronic poverty well (Grosh *et al.* 2008) which makes it an appropriate targeting option in the context of Bangladesh, where the depth and severity of poverty is relatively high compared to other South Asian countries.

There are, however, some drawbacks to using Proxy Means Tests. As the formula is only a prediction, there can be inherent inaccuracies, especially when targeting the poorest of the poor. The challenge of targeting the bottom 10 per cent of the population essentially stems from the fact that it is harder to predict consumption with reasonable accuracy at the left tail of the consumption distribution. For instance, Grosh and Baker (1995) find that proxy means tests have significant levels of errors of exclusion when trying to target the bottom 10 to 20 per cent of the population (even though they do cut down errors of inclusion enough to have a better impact on poverty than if no targeting is done). There is also recent evidence from Pakistan which is con sistent with the above view (Hou 2008). Such evidence suggests caution when using a PMT-based household targeting system for safety net programmes, and asks that programmes be designed in such a way so as to minimise these targeting errors. For example, combining the PMT with geographic or community level outreach and validation where appropriate and feasible can improve accuracy. Further, existing international experience suggests that PMT based targeting systems take time (at least 18 months) to design, pilot and implement on a large scale (Castaneda and Lindbert 2005). Having the institutional set up to implement the targeting system is just as important as having a robust PMT formula. There is a need, for example, to have an appropriate data collection strategy and adequate management systems to ensure (i) the accuracy of household assessment mechanisms and (ii) appropriate monitoring and oversight mechanisms to ensure transparency, credibility and control of fraud.

This paper is organised as follows. In the next section, the paper summarises the challenges public safety net programmes in Bangladesh face as they pertain to the targeting of poor households. Section III explains proxy means testing and how it is implemented to determine programme eligibility. Using the latest Bangladesh Household Income and Expenditure Survey (HIES) 2005, section IV goes on to discuss the various steps taken to derive the Proxy Means Tests Formula (PMTF) for Bangladesh. Discussions regarding the various checks and balances undertaken to identify the best possible PMTF as well as recommendations on the choice of the cut-off line when determining household eligibility status are included in this section. Comparisons between the targeting accuracy of the PMT model and existing programmes are also discussed. In section V, we present some of the implementation challenges associated with using a PMT-based targeting system in the Bangladeshi context. The paper concludes in section VI.

II. PUBLIC SAFETY NET PROGRAMMES IN BANGLADESH

The Bangladesh government currently implements a wide range of safety net programmes targeted to the poor including both cash and in kind (or food) programmes. The broad categories of safety net programmes include: (i) infrastructure-building programmes that are essentially self-targeted workfare programmes; (ii) training programmes on income generating activities and awareness building regarding health, nutrition and legal rights; (iii) education programmes that deliver food conditional on children's education at both primary and secondary levels; (iv) relief programmes that are designed to mitigate the consequences of disasters; and (v) programmes for disadvantaged groups like the elderly, the widowed, the disabled, and freedom fighters. The larger programmes include the Vulnerable Group Feeding (VGF) programme which has the highest coverage, followed by Old Age Pension, Vulnerable Group Development (VGD) and Test Relief (TR) programmes. The administrative structure and the implementation mechanisms of some of these safety net programmes have gone through substantive changes over the last thirty years–from being mostly relief oriented to ones with a much more focus on poverty reduction and employment generation. For example, food price subsidies were replaced by targeted food distribution. Partnerships with NGOs were forged to implement various training and microfinance programmes. The government has shown remarkable willingness to evaluate programme effectiveness, confront shortcomings and cancel or modify programmes to improve performance. For example, the high costs and levels of leakage found in the *Palli* rationing programme influenced the government to abolish and replace it with an innovative Food for Education (FFE) programme in 1993. Moreover, there has also been a gradual shift from food to cash based programmes, given the high leakage associated with the former. For example, the Food-for-Education programme was transformed into a cash-based stipend programme, and Cash-For-Work is gradually replacing the Food-For-Work (FFW) programme. The willingness and the ability to reform safety net programmes thus represent a dynamic aspect of safety net policy in Bangladesh.

The number of people covered by public safety net programmes, however, represents only a fraction of the poor. About 22 per cent of households in the lowest consumption quintile receive benefits from safety net programmes. As shown in Table I, even among the bottom 10 per cent of the population, the combined coverage of all safety net programmes is just 23 per cent, and for targeted programmes it is only 16 per cent. There is also an urban-rural imbalance in terms of safety net coverage: 15 per cent of rural households report being a member of at least one safety net programme compared to only 5 per cent among urban households (Ahmed 2007).

TABLE I
COVERAGE OF HOUSEHOLDS PARTICIPATING IN AT LEAST ONE SAFETY NET PROGRAMME (%)

Quintiles	Non-Targeted	Targeted	Pension	Total
Lowest	2.3	15.7	3.6	21.6
2nd	2.7	10.6	2.2	15.4
3rd	3.3	7.9	2.2	13.4
4th	2.3	5.3	2.2	9.8
5th	1.6	2.2	0.6	4.4
Total	2.4	8.1	2.1	12.6
Bottom 10%	2.4	16.0	4.6	23.1

Source: HIES 2005 in Ahmed (2007).

While the overall coverage is pro-poor, a sizeable number of non-poor households also receive benefits. Table II shows that the per cent of households who benefit from targeted programmes declines progressively for higher quintiles. While such progressive incidence of coverage is a positive feature, a strong area of concern is the considerable level of inclusion errors across programmes. For example, 48 per cent of beneficiaries of old age pensions are in the top three quintiles compared with 39 per cent of TR, VGF and VGD beneficiaries. Further, 41 per cent of the beneficiaries of *all targeted* programmes are in the top three quintiles. Among the beneficiaries of *all non-targeted* programmes, 45 per cent are among the top three quintiles. This suggests that targeted safety net programmes do not achieve much efficiency gains over untargeted programmes (see Table II).

TABLE II
INCIDENCE OF TARGETING BY PER CAPITA CONSUMPTION QUINTILES

Programme	Lowest Quintile	2nd Quintile	3rd Quintile	4th Quintile	Top Quintile
VGD	31.7	29.1	19.4	14.3	5.5
TR	38.9	22.2	18.9	13.3	6.7
VGF	36.1	25.0	20.7	13.0	5.2
Old Age Pension	31.9	20.0	21.1	20.5	6.5
Total (targeted)	34.2	24.6	20.0	15.2	6.0
Total (non-targeted)	30.9	23.8	21.6	16.2	7.5

Source: HIES 2005 in Ahmed (2007).

The low coverage of the target group and relatively high errors of inclusion of certain programmes appear to be in part due to weaknesses in targeting mechanisms. First, programme allocations do not take into account the geographic variation in poverty rates across the country.[5] Instead, the general targeting strategy involves an initial guideline prepared by the implementing ministry, which sets the targeting criteria at the household level, the total number of beneficiaries, the type of beneficiaries (including caps on male and female beneficiaries) per union, and the amount of transfer per beneficiary. Second, similar programmes use different criteria for targeting benefits, and these are not applied universally. For example, programmes such as VGD, VGF and Old Age Allowance target similar low income groups but use different criteria to identify beneficiaries. Beneficiary surveys show that selected individuals rarely fulfill all the criteria for a specific programme (Ahmed 2005). A number of indicators used to select beneficiaries are difficult if not impossible to observe and verify. For example, means testing is widely known to be problematic since income (used by most programmes) is difficult to measure and verify as is the indicator "members consume less than two full meals a day" (a VGD criterion) (Ahmed *et al*. 2007). Third, the total amount of transfers often does not reach beneficiaries. According to Ahmed (2005), multiple and ineffective targeting systems, combined with the large number of intermediaries, particularly in the food-based safety net programmes, increase leakage in the programmes in terms of reduced amount of benefits. IFPRI estimates that the leakage of transfers at the beneficiary level can range between 2 and 13.6 per cent (Ahmed, Rashid, Sharma and Zohir 2003).

Poor programme implementation, monitoring and evaluation are likely to cause some transfers to leak to non-poor beneficiaries as well. Programmes are often administered by multiple ministries despite having considerable overlap with little monitoring of benefit allocations (Ahmed 2007). The lack of an overall coordinating authority constrains the development of a coherent approach to the implementation of targeted programmes and the efficient allocation of public re-distributive expenditures. Thus there are potential cost-saving benefits to implementing a PMT-based targeting approach: the system can be used by several programmes for different target groups, and thus can maximise the return on fixed overhead costs associated with initial investments. The systematic use of information via a PMT-based targeting system not only improves the administrative capacity of programmes, but it also simplifies the monitoring and

[5]For example, Sylhet has a poverty rate much lower than the national rate but nevertheless has the highest coverage of safety nets among all divisions. In contrast, Khulna, which has the second-highest poverty rate in the country, has the least coverage of safety nets (Ahmed 2007).

the verification of claims and payment systems. Implementing such a targeting mechanism as part of an effort to improve the overall efficacy of the safety net system in Bangladesh thus appears to be a reasonable step forward.

III. DETERMINING ELIGIBILITY AND TARGETING ACCURACY USING A PMTF

Developing a proxy means test formula (PMTF) involves finding a *weighted* combination of "proxy" variables or indicators that *together* identify or predict whether a household is poor or not. The data this paper uses to identify an appropriate set of variables and weights is the latest Household Income and Expenditure Survey (HIES) of 2005 conducted by the Government of Bangladesh. Used for the latest calculations on the incidence of poverty in Bangladesh, the HIES 2005 is well-suited for the purposes of this exercise as it contains rich and detailed information on most correlates of welfare. On the downside, it only includes community level information for rural areas, thereby limiting us to only household level proxies when predicting welfare in urban areas. The HIES 2005 was conducted more than six years ago, and thus in our analysis we avoid variables that even though are highly correlated to poverty are also likely to rapidly change over time, such as the use of mobile phones.[6]

For the purposes of this exercise, welfare is proxied by monthly per capita household consumption expenditure. The PMTF assigns a "score" to every household, based on information collected from the household for all variables that are included in the formula. All scores are derived from ordinary least squares (OLS) regressions of (log of) per capita consumption expenditure on a set of variables. OLS is generally used to predict welfare mainly due to the convenience and ease of interpretation. For instance, the weight for each variable is its coefficient in the regression, rounded to the nearest integer. The aggregate score for each household is calculated as the constant plus or minus the weight on each variable, and reflects predicted expenditure or welfare: the *lower* the score, the *poorer* the household.

The weights on these variables are then used to identify those who will be eligible to receive benefits using an eligibility cut-off line. Cut-off lines are

[6] Even though multivariate regressions show that owning a mobile is positively correlated with consumption, we exclude it from the PMTF for the following two reasons: (i) the use of mobile has seen a drastic increase since 2005, and thus using this variable as reported by HIES 2005 may be misleading; and (ii) the coefficient on this variable is substantially larger when compared to the other asset variables, and thus an erroneous entry in the PMT form regarding ownership of a mobile phone will have a larger effect on the probability of being eligible than in the case of any other asset variables.

drawn along the actual expenditure distribution (e.g. 25th percentile, 30th percentile and 40th percentile). A household is considered poor and thus eligible to participate in a programme if its predicted expenditure (or the PMT score) is less than the chosen cut off line, also known as the targeting line. Policy makers generally determine this cut-off line such that the maximum number of the poorest households is served, given the available budget. The choice of the cut-off line is also crucial in determining the level of targeting errors. As prediction by any model is never exact, we expect that some poor will be incorrectly identified as non-poor, and some non-poor will be incorrectly identified as poor. Those whose "true" and predicted consumption levels fall below the cut-off line are targeting successes. Similarly, those who should not and do not get the transfers are also targeting successes. However, when "true" and predicted consumption levels fall on different sides of the eligibility cut-off line, a targeting error occurs. A person whose "true" consumption is below the cut-off but whose predicted consumption falls above the cut-off, this person is wrongly identified as "ineligible." This kind of error is called an error of exclusion. Dividing the exclusion error by the total number of households who should get benefits gives us the per centage of those whom the programme is meant to cover but who are not covered, otherwise known as "undercoverage." This undercoverage negatively affects the ability of the programme to impact the welfare of some poor people but it carries no budgetary costs.

The other type of error occurs when a household's "true" consumption level is above the cut-off line but its predicted welfare is below it. These households are incorrectly identified as eligible and they constitute an error of inclusion. The per centage of benefits that are received by these ineligible households is known as the "leakage." Thus lower levels of undercoverage and leakage are preferable to higher ones. Which of the two targeting performance indicators is given priority over the other is essentially a policy decision. The higher the priority assigned to lowering poverty, the greater should be the importance placed on minimising undercoverage. Whereas the higher the priority assigned to savings associated with limited budgets, the more important it will be to minimise leakage. Given that for developing countries, both undercoverage and leakage are important considerations, an appropriate PMT model would be one that to the extent possible minimises both. Thus, when devising the PMT formula, one needs to test a number of cut-off lines to identify the cut-off line that gives the best targeting outcomes.

The coverage rate or the sum of the total beneficiaries as a proportion of the total population will also vary with the eligibility cut-off line but is not necessarily equal to the eligibility cut-off line. For instance, even though the cut off line is set at the 30th percentile, the model may target less than 30 per cent of the population on the aggregate. This is because the 30th percentile in terms of *actual* consumption is not equal to the 30th percentile in terms of *predicted* consumption. Thus the choice of the cut-off line could also depend on the size of the population expected to be targeted as determined by the size of the benefit and the total budget available for programmes. Table A1 in the Annex explains these concepts in greater detail.

The targeting efficiency of the PMTF depends on these following four key features. First, the variables chosen to estimate the model should be very good predictors of consumption (so that a substantial proportion of the variation in consumption is explained by the regression model). Second, the proxies used should be relatively few but easy to measure and verify. Third, the model should achieve a reasonable level of targeting accuracy such that *undercoverage, leakage and coverage rates* associated with the model are at acceptable levels. Fourth, the *incidence* of beneficiaries should be acceptable, i.e. the PMT should be able to rank selected beneficiaries mostly in the bottom end of the consumption distribution. While we would like the model to cover all of those who fall below the poverty line, the error is less grave if the households who are excluded fall only just below the poverty line rather than at the very bottom of the consumption distribution. Similarly, out of those households who are included by the model, it is preferred that a higher proportion of the identified beneficiaries belong to the bottom section of the consumption distribution. The next section explains the various steps and approaches undertaken to arrive at a Proxy Means Test Formula (PMTF) using HIES 2005, and evaluates the targeting efficiency of this proposed PMTF.

IV. A PROXY MEANS TESTING FORMULA FOR BANGLADESH

4.1 Selecting a PMT Model

The dependent variable of the PMT model - the natural log of per capita household consumption—represents the sum of food and non-food expenditures (excluding durable goods) and is adjusted for spatial price differences using the upper poverty line, as reported in the 2008 Bangladesh Poverty Assessment (World Bank 2008b). The proxy variables entered in the formal algorithm are chosen primarily from the determinants of poverty, as identified in the Bangladesh 2008 Poverty Assessment. The final choice of variables was made based on the following: (i) that they are easily observable and measurable; (ii) that they cannot be manipulated easily by households; and (iii) that they are not politically sensitive. There are often trade-offs when choosing variables based on these criteria and in the end a pilot testing of the variables on the ground is preferable to ensure that the final choice of the model is robust. The variables that have been found to be highly correlated with poverty in Bangladesh and are included in this exercise fall broadly into four categories: (1) household demographics and characteristics of household head; (2) ownership of easily verifiable assets; (3) housing quality, access to facilities and remittances, and participation in anti-poverty programmes; and (4) location variables.

(1) Household demographics and characteristics of household head: As is the case in many countries, multivariate regressions suggest that the number of infants, children and adults were negatively correlated with per capita expenditures in 2005. This negative association is much stronger with number of infants or children than that of adults—as additional child (age 1 to 14) in the household is associated with around 18 per cent lower per capita household expenditures. This negative association is even stronger for infants of age less than one year. These results are consistent with the fact that the dependency ratio is higher in poor households than in non-poor households in Bangladesh (World Bank 2008b).

The Poverty Assessment also suggests a negative correlation between household size and poverty. This result holds even after adjustments for economies of scale and equivalence scales in consumption. Both religion and age of the household head also affect the economic status of households. Non-muslim household heads tend to be poorer, while household per capita expenditure increases with the age of the household head; the effect declining with increasing age. However, due to the sensitivity of religion in the context of Bangladesh, we do not include the religion of the household head in the formula for the PMT.

To capture the associations between poverty and gender we take our cue from the Poverty Assessment in that instead of using the gender of the household head, we use information on the marital status of female-headed households. Given that many female-headed households in rural areas receive remittances from male members, the Poverty Assessment finds that the correlation between the gender of the household head and household economic status is affected by how one distinguishes between *de facto* and *de jure* female headed households. The data suggests that female headed households are likely to be poorer when the head is widowed, divorced or separated, i.e., they are less likely to have an adult male in the household.

Education is a key determinant of poverty as shown by multivariate regressions that test the impact of the education level of the household head on per capita household expenditure. The education premiums are even higher when the head has an education level of tenth grade or higher. The education of the spouse of the household head has a similar impact on poverty, though smaller in magnitude compared to equivalent levels of education of the household head. Given that Bangladeshi girls and women continue to make considerable progress in terms of school enrolments and increased levels of participation in economic activities respectively, the education of the spouse will be an important variable to include in the PMTF. Occupational status of household members is also associated with household poverty in Bangladesh. Nearly a third of total employment is in the daily wage sector where poverty rate among households, when the household head works as a agricultural daily wage labourer, is 72 per cent compared to 60 per cent when the head works as non-agricultural daily wage labourer.

(2) Ownership of easily verifiable assets: Ownership of assets is typically associated with poverty. Accordingly, the Bangladesh Poverty Assessment finds that ownership of land is highly correlated with household poverty. Poverty rate for the landless (less than 0.05 acre of land) was 57 per cent in 2005 compared to 24 per cent for small landowners (1.5 to 2.5 acres of land), and 13 per cent for medium/large landowners (2.5 acres or more). Multivariate regressions show that ownership of land raises household per capita consumption progressively with land size for rural households. Urban households face a similar situation though the effects are relatively smaller and are significant for land size of 0.5 acre and above—reflecting the lower importance of land for livelihoods in urban areas. Other important household assets owned by the poor include livestock ownership, especially in rural areas. Between 2000 and 2005, the average livestock asset value in real terms increased by about 20 per cent for all households, and for poorer households (e.g. bottom five deciles) the increase was almost 50 per cent. This increase appears to have come from both households increasing their existing stock and from a higher number of households owning livestock. For the PMTF, we test additional household assets in our OLS regression to assess their correlations with household poverty. These assets include house, TV, tube well, fan, and bicycle.

(3) Housing quality, access to facilities, remittances and participation in anti-poverty programmes: The Bangladesh Poverty Assessment points to a range of characteristics that are also correlated with consumption. These include better quality houses, built with superior materials and equipped with electricity and access to clean drinking water and hygienic sanitation facilities. Households with such facilities are also expected to have higher consumption levels.[7] The Poverty

[7]In fact, earlier work on poverty in Bangladesh found the quality of housing to be correlated with poverty. Hossain (1995) finds that households who live in houses with straw roofs are typically extremely poor.

Assessment does find that over the period 2000 and 2005, housing conditions improved dramatically with a larger percentage of households with walls and roofs of corrugated iron sheets and cement, materials that are more resilient to adverse weather conditions (Serajuddin, Zaman and Narayan 2007).

The Poverty Assessment also highlights the growing importance of the role of both domestic and foreign remittances as a key driver of poverty reduction in Bangladesh: access to remittances is highly correlated with household expenditure in both urban and rural areas. The data shows that while the incidence of domestic remittances has increased by 12 per cent between 2000 and 2005, suggesting increased internal migration, the correlation of household consumption with foreign remittances is nearly three times larger than that with domestic remittances. There is a caveat, however, that international migration often requires large up-front costs which are not factored into these regressions. Despite such large costs, many existing studies suggest that even the poor are able to gain from overseas employment (Siddiqui and Abrar 2003).[8] The variable "whether the household receives domestic remittances," however, is dropped from the PMT model as it may be problematic to verify at any one point in time since many members of poor households are temporary migration workers.

The link between microfinance and poverty is also an important consideration, as pointed out by the Poverty Assessment. Although the lack of data does not allow for a rigorous assessment of the role of microfinance in poverty reduction, there is some evidence that suggests that expansion in the membership in microfinance programmes at the *Thana* level and household consumption levels are found to be positively correlated. The HIES 2005 does not provide any information on household membership in microfinance programmes, but does provide data on household membership in safety net programmes—some of which offer microcredit. Although this variable is not a precise measure, we explore its impact in the PMTF and find that it is a significant determinant of household per capita consumption. However, we decide to drop the variable from the final model for a practical reason: the variable cannot be used for recertification of eligibility status over time after the first time that an applicant fills up the PMT form.

(4) Location variables: The Poverty Assessment shows that the incidence of poverty has a clear regional pattern in Bangladesh, which suggests that the geographical location of a household plays an important role in determining its consumption levels. Detailed analysis of this pattern suggests that significant consumption gains among the poor were largely limited to the eastern part of the

[8] See Bangladesh Poverty Assessment for further details.

country that has better access to major urban growth centres of the country. The east includes the Dhaka, Chittagong and Sylhet divisions, while in the west the lagging regions include the Khulna, Rajshahi and Barisal divisions. All of the eastern districts had significant reductions in poverty, a phenomenon that has been explained by spillover effects from the Dhaka district—which has had historically the lowest poverty incidence—on other surrounding areas. In contrast, some of the areas in the West have actually grown poorer whiles others have stagnated (see Table III).

The need to include location variables in the PMTF is also important from the view to improve existing regional coverage of safety net programme. Table III shows that the coverage of safety net programmes varies significantly by division and is not well correlated with divisional level poverty rates. For example, Sylhet has a poverty rate much lower than the national rate but nevertheless has the highest coverage of safety nets among all divisions. In contrast, Khulna, which has the second-highest poverty rate in the country, has the least coverage of safety nets. Low coverage among the total population of the relatively poorer districts also translates to low coverage among the poorest. Around 41 and 28 per cent of households from the poorest decile participate in safety net programmes in Sylhet and Chittagong respectively, compared to 15 per cent in Barisal and Khulna (Ahmed 2007).

TABLE III
POVERTY HEADCOUNT AND THE DISTRIBUTION OF SAFETY NET BENEFICIARY HOUSEHOLDS (%)

Division	Poverty Headcount		Distribution of Beneficiary Households		
	2000	2005	2005	2005	2005
			Total	Rural	Urban
Dhaka	46.7	32.0	14.27	19.98	4.94
Barisal	53.1	52.0	13.34	14.79	5.00
Chittagong	45.7	34.0	11.06	12.89	5.72
Khulna	45.1	45.7	9.58	11.03	4.23
Rajshahi	56.7	51.2	12.07	13.02	6.71
Sylhet	42.4	33.8	22.42	24.31	11.25
National	48.9	40.0	13.02	15.54	5.45

Source: HIES 2000 and 2005 in Ahmed (2007).

These four categories of variables identified from the Poverty Assessment are included in a basic model as a first step to develop the PMTF. Most of the continuous variables, however, were converted to dummy variables to allow for a flexible form for the regression. Continuous variables are also more likely to be mis-reported at the right tail. Different subsets of variables are then checked for possible multicollinearity and adjustments are made accordingly. Multiple models are then generated that are then evaluated based on their respective levels of coverage, undercoverage and leakage rates to decide on the final model used to arrive at the PMTF. The optimal model is selected based on the overall effectiveness in prediction and the undercoverage, leakage, and coverage rates, and the incidence of targeting. Table A2 in Annex reports the first three performance indicators for cut-off lines ranging from the 15th percentile to the 40th percentile. These cut-off lines are chosen given the latest 2005 poverty calculations that show that the extreme poverty line in Bangladesh ranged from 14.6 per cent in urban areas to 28.6 per cent in rural areas in 2005. The national extreme or “lower” poverty line is estimated to be 25.1 per cent, whereas the “upper” poverty line is at 40 per cent. Regression results for the proposed PMT model are presented in Table A3.

Some countries (e.g. Jamaica) use different PMT models for urban and rural areas due to differing “manifestations” of poverty in these respective areas. Theoretically this is ideal as it offers the best model for each areas allowing for structural differences, and thus would naturally minimise the respective error rates. However, from a practical standpoint using two separate models for urban and rural areas respectively has administrative cost implications as well as operational complications such as the ambiguity of distinction between rural and urban in some areas in Bangladesh. The ultimate decision should be based on further analysis of the PMT model’s predictive power by urban and rural areas, and a subsequent assessment of targeting performance. However, calibrating two regressions for rural and urban areas separately, even with a larger set of variables, fails to result in any substantial improvement in the targeting accuracy when compared with the errors associated with the national model conditioned by urban and rural status (See Figures A1 and A2 in Annex). Given these results, we recommend using one national PMT model.

The proposed PMTF is more likely to assign benefits to larger households; households who own fewer durable goods and less land, live in poor quality housing; households with younger or older household heads who are less educated; and where the head is a female or who is either widowed, separated or divorced, and has lower levels of education. These variables are generally associated with low welfare, as evidenced by the 2008 Bangladesh Poverty Assessment (World Bank 2008). The weight on each variable is also consistent with the results of the 2008 Poverty Assessment. Table A4a in the Annex presents the weights on each variable for the PMT model. Table A4b explains how eligibility is determined based on the PMT scores using a number of eligibility cut-off lines or various percentiles of the actual per capita consumption distribution. Given the characteristics of the households and the respective weights on each of their characteristics, household A receives a score of 616 while household B receives a score of 716. Using a cut-off line of either the 15th or the 40th percentile, and comparing with the relevant cut-off score, we find the household A not B, is eligible.

4.2 Comparing the Proposed PMTF with Models Developed in Other Countries

A comparison of the regression models used for proxy means testing in other countries indicates that our model performs quite well in terms of predicting household welfare and targeting accuracy. For example, Narayan *et al.* (2006) achieved R^2=0.56 in the case of Sri Lanka, while the predictive power of the model used in Pakistan was 0.53 (Hou 2008). Proxy means test models developed elsewhere had a much lower R^2: Glinskaya and Grosh (1997) achieved R^2= 0.20 in Armenia, while Grosh and Baker (1995) achieved R^2=0.30 to 0.40 in Latin American countries, Ahmed and Bouis (2002) used a model with R^2= 0.43 in the case of Egypt. In terms of targeting accuracy, at the 30th percentile cut-off line, the proposed PMT model generates an undercoverage rate of 43 per cent and a leakage rate of 30 per cent. Recent work on Pakistan by Hou (2008) identifies a PMTF that at the same cut-off line results in undercoverage and leakage rates of 48 and 35 per cent respectively. In the case of Sri Lanka (Narayan *et al.* 2006) for a cut-off of 30th percentile, the PMTF yields an undercoverage rate of 43 and a leakage rate of 35 per cent. In terms of some of the other countries that currently use a PMT-based targeting system, we find that Jamaica utilises a model that, for the 30th percentile cut-off, yields an undercoverage rate of 69 per cent and a leakage rate of 44 per cent (Grosh and Baker 1995). The corresponding rates are 39 per cent and 24 per cent for urban Bolivia, 54 and 35 per cent for urban Peru (Castenada and Lindert 2005). Thus the targeting accuracy of the PMT model presented in this paper for Bangladesh compares well with those from other countries, both in South Asia and beyond. The variables included in the proposed PMT model for Bangladesh are also similar to the ones used by other models in South Asia. Common variables include location, housing quality, ownership of durables, family demographics, and characteristics of household head. Table A5 in the annex compares the variables used for PMTs in Sri Lanka and Pakistan with those proposed for Bangladesh.

4.3 Robustness Check for Undercoverage and Leakage Rates

As the same sample is used for modeling and testing—which can cause the so-called "over-fitting" problem—the result may bias in favour of the model because the prediction from the model is tested on the same observations that were used to derive coefficients. To check for this, the sample is split randomly at the *mauza* (or PSU) level where half of the households are assigned to the modeling sample and the other half to the testing sample. This method has been applied in a number of other papers (Hou 2008). We do this for the PMT model, and find that there are no significant differences between the two samples for all the variables used. Table A6 shows that error rates using split samples are similar to those in the original model for the various cut-off lines. The results suggest that estimations using the whole sample are quite robust.

4.4 Evaluating the Targeting Efficiency of the Proposed PMTF

There are important questions regarding implementation that need to be asked when evaluating the PMTF. As both undercoverage and leakage rates fall as the cut-off line or the threshold that defines the target group is increased, it is important to consider which cut-off line to choose that generates a reasonable level of targeting accuracy and is also fiscally feasible. The latter will depend on the population covered. Other questions to consider include who is wrongfully missed and who is wrongfully included? Are these errors consistent across the country or is the targeting efficiency better in some areas than others? Finally, if possible it is also important to address how the new selection criteria as proposed by the PMTF compare with existing programmes in terms of their targeting efficiency in identifying the poor.

4.4.1 Error and Coverage Rates by Divisions and Urban/Rural Status

Simulations using the proposed PMT model across the various divisions and sectors in the country show that there are some caveats to the model that are noteworthy. In the Dhaka division, the undercoverage rate is much higher compared to the rest of the country. At the 30th percentile cut-off, the undercoverage rate in Dhaka division is 62 per cent (Table A7), whereas the country average is 43 per cent. In contrast, undercoverage is much below the country average for Rajshahi (31 per cent) and Khulna (36 per cent) divisions which are substantially poorer than Dhaka. Using a higher cut-off of 40th percentile while reduces the undercoverage rate to 46 per cent in Dhaka, it also significantly lowers the same in the rest of the divisions to as low as 21 per cent in Rajshahi. The variations in the error rates across divisions are also reflected in the wide range found in the coverage rates: using a 30th percentile cut off, the sum of the total beneficiaries as a proportion of the total population covered in Dhaka is at a minimum of 13.5 per cent while the same is 39 per cent in Barisal. Thus the variations in the targeting efficiency of the proposed PMTF across different divisions allow for the possibility of using different cut-off lines across different divisions if achieving spatial equality across divisions in terms of the size of the beneficiary population is an important policy consideration.

The undercoverage (coverage) rate in urban areas is also considerably higher (lower) than in rural areas. The gap between rural and urban leakage rates, however, is much smaller. The problem of undercoverage in urban areas perhaps is less important than it appears. The urban sector constitutes 25 per cent of the total population, and has a lower incidence of extreme poverty (15 per cent) than the rural sector (28.6 per cent). This implies that a lower number of extreme poor in the urban sector is actually left out by the PMTF. A similar argument could be made in the case of Sylhet (and Chittagong), with only about 6 (19) per cent of the population and an incidence of extreme poverty of about 20.8 (16) per cent. However, about 60 per cent of the poorest households in the country are located in Barisal, Khulna and Rajshahi divisions where the PMT model performs better than the national average in terms of generating lower undercoverage and leakage rates.

It will be important to explore options to minimise errors in the urban areas of the Dhaka division where over 30 per cent of the population resides, and where the incidence of extreme poverty is 19.9 per cent. As we find in Table A7, the undercoverage rate is much higher in urban areas of Dhaka (which would include Dhaka metropolitan city) than in rural areas of Dhaka. The differences in the leakage rates, however, are minimal. But the undercoverage and leakage rates in urban and rural areas of Dhaka are relatively higher than the national levels respectively. To explore this point even further, we compare the targeting accuracy between the urban (rural) Dhaka with the urban (rural) areas in the rest of the country. We find that the performance in both rural and urban Dhaka is still significantly poorer compared to the rural and urban areas of the rest of the country respectively. For instance, using a 25th percentile cut-off, we find the undercoverage rate for urban Dhaka is 79 per cent compared to 53 per cent in the rest of the urban areas of the country. The undercoverage rate for rural Dhaka using the same cut-off line is 65 per cent compared to 41 per cent in the rest of the rural areas of the country. Targeting the bottom 25 per cent of the population results in the total coverage of beneficiaries as a proportion of the population of about 4 per cent in urban areas of Dhaka compared to 14 per cent in the rest of the urban areas in the country. Similarly, for the same target group, the coverage rate is 13 per cent in rural Dhaka compared to 26 per cent in the rest of the country. These results indicate certain peculiarities associated with the Dhaka division that is perhaps not captured well by a national level PMT model.

One option would be to have a separate PMTF for Dhaka only. However, such a policy would be politically impractical and pose administrative complications. An alternative option would be to use a higher eligibility cut-off line in the Dhaka division to circumvent this problem of low coverage rate. This appears to be possible even with a budgetary limit on resources or a requirement of spatial equality of coverage across the country. For example, as we see in Table A7, with an eligibility cut-off of 20th percentile, the model is able to cover around 6.6 per cent of the population in Dhaka, while 17 per cent in the rest of the country. The undercoverage and leakage rates in Dhaka at the 20th percentile cut-off are 75 and 42 per cent respectively, as compared to 53 and 38 per cent in the rest of the country respectively. Using a higher cut-off of 30th percentile, the model is able to increase the coverage rates in Dhaka to 13 per cent while lowering the errors associated with undercoverage and leakage to 62 and 33 per cent respectively. This results in a substantial reduction in the gap in coverage and error rates between Dhaka and the rest of the country. This also means a total coverage of 28 per cent of the population in the rest of the country, which may be fiscally difficult to accommodate. Thus, policy makers would need to weigh the political trade-offs between (a) using the same cut-off line nationally; (b) using a different cut-off for specific areas such as the Dhaka division and a separate one for the rest of the country; and (c) plausible budgetary allocations which will determine coverage and benefit levels.[9] If option b is not politically feasible, a possible compromise would be to use the 20th percentile cut-off nationally which is intuitively appealing as it represents the population that reside below the national extreme poverty line. This would result in a total national coverage of 17 per cent of the population, and tolerable levels of undercoverage rate of 52 per cent and a leakage rate of 38 per cent. In the Dhaka division, a 20th percentile cut-off will allow 6 per cent of the population to be covered with an undercoverage rate of 75 per cent and a leakage rate of 42 per cent.[10]

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[9]It is important to note that these figures provide us only an indication of the fiscal costs that may be associated when targeting a certain portion of the population in various parts of the country. The exact amount of the costs will depend on the budget constraint and the size of the benefits levels or the type of payment scheme implemented.

[10]Note that the model covers less than the target population. This is because 20th percentile in actual consumption expenditure is not equal to the 20th percentile in terms of predicted expenditure. For example, the model predicts expenditure such that only 13 per cent of the population has predicted expenditure less than the true expenditure of the 20th percentile of the population.

4.4.2 Incidence of Targeting and Distribution of Errors

Due to the relatively high rate of undercoverage generated by the PMT model at the 20th percentile cut-off line, it is important to explore which type of households are actually selected as eligible and who are missed, and where they belong on the expenditure distribution. The problem of undercoverage is less of a concern if (i) most of the selected households are located in the bottom part of the expenditure distribution, (ii) those target groups who are erroneously excluded fall just below the cut-off or poverty line, and (iii) those non-target groups who are erroneously included fall just above the poverty line. Table A8 shows that the incidence of coverage across the distribution of actual per capita consumption expenditure, i.e. how the selected beneficiary population is distributed among various groups when the cut-off line is set at the 20th percentile. The model shows highly progressive targeting: depending on which area is chosen, up to one per cent of the richest quintile is identified as eligible beneficiaries whilst over half to more than two-thirds of those in the bottom quintile are identified as eligible.

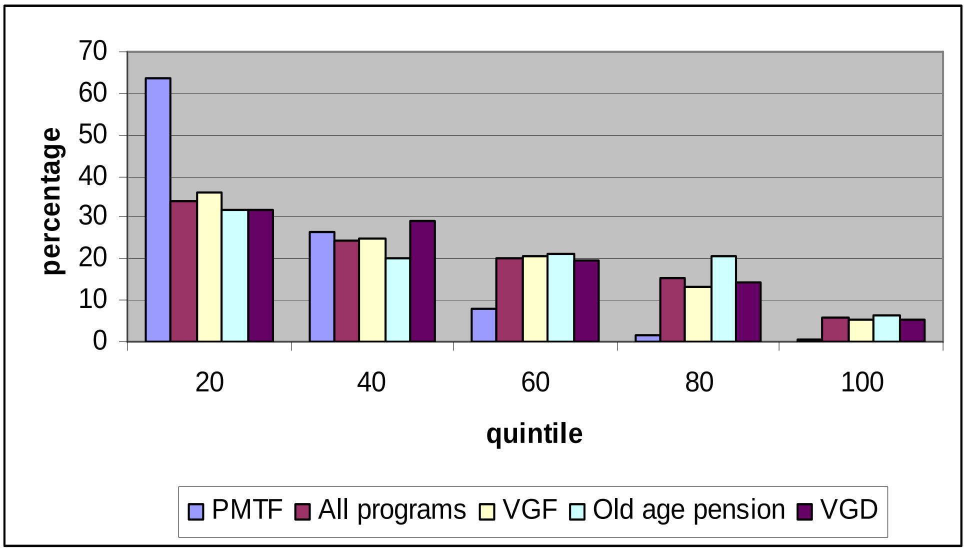
Figure A3 in the annex shows the incidence of targeting by per capita expenditure decile is also progressive. Given the 20th percentile cut-off line, about 36 per cent of beneficiaries are from below the bottom 10 percentile and about 23 per cent of beneficiaries are between 10th percentile and 20th percentile. This is a marked improvement over the incidence of targeting found in many of the public safety net programmes (see Table II).

In Table A9 we check the distribution of the exclusion and inclusion errors for the 20th percentile cut-off nationally, by urban/rural status, and in the Dhaka division. In all three cases, the largest proportion of eligible households or the target group, who are erroneously missed by the model belong to the group close to the cut-off lines, followed by households in the lower deciles. At the 20th percentile cut-off, 58.65 per cent of the target group erroneously missed belonged to the second decile, while 41.35 per cent belonged to the bottom decile (see Figure A3). In the terms of the undeserving households or the non-target group that are erroneously included by the model, we find that a higher proportion of this group is located just above the cut-off lines. The proportion declines monotonically with higher deciles. More than two-thirds of the non-target population predicted by the model as eligible belongs to the two deciles just above the cut-off lines. Similar distributions of the errors are found for Dhaka as well as in both rural and urban areas.

4.4.3 Comparing the PMT Model with Existing Programmes

The targeting efficiency of the proposed PMT model compares quite favourably with the performance of safety net programmes currently found in Bangladesh. A more or less fair comparison between the PMT model and the current safety nets in place can be conducted for a cut-off at the 20th percentile of the actual per capita consumption expenditure. This is possible as the combined coverage of the total population by all safety net programmes is approximately 12.6 (see Table I). Using the PMT model with a cut-off of 20th percentile, a similar coverage rate of 13.5 per cent of the population can be achieved. When the 20th percentile cut-off is chosen, the PMT model is able to select 52 per cent of the beneficiaries from the bottom 10 per cent of the population (see Table A8) compared to only 23 per cent in the case of current safety net programmes (Table I). The incidence of targeting is also much more progressive than that found among the largest safety nets programmes, VGF, VGD and Old Age Pension programmes (see Figure 1).

Figure 1: **Comparing PMT Model and all Existing Programmes: Incidence of Targeting by Per Capita Consumption Quintiles**

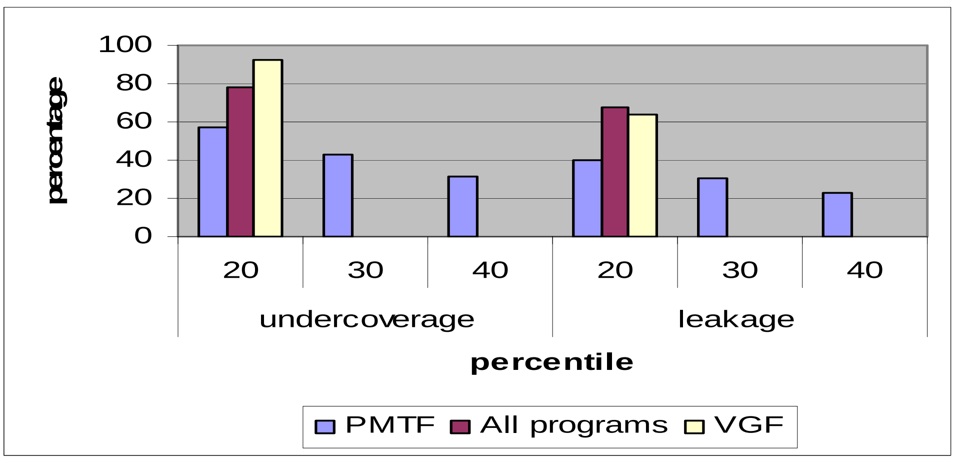


Source: HIES 2005 and simulations.

Further, when we compare the targeting accuracy, we find that both the undercoverage and leakage rates of the PMT model are substantially lower than those of the current programmes combined (see Figure 2). The difference in the undercoverage rate is around 20 percentage points, and in the leakage it is around 28 percentage points. The largest safety net programme, VGF, appears to have higher error rates compared to the PMT model in terms of covering the bottom 20 per cent of the population. It should be noted, however, that the results of the PMTF are biased toward better targeting accuracy due to the following assumptions: (i) the outreach of beneficiaries is perfect; (ii) the up-take by beneficiaries is 100 per cent; and (iii) there is perfect programme implementation. Nevertheless, these comparisons, albeit imperfect, suggest replacing existing targeting mechanisms with a PMT model could potentially improve the targeting accuracy of public safety net programmes significantly.

What these results, however, are unable to show is the impact of a PMT based targeting scheme on the actual welfare of the eligible beneficiaries. This would require the identification of a payment schedule and a budget envelop that would allow for the share of the benefits to be the highest among the bottom 10 to 20 per cent of the population. We simulate the impact of various payment schedules, presented below, using a number of feasible budget constraints on the national poverty rate and poverty gap, and compare the incidence of benefits.

Figure 2: **Comparing PMT Model with Performance of Existing Safety Net Programmes: Error Rates**



Source: HIES 2005 and simulations.

The total public spending on safety net programmes by the Government of Bangladesh was less than 1 per cent of GDP till the late 1990s, and increased to 1.6 per cent by 2007-2008 (World Bank 2008). This would imply around Taka 98 billion was spent on safety nets in 2007-2008, which is fairly substantial when compared to social spending in other low-income countries. The Bangladesh Government increased expenditures on social welfare programmes even higher in the following years to increase both coverage as well as amount of benefit per capita. Even if a third of the 2007-2008 safety net budget of around Taka 34 billion spent in programmes used a PMT-based targeting mechanism to cover 20-30 per cent of the population, simulations using HIES 2005 data show that under various payment schedules, there would have been the potential for a 7.5 per centage reduction in the poverty rate (representing a drop from 40 to 37 per cent) and a 22 percentage decrease in the poverty gap (representing a decrease from 9 to 7). Table IV shows the coverage, undercoverage and leakage rates[11] associated with three types of payments schedule: (A) Taka 300 per household per month; (B) Taka 500 per household per month; and (C) Taka 710 per household per month.[12] We find that if the average amount of benefits is not increased and kept at the current average level of Taka 300 per household per month, it allows for a coverage of over 33 per cent of the population. However, if the amount of benefit is increased to Taka 500 or Taka 710, even though a lower number of the population are covered, the leakage in the programme decreases at the expense of leaving more numbers of poor people outside of the scope of the programmes.[13]

TABLE IV
COVERAGE, UNDERCOVERAGE, LEAKAGE AND BENEFIT INCIDENCE USING DIFFERENT PAYMENT OPTIONS

Option	Payment hh/month, Taka)	Population coverage	No. of beneficiary Households (million)	Under coverage	Leakage	Incidence of Benefits				
						Q1	Q2	Q3	Q4	Q5
A	300	33.6	8.5	34.56	22.11	46.7	31.2	16.4	4.9	0.8
B	500	20.2	4.9	56.29	13.32	56.2	30.5	10.3	2.6	0.5
C	710	14.2	3.4	68.09	10.14	62.6	27.3	8.3	1.8	0.1
D	*710*	*28.8*	*7.3*	*41.75*	*19.38*	*49.5*	*31.1*	*14.8*	*3.9*	*0.7*

Table IV presents a dilemma regarding which payment option to choose given that all three have similar impacts on the poverty rate and poverty gap.

[11]The leakage rate is the same for in terms of beneficiaries as well as level of benefits since the levels of benefits are uniform and not progressive.
[12]These simulations were conducted using AdePT-Targeting, a STATA programme developed by Michael Lokshin and Zurab Sajaia of the Development Research Group in the World Bank. Simulations using different progressive payment schedules were also conducted but are not reported as the impact on the poverty rate and poverty gap was not significantly different.
[13]Tk. 300 represents only 5 per cent of the average per capita monthly household expenditure which is much lower when compared to other developing countries. Thus there is ample room to raise the benefit levels without having to worry about work disincentives.

However, when we look at the incidence of benefits, we find it to be far more progressive for option C compared to option A. Thus, the results in Table IV present a number of trade-offs between: (i) the level of benefits and coverage; (ii) undercoverage and leakage; and (iii) coverage and benefit incidence. A reasonable payment option, given a budget constraint of Taka 34 billion, is option B which allows the coverage of the bottom 20 per cent of the population with reasonable targeting accuracy and incidence of benefits. The results also suggest that large numbers of poor people live around the poverty line, which is why the impact on poverty measures remains unaffected when we increase the level of benefits. Further simulations suggest that if the total budget envelop is increased to Taka 68 billion, a much higher impact on poverty can be achieved (see Option D in Table IV). With a benefit amount of Taka 710 per household per month reduces poverty rate from 40 to 33.4 per cent (16.5 per cent decrease) and poverty gap from 9 to 5.6 (37 per cent decrease). This would cover around 7.3 million households and allow for a similar benefit incidence as found in Option A. Whichever payment option and budget envelop is chosen, these results in Table IV show that in terms of benefits, a PMT-based targeting system will always allocate a higher share of the benefits to the poorest at the cost of losses incurred by the less poor sections of the population. The share of benefits for the bottom 20 per cent under the PMTF is much higher, as shown in Table IV–and conversely the share of the top quintile is much lower—than that under the existing targeting system employed by various programmes (Table II). However, it is important to note that simulations reported in Table IV are rough calculations using a number of simplifying assumptions regarding perfect implementation and do not account for administrative and implementation costs.

V. PMTF IMPLEMENTATION CHALLENGES

Developing the PMTF is only one key aspect of a household targeting system. Ensuring that the PMTF is properly implemented is equally critical, especially if it is to serve multiple programmes (with differing thresholds for eligibility) as in the case of Bangladesh. The administrative responsibilities that are associated with implementing a PMT based targeting system include: (a) a household interview and/or home visit to apply a short questionnaire to collect data on the PMTF; (b) an automated information system for data entry, validation and processing a beneficiary registry; and (c) a monitoring, updating and quality control audits system.[14] This section briefly discusses these administrative requirements associated with a PMT-based household targeting system to

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[14] See Castaneda and Lindert (2005) for more details on cross-country experiences with implementing PMT-based household targeting systems.

identify the key implementation challenges in the context of the institutional setting in Bangladesh.

5.1 Data Collection Processes

The process through which household information is collected is a crucial challenge that needs to be overcome to ensure successful targeting results. First, budgetary constraints may not allow programmes to do a door-to-door collection of information from households, as is generally recommended when using a PMT-based targeting approach. A household visit makes it possible to verify the location and housing quality and other variables used in the PMTF. However, household visits are time consuming and costly, especially when the expected programme coverage is large. An intermediate solution is to collect the information at programme offices, and to make household visits for a sample of beneficiaries to verify the information collected.[15] After verification, households that had given inaccurate information would then have to pay some sort of a penalty. To encourage households to report information accurately, the probability of being caught would have to be high and the penalty severe so that households are serious about voluntary compliance. A second challenge is that many extreme poor people may not actually come to programme offices to apply ,given that these groups are most likely to be isolated and have less access to information in general. This implies that an outreach effort will be needed to inform and encourage potential beneficiaries to apply. One option is to use community based organisations to get the information out regarding procedures for application and entry. A third challenge will be to have a continuous and an open registration system allowing households to apply at any time. This is particularly important in the context of Bangladesh, where households face frequent shocks and the safety net system should be designed such that it is able to "catch them when they fall." Such an on-demand registration system would require a permanent set of local welfare offices which would be in charge of ensuring a transparent, credible and quality data collection process.

5.2 Management of Household Information Registries

Once household data is collected, they need to be entered into a database of a household information registry where each household has a single identification

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[15] However, the costs savings of collecting information in this way would have to be weighed against the likely degree of misreporting and the costs of leakage, especially given the high population density in a country such as Bangladesh.

number under which to enter the household information. This is a major challenge in the case of Bangladesh since other than the recently produced voter registration identification system no other forms of population-wide identification currently exists. Countries with similar challenges have adopted a system whereby at the time of application, the household and its members receive a unique number. However, this means that a single database for beneficiary selection is maintained and managed so that duplication of information is avoided. There are a number of advantages to having a unified database. This database could be shared with various central and local level agencies so that it may be used as a screening device for multiple programmes and for cross-checking purposes. This would imply that there could be programme-specific sub-sets of this single, unified database which would include information on households that have been deemed eligible for programme benefits given programme-specific eligibility thresholds. These programme-specific beneficiary lists also help to monitor payments, support case management, screen for duplicate benefits (within or between beneficiary databases) and provide information for programme financial and other statistical reports. The important thing is to ensure that both these two types of databases (unified or the master database and programme-specific database) are updated simultaneously. This would require extensive coordination among the various ministries implementing various programmes and thus could be a major challenge. One option to overcome this problem of coordination is to install a common software application so that there is compatibility of systems across ministries for uploading of data but assign a single institution within an appropriate ministry as the "keeper" of the database. Such data management systems will be especially important if data collection, entry and validation activities are decentralised.

5.3 Institutional Responsibility

While decentralisation of all activities is not essential for the success of a PMT-based household targeting system, having clear institutional roles as to who is responsible for the design of the system, data collection and database management is extremely important. Some of these key functions include the following:

- Develop the PMTF using nationally representative household surveys as well as the operational manual and procedures for data collection, entry and maintenance. AS the PMTF would have to be updated from time to time as new national level data becomes available, a central body that is proficient in the analysis of household surveys could be in charge of this activity.

- Collect household level information at the local level with the help of community organisations. As using an on-demand approach to collect or register households seeking support would be important, this function is well-served if conducted by local level authorities such as at the municipality and *upazila* level. However, these data collection activities would have to be funded centrally.
- Enter household level data to build household database. This activity could de done centrally or locally and would depend on the capacity level at the local level.
- Manage unified and project-specific databases. Since the main database will have to be shared with multiple programmes (and in the case of Bangladesh, with multiple ministries), it is best that it is managed centrally in one ministry while the programme-specific databases are maintained by various ministries in charge of their respective programmes.
- Carry out random-sample audits and quality control reviews to provide oversight of the data collection process at the local level. This activity is generally centrally managed and coordinated with authorities who are in a position to impose penalties in cases of fraud.

5.4. Monitoring, Verification and Fraud Control

Oversight functions are critical for the success of any targeting system, especially when major responsibilities are decentralised. While creating a fool-proof system is extremely difficult, if not simply impossible, the goal should be to develop a feasible and cost-efficient system to minimise fraud to the extent possible. Some of the oversight instruments implemented in various countries range from having supervisors to oversee the data collection process to including the community members to monitor and handle appeals cases. Software applications used to develop and manage household databases can have built-in checks for consistency, duplication and missing information. Finally, as mentioned earlier, random sample re-interviews of households or “spot checks” can provide important feedback on the quality of the data collection process. Having a well-publicised oversight mechanism also helps to secure public confidence in the targeting system. Finally, having full transparency by making all information publicly accessible (such as the list of beneficiaries and financial reports) serves the dual purpose of providing the right incentives to programme officials while securing public confidence in the system.

VI. CONCLUSION

The effective implementation of any targeted safety net programme requires the identification of both the needy and non-needy households, an exercise that is not easily accomplished. In developing a formula for proxy means testing, this paper presents an option to set up a household targeting system that is transparent, uses objective criteria and is administratively simple. The results presented in the paper indicate that despite the relatively high exclusion errors in some areas like the Dhaka division, the proposed model for establishing a PMTF for Bangladesh is highly progressive in its targeting performance and reasonable in its targeting accuracy. The results also highlight the sensitivity of the choice of the cut-off vis-à-vis the targeting performance of the model. They open up the possibility of using higher cut-off lines in areas where the model does not do as well such as in the Dhaka division. However, the choice of the cut-off line would also have to depend on the fiscal space available for implementing safety net programmes. The overall results that a cut-off line of the 20th percentile may be a reasonable choice that offers decent targeting accuracy without putting much of a strain on resources.

The PMTF, however, has its limitations. First, the results presented in this paper suggest targeting the extreme poor in Bangladesh using a PMTF and a limited budget is a challenge. The errors are large, and quite disproportionate across divisions when we use lower cut-offs. Thus, additional strategies to minimise these errors such as involving communities in outreach activities could be explored when budgets are limited. Second, there could also be some systematic omissions of certain types of households due to the PMT formula itself. Some poor households might be missed, such as small households, as household size has a large weight in the PMTF. For example, a household with two old persons living with a grandchild is less likely to be picked up by the formula. Third, the data used to develop the PMTF is from 2005 and some of the variables may have changed since, which may mean that their respective weights could have changed as well. Thus it would be important to use the latest HIES 2010 data to update the formula. Finally it will be prudent to validate the proposed PMT formula or an updated version via a pilot to: (i) ensure ways to cover poor households that are likely to fall through the cracks (small families for example); (ii) refine the formula based on the above findings and any other location-specific or information verification factors; (iii) understand the implications/lessons for field work or data collection efforts, specifically with regard to ensuring the accuracy of self-reported information; and finally (iv) ensure that that the analysis is consistent with current patterns of household consumption.

There are other concerns with using a PMTF-based household targeting system that have policy and institutional implications. For instance, the formula needs to be updated over time using household surveys, and thus policy makers would need to ensure that there is some level of consistency between the household surveys that are conducted over time. Having a robust PMT formula is a necessary but not a sufficient pre-condition to developing an effective household targeting system. Equally important is the institutional framework that will allow for: (i) a cost-efficient data collection process through an appropriate outreach campaign; (ii) effective management of information or a database that is up-dated in regular intervals; and (iii) a feasible and cost-efficient monitoring and verification system to minimise fraud and leakage.

Notwithstanding these caveats, the analysis presented in this paper suggests that the proposed PMTF has the potential to improve the targeting efficiency a considerable amount when compared to existing targeted social assistance programmes. Simulations suggest delivering as little as a third of the current safety net budget via a PMT-based targeting system results in a 7.5 percentage drop in the poverty rate, and a 22 percentage drop in the poverty gap. A key caveat underlying these results is the assumption that there is 100% take up of programmes and zero implementation costs. Nevertheless, the analysis illustrates the usefulness of a PMT based targeting system in making policy decisions regarding government expenditures in social sectors. Another merit of using the PMT-based targeting system is perhaps one regarding implementation where once the system is put in place, government safety net programmes can be easily scaled up to cover larger numbers of poor households over a shorter period of time. Being in such a position is especially attractive for any government in the event of crises situations such as those associated with food, fuel and finance in recent times. Generally means tests used by the large cash transfer programmes in Bangladesh (e.g. IGVGD, Primary Education Stipend Programme, Road Maintenance Programme) already gather some information on household characteristics in addition to income (e.g. land ownership, female-headed households, occupation, family size, etc.). By using PMT based targeting, a more systematic use of that information could potentially improve current targeting outcomes as well as the fairness and transparency in the allocation of resources to the poor by these programmes.

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ANNEX

TABLE A1
ILLUSTRATION OF TYPE I ERROR AND TYPE II ERRORS

	Target Group: (actual welfare ≤ cut-off line)	Non-target group: (actual welfare>cut-off line)	*Total*
Beneficiary: (predicted welfare ≤cut-off line)	Targeting Success (S1)	Inclusion errors (E2)	*M1*
Nonbeneficiary: predicted welfare > cut-off line	Exclusion error (E1)	Targeting Success (S2)	*M2*
Total	*N1*	*N2*	*N*

Source: Huo (2008).

Note: A person who is incorrectly excluded by the PMT formula is a case of an exclusion error and conversely, a person who is incorrectly included by the formula is a case of inclusion error. Given these exclusion and inclusion errors, *under-coverage* is calculated by dividing the number of cases of exclusion errors by the total number of individuals who should get benefits or the target group [E1/N1] and *leakage* is calculated by dividing the number of inclusion errors by the number of persons that are determined eligible by the formula (E2/M1). The coverage rate is the sum of total beneficiaries as a proportion of the total population (M1/N).

TABLE A2
TARGETING ERRORS BY DIFFERENT NATIONAL AND SECTORAL MODELS

Model	Adj R2	15th percentile			20th percentile			25th percentile			30th percentile			40th percentile		
		cov	undercov	leak	cov	undercov	leak	cov	undercov	leak	cov	undercov	leak	cov	undercov	leak
PMT	***0.57***	***0.084***	***0.685***	***0.4***	***0.141***	***0.573***	***0.397***	***0.19***	***0.492***	***0.333***	***0.246***	***0.427***	***0.302***	***0.357***	***0.315***	***0.233***
A	0.64	0.173	0.473	0.543	0.236	0.401	0.494	0.288	0.337	0.427	0.345	0.28	0.374	0.444	0.217	0.295
B	0.52	0.069	0.733	0.42	0.129	0.601	0.384	0.175	0.524	0.322	0.228	0.454	0.282	0.338	0.344	0.225
C	0.66	0.172	0.466	0.536	0.235	0.399	0.489	0.297	0.314	0.423	0.352	0.265	0.374	0.46	0.199	0.305
D	0.54	0.68	0.724	0.4	0.127	0.597	0.368	0.175	0.517	0.313	0.227	0.449	0.275	0.346	0.331	0.228

TABLE A3
REGRESSION RESULTS

Proposed PMT Model	
Dhaka	-0.101
	(6.53)**
Barisal	-0.306
	(15.15)**
Chittagong	-0.119
	(7.46)**
Khulna	-0.260
	(14.74)**
Rajshahi	-0.256
	(15.80)**
Access to foreign remittances	0.126
	(10.38)**
Household size of 2, omitted	
Household size of 3	-0.132
	(5.76)**
Household size of 4	-0.199
	(8.67)**
Household size of 5	-0.256
	(10.77)**
Household size of 6	-0.293
	(11.79)**
Household size of 7	-0.317
	(12.08)**
Household size of 8 or more	-0.356
	(13.34)**
No. of children aged 0 to 15 years: 0, omitted	
No. of children aged 0 to 15 years: 1	-0.094
	(7.25)**
No. of children aged 0 to 15 years: 2	-0.161
	(11.85)**
No. of children aged 0 to 15 years: 3	-0.171
	(11.10)**
No. of children aged 0 to 15 years: 4 or more	-0.234
	(13.52)**
Education of spouse: none, omitted	
Education of spouse: less than 5 years	0.005
	(0.42)
Education of spouse: 5 to 9 years	0.029
	(2.49)*
Education of spouse: 10 years or more	0.147
	(11.13)**

(Cont. Table A3)

Age of household head: less than 30 or more than 50 yrs, omitted	
Age of household head: 30 to 50 yrs	0.049
	(6.99)**
Education of household head: none, omitted	
Education of household head: less than 5 years	0.071
	(6.25)**
Education of household head: 5 to 9 years	0.124
	(10.83)**
Education of household head: 10 years or more	0.188
	(13.24)**
1, if hh member engaged as agricultural labourer	-0.088
	(9.15)**
1, if hh member engaged as non-agricultural labourer -0.054	
	(5.91)**
1, if no spouse; separated or divorced	-0.178
	(9.50)**
Amount of land owned: none, omitted	
1, if amt of land owned is between 0 to 1.5 acres	0.054
	(6.53)**
1, if amt of land owned is more than 1.5 acres	0.226
	(19.98)**
1, if hh owns a fan	0.069
	(5.70)**
1, if hh owns a TV	0.119
	(11.89)**
1, if hh owns cattle	0.029
	(3.64)**
1, if hh owns a bicycle	0.032
	(3.60)**
1, if hh owns a drinking tube well	0.077
	(9.23)**
No. of members per room	-0.041
	(14.04)**
1, if hh has no electricity	-0.023
	(2.10)*
1, if hh owns house	0.041
	(3.59)**
1, if hh has cement roof, omitted	
1, if hh has tin roof	-0.284
	(18.00)**
1, if hh has wood roof	-0.362
	(12.06)**

(Cont. Table A3)

1, if hh has straw roof	-0.308
	(14.90)**
1, if hh has no latrine, omitted	
1, if hh has sanitary latrine	0.109
	(7.52)**
1, if hh has kacha permanent latrine	0.063
	(4.42)**
1, if hh has kacha temporary latrine	0.063
	(4.49)**
1, if hh was brick wall, omitted	-0.131
1, if hh has mud wall	(9.41)**
1, if hh has tin wall	-0.106
	(8.79)**
1, if hh has straw wall	-0.161
	(11.96)**
Constant	7.557
	(230.49)**
Observations	10078
R-squared	0.57

Note: Absolute value of t statistics in parentheses.
*significant at 5%; ** significant at 1%.

TABLE A4a

WEIGHTS ON EACH VARIABLE

Variables		*Dummy*	*Weights*	*Variables*	*Dummy*	*Weights*
Location				Household assets		
	Sylhet	*	0	Own tube well	*	8
	Dhaka	*	- 10	Own house	*	4
	Barisal	*	- 31	Own fan	*	7
	Chittagong	*	- 12	Own TV	*	12
	Khulna	*	- 26	Own cattle	*	3
	Rajshahi	*	- 26	Own bicycle	*	3
Household characteristics				Own land:		
	household size =2	*	0	none	*	0
	household size =3	*	- 13	>0; < 1.5 acres	*	5
	household size =4	*	- 20	> 1.5 acres	*	23
	household size =5	*	- 26	Housing	*	
	household size =6	*	- 29	No. of members per room	*	- 4
	Household size=7	*	- 32	Roof: cement	*	0
	Household size=>8	*	- 36	Roof: wood	*	- 36
	No. of children (0<yr<15)=0	*	0	Roof: tin	*	- 28
	No. of children (0<yr<15)=1	*	- 7	Roof: straw, bamboo, other	*	- 31
	No. of children (0<yr<15)=2	*	- 10	Wall: brick	*	0

(Cont. Table A4)

Variables		*Dummy*	*Weights*	*Variables*	*Dummy*	*Weights*
	No. of children (0<yr<15)=3	*	-11	Wall: mud	*	-13
	No. of children (0<yr<15)=>4	*	-16	Wall: tin	*	-10
	Spouse educ: none	*	0	Wall: straw, bamboo, other	*	-16
	Spouse educ: below 5 yrs	*	0	Access to facilities & remittances		
	Spouse educ: 5 to 9 yrs	*	3	No electricity	*	-2
	Spouse educ: more than 10 yrs	*	15	No latrine	*	0
	HH member work: agri labourer	*	-9	Kacha permanent latrine	*	6
	HH member work: non-agri labourer	*	-5	Kacha temporary latrine	*	6
	No spouse; separated;widowed	*	-18	Sanitary latrine	*	11
Household head characteristics				Household receives foreign remittances	*	13
	Age: <=30 yrs; >=50 yrs	*	0			
	Age: 30<yrs<50	*	5			
	Educ: none	*	0			
	Educ: below 5 yrs	*	7			
	Educ: 5 to 9 yrs	*	12			
	Educ: more than 10 yrs	*	19	Constant		757

TABLE A4b

COMPUTATION OF HOUSEHOLD PMT SCORE

Variable	Weight	Household A	PMT score of A	Household B	PMT score of B
Sylhet	0	0	0	0	0
Dhaka	-10	0	0	1	-10
Barisal	-31	1	-31	0	0
Chittagong	-12	0	0	0	0
Khulna	-26	0	0	0	0
Rajshahi	-26	0	0	0	0
household size =2	0	0	0	0	0
household size =3	-13	0	0	0	0
household size =4	-20	0	0	1	-20
household size =5	-26	1	-26	0	0
household size =6	-29	0	0	0	0

(Cont. Table A4b)

Variable	Weight	Household A	PMT score of A	Household B	PMT score of B
household size =7	-32				
household size >=8	-36				
No. of children (0<yr<15)=0	0				
No. of children (0<yr<15)=1	-9	0	0	0	0
No. of children (0<yr<15)=2	-16	0	0	1	-16
No. of children (0<yr<15)=3	-17	1	-17	0	0
No. of children (0<yr<15)=4	-23	0	0	0	0
Spouse educ:none	0	1	0	0	0
Spouse educ: below 5	0	0	0	1	-3
Spouse educ: 5 to 9 yrs	3	0	0	0	0
Spouse educ: > 10 yrs	15				
HH head age: <=40 yrs; >=60 yrs	0	0	0	0	0
HH head age: 40<yrs<60	5	1	5	1	5
HH head educ: none	0	1	0	0	0
HH head Educ: below 5 yrs	7	0	0	1	7
HH head Educ: 5 to 9 yrs	12	0	0	0	0
HH head educ: > 10 yrs	19	0	0	1	19
HH member work: agri labourer	-9	1	-9	0	0
HH member work: non-agri labourer	-5	0	0	0	0
No spouse; separated;widowed	-18	0	0	0	0
Own tube well	8	0	0	1	8
Own house	4	0	0	1	4
Own fan	7	0	0	1	7
Own TV	12	0	0	0	0
Own cattle	3	0	0	0	0
Own bicycle	3	0	0	0	0
Own land: none	0	1	0	0	0
Own land: >0; < 1.5 acres	5	0	0	1	5
Own land: > 1.5 acres	23	0	0	0	0
No. of members per room	-4	5	-20	4	-16
Roof: cement	0	0	0	0	0
Roof: wood	-36				
Roof: tin	-28	1	-28	1	-28
Roof: straw, bamboo, tile, other	-31	0	0	0	0
Wall: brick	0	0	0	0	0
Wall: mud	-13	1	-13	0	0
Wall: tin	-11	0	0	1	-11
Wall: straw, bamboo, other	-16	0	0	0	6
No electricity	-2	1	-2	0	0
No latrine	0	0	0	0	0

(Cont. Table 4B)

Variable	Weight	Household A	PMT score of A	Household B	PMT score of B
Kacha permanent latrine	6	0	0	1	6
Kacha temporary latrine	6	1	6	0	0
Sanitary latrine	11	0	0	0	0
Household receives foreign remittances	13	0	0	1	13
Constant	757				
PMTF score			622		733
Cut-off percentile	15	20	25	30	40
Cut-off score	659	663	664	670	676

Note: *At any of the above cut-offs, household A is eligible while household B is ineligible.

TABLE A5
COMPARISONS OF VARIABLES INCLUDED IN PMT MODELS IN SOUTH ASIA

Variable	Sri Lanka	Pakistan	Bangladesh
Location			
Rural/urban/estate sectors	X		
Divisions			X
Community characteristics	X		
Access to foreign remittances			X
Household Assets			
Tube well			X
Fan	X		X
TV	X	X	X
Cattle/livestock	X	X	X
Bicycle	X		X
Car/van	X		
Cooker	X		
Refrigerator	X	X	
Motorcycle/scooter	X	X	
Radio/CD or cassette player	X		
Sewing machine	X		
tractor	X	X	
phone		X	
Watch		X	
Airconditioner		X	

(Cont. Table A5)

Variable	Sri Lanka	Pakistan	Bangladesh
Computer		X	
Land ownership/lease/rent	X	X	X
Household head			
age	X	X	X
education	X	X	X
occupation	X	X	X
Marriage status	X	X	X
gender	X	X	X
Household demographics			
Household size	X	X	X
Member age	X	X	X
Housing characteristics			
Own house	X	X	X
No. of rooms per member	X	X	X
Type of wall	X	X	X
Type of roof		X	X
Type of latrine	X	X	X
Fuel for cooking	X	X	
electricity	X	X	X

Figure A1: **Comparing Targeting Accuracy of Separate Models for Urban Areas**

undercoverage leakage

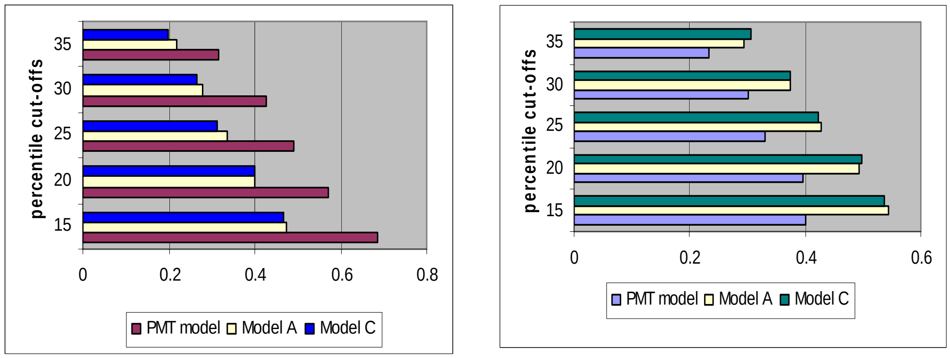
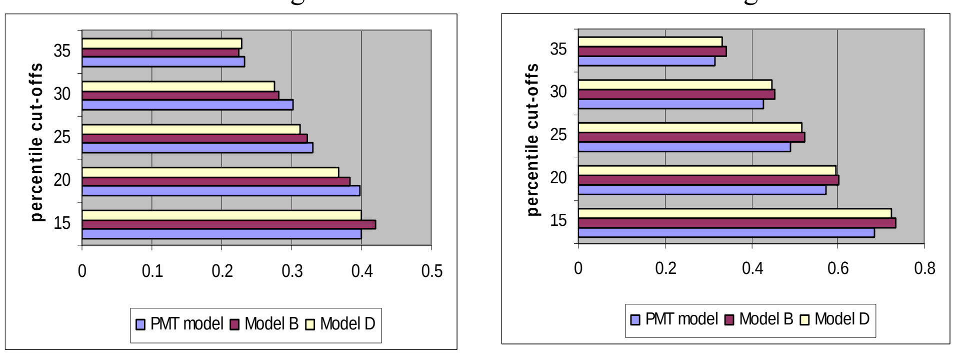


Figure A2: **Comparing Targeting Accuracy of Separate Models for Rural Areas**

undercoverage leakage



- Model A – PMT model conditioned in urban areas
- Model B – PMT model conditioned in rural areas
- Model C – stepwise regression for all possible variables to predict urban welfare
- Model D – stepwise regression for all possible variables to predict rural welfare.

TABLE A6
ROBUSTNESS CHECK

Model	Adj R2	15th percentile			20th percentile			25th percentile			30th percentile			40th percentile		
		cov	under cov	leak	cov	under cov	leak	cov	undercov	leak	cov	under cov	leak	cov	under cov	leak
PMT model	0.57	0.084	0.685	0.4	0.141	0.573	0.397	0.19	0.492	0.333	0.246	0.427	0.302	0.357	0.315	0.233
PMT model using sample	0.57	0.085	0.684	0.435	0.14	0.578	0.381	0.19	0.498	0.321	0.245	0.435	0.3	0.364	0.312	0.225

TABLE A7

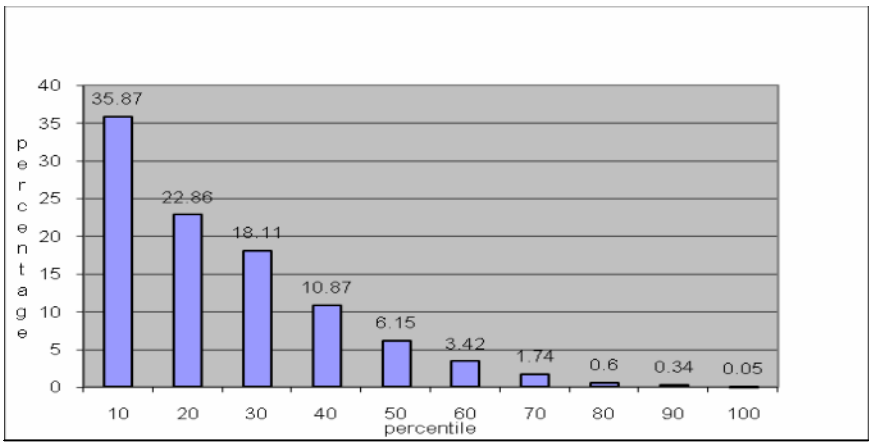
ERROR RATES BY DIVISION AND URBAN/RURAL AREAS

Division	15th percentile			20th percentile			25th percentile			30th percentile			40th percentile		
	cov	undercov	leak	cov	undercov	leak	cov	undercov	leak	cov	undercov	leak	cov	undercov	leak
Barisal	0.157	0.672	0.415	0.241	0.540	0.392	0.304	0.481	0.370	0.386	0.398	0.335	0.510	0.281	0.267
Chittagong	0.060	0.653	0.465	0.100	0.556	0.422	0.155	0.478	0.400	0.216	0.413	0.366	0.331	0.326	0.310
Dhaka	0.034	0.827	0.439	0.066	0.748	0.420	0.095	0.684	0.364	0.132	0.620	0.333	0.225	0.460	0.233
Khulna	0.126	0.646	0.486	0.205	0.506	0.390	0.256	0.411	0.299	0.304	0.357	0.258	0.437	0.278	0.244
Rajshahi	0.145	0.577	0.416	0.230	0.465	0.383	0.294	0.388	0.298	0.368	0.313	0.261	0.488	0.213	0.175
Sylhet	0.027	0.894	0.514	0.090	0.687	0.397	0.149	0.510	0.312	0.201	0.470	0.328	0.304	0.321	0.247
Urban areas	0.037	0.732	0.225	0.066	0.666	0.270	0.092	0.611	0.242	0.120	0.562	0.220	0.188	0.457	0.179
Rural areas	0.100	0.674	0.466	0.166	0.552	0.413	0.222	0.466	0.345	0.287	0.398	0.313	0.413	0.285	0.241
Dhaka urban	.0.009	0.863	0.153	0.025	0.837	0.404	0.036	0.794	0.368	0.051	0.757	0.334	0.091	0.644	0.209
Dhaka rural	0.050	0.819	0.471	0.091	0.724	0.422	0.131	0.653	0.363	0.181	0.581	0.333	0.305	0.403	0.231
ROC – urban	0.063	0.687	0.235	0.106	0.591	0.240	0.144	0.530	0.212	0.186	0.471	0.190	0.279	0.357	0.170
ROC – rural	0.118	0.629	0.465	0.193	0.50	0.411	0.257	0.409	0.342	0.326	0.342	0.309	0.452	0.248	0.242
Dhaka	0.034	0.827	0.439	0.066	0.748	0.420	0.095	0.684	0.364	0.132	0.620	0.333	0.225	0.460	0.233
ROC	0.105	0.655	0.451	0.171	0.525	0.384	0.23	0.452	0.338	0.286	0.384	0.286	0.415	0.268	0.227

TABLE A8
COVERAGE BY PER CAPITA CONSUMPTION DECILES: 20TH PERCENTILE CUT-OFF

Decile	National	Urban areas	Rural areas	Dhaka
1	0.52	0.51	0.53	0.29
2	0.31	0.18	0.37	0.18
3	0.23	0.14	0.27	0.10
4	0.13	0.08	0.15	0.08
5	0.06	0.02	0.08	0.06
6	0.05	0.01	0.06	0.01
7	0.02	0.00	0.03	0.01
8	0.00	0.00	0.00	0.00
9	0.004	0.00	0.01	0.01
10	0.00	0.00	0.00	0.00
Total	0.135	0.08	0.164	0.06

Figure A3: **Incidence of Targeting by Per Capita Consumption Decile (Cut-Off =20th Percentile)**



`TABLE A9

DISTRIBUTION OF INCLUSION AND EXCLUSION ERRORS: 20TH PERCENTILE CUT-OFF

Decile	National		Urban areas		Rural areas		Dhaka	
1	42.48		40.81		43.41		46.31	
2	57.52		59.19		56.59		53.69	
3		43.11		46.27		42.56		28.13
4		27.33		32.84		26.37		37.50
5		14.89		17.91		14.36		20.31
6		9.11		2.99		10.18		7.81
7		3.78				4.44		4.69
8		1.33				1.57		1.56
9		0.44				0.52		
10								
Total	100	100	100	100	100	100	100	100

Figure A4: **Distribution of Exclusion and Inclusion Errors (using a 20th percentile cut-off)**