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Participatory Wealth Ranking (PWR)
in Socio-economic Poverty Comparisons

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Accuracy Analysis of Participatory Wealth Ranking (PWR) in Socio-economic Poverty Comparisons

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Abstract

This paper[1] describes Participatory Wealth Ranking's (PWR) accuracy in predicting the poverty status of groups identified by socio-economic indicators. On the basis of a census in 8 villages located in three of the six divisions of Bangladesh, 1660 households were scored using the Participatory Wealth Ranking (PWR) method. A randomly selected sub-sample of 320 households was further interviewed using an LSMS-type questionnaire. Based on four main socio-economic descriptors, our findings reveal Balanced Poverty Accuracy Criterion (BPAC) values above -7% and below 33% if the PWR tool is defined at the national level by the cut-off score of 86.67. However, for some socio-economic categories comprising 100 households or more, a special calibration to set up a second-step tool type was carried out to improve accuracy performance. Hence, some additional and more rewarding group-specific BEST scores were discovered. Irrespective of the socio-economic indicators, accuracy was lower among the very-poor (VP) compared to the not very-poor (NVP) class. Local perceptions frequently deviated sharply from the benchmark, especially among the characteristics 'land holding' and 'household head's education.' Two indicators out of five, namely 'housing' and 'occupation' substantially overcame misclassification rates among the poor leading, thereby, to on the average positive BPAC values. Our findings can be useful to improve facilitation during PWR's field process which would have a positive influence on the total accuracy.

[1] The data were collected by the survey firm DATA in Bangladesh within the scope of the project "Developing Poverty Assessment Tools" which is carried out by the IRIS Center, Maryland, and funded by the United States Agency for International Development (USAID). We gratefully acknowledge the source of the data. The cleaning and aggregation of the data (including the daily per-capita expenditures) were carried out at the Institute of Rural Development, University of Göttingen. We are grateful for comments received from Thierry van Bastelaer, Christian Grootaert, Kate Druschel, and Laura Foose on a previous version of our analysis regarding PWR that is contained in Zeller et al. (2004). Anton Simanowitz provided helpful advice for the preparation of the PWR field research. We are also thankful to Gabriela Alcaraz, doctoral student, Institute of Rural Development, for her remarks during the analysis. Any remaining errors are our own.

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List of Abbreviations and Acronyms

BPAC	Balanced Poverty Accuracy Criterion
CGAP	Consultative Group to Assist the Poor
CPI	Consumer Price Index
DATA	Data Analysis and Technical Assistance
IFAD	International Fund for Agricultural Development
LL	Ladder of Life
LSMS	Living Standard Measurement Survey
MDG	Millennium Development Goal
MFIs	Microfinance Institutions
NPA	Non-poverty Accuracy
NVP	Not Very Poor
PA	Poverty Accuracy
PAT	Poverty Assessment Tool
PIE	Poverty Incidence Error
PL	Poverty Line
PPP	Purchasing Power Parity Exchange Rate
PWR	Participatory Wealth Ranking
SEF	Small Enterprise Foundation
SPSS	Software Package for Social Sciences
TA	Total Accuracy
UN	United Nations
UNDP	United Nations Development Programme
USAID	United States Agency for International Development
VI	Visual Impression (of the interviewer)
VIP	Visual Indicator of Poverty
VP	Very Poor
WR	Wealth Ranking

1 Introduction

A good poverty tool should, among other assets, also reliably measure and compare different poverty situations. The aim of poverty measurement is poverty comparisons, i.e., to see which situation reveals more poverty than another (Ravallion, 1992). Most studies on PWR focus on poverty comparisons with respect to geographical levels. They usually compare poverty situations as measured by PWR across villages and aggregated levels as well (districts, nation). However, it is not well known how the accuracy of PWR varies among groups regarding the categories of main socio-economic characteristics such as education, housing, land holding, and occupation.

We intend to describe the variations in accuracy within and across the classes in each of the examined socio-economic indicators once a tool is calibrated, i.e., correlated with the standard (here the benchmark) to find out the desired cut-off scores. This enables us to determine which socio-economic characteristics are, in terms of accuracy, the most recommendable for targeting and/or assessing the poor and portray well the prediction link between PWR and the standard. Knowledge of such characteristics may help to build combinable tools so that specific cut-off scores can be applied to households pertaining to some socio-economic classes to improve accuracy performance. Furthermore, we focus primarily on the 'national' level. Other lower geographical levels could have been chosen as well with the expectation that the lower the level, the more the total accuracy would increase. Our focus on the 'national' level gives us the opportunity to have enough cases wherein we can examine accuracy for as many categories existing within socio-economic characteristics as possible, which was not always possible in our sample at lower geographical levels (district, village, and hamlet).

This paper seeks to investigate how the accuracy of PWR varies when subjected to socio-economic differences. We examine the following questions:

(1) How does accuracy vary between VP and NVP across groups defined by main socio-economic characteristics?

(2) Can the use of a two-step tool improve accuracy performance measures?

(3) Is there any change in the potential level of accuracy within and across categories when groups are identified by their main socio-economic characteristics?

This paper is organized in four sections as follows. First, the structure of the socio-economic groups and a brief literature review are presented. Second, accuracy performance measures within the categories in each of the five socio-economic characteristics to be examined are expounded. Moreover, the average accuracy by main socio-economic characteristics is simulated so as to estimate the potential level of accuracy from the perspective of socio-economic poverty comparisons. Third, the effect of the combination of tools on BPAC is analysed. The fourth and last section presents the main conclusions.

2 Structure of Socio-economic Groups and Literature Review

Only little is known about the effect of socio-economic descriptors when rating with PWR. Table 1a and Table 1b present possible categories that pertain to socio-economic characteristics observed in this paper. Analysis of their influence on the accuracy of PWR is likely to ease the certification process and improve knowledge in the existing literature. Previous research has already underlined the role played by most of the socio-economic descriptors examined in this paper. For instance, the UNDP's poverty reduction team in Bangladesh asserts that a "lack of employment opportunities and limited land make it difficult for people, especially those in rural areas, to break the cycle of poverty" (UNDP, 2005a). The IRIS (2004) already mentioned the "powerful" prediction ability of the value of total assets, including land and house, on accuracy.

Furthermore, Gibbons (1998) pointed out that the roof material is a 'powerful way' of identifying the very poor from the poor in most Asian countries: people who live under temporary roofs (i.e., roofs made of twigs, straw, banana leaves, etc.) belong nearly always to the very poor. He went further to add that a combination of life under temporary roofs along with the small size of a house and very simple building materials such as mud, jute sticks, etc. is a "very close“ way to identify most of the very poor. However, though housing can be an "excellent proxy" for ranking households, it should not be generalized across contexts (urban/rural, countries) (CGAP, no date). Other similar characteristics help to trace the poor. Wit (1998) noticed that clients from micro-enterprise programs generally live in brick structures that are sometimes plastered, whereas clients from his poverty programs live in mud buildings. In addition to that, he underlined the fact that 30% of the children in the poverty program did not receive a school education. Another experience comes from Deutsch and Silber (2005) who, through four different approaches, showed that poverty decreases with an increasing educational level of the head of the household.

Table 1a: Socio-economic levels by group identification options

Level	Groups' socio-economic identification options		
Main characteristics	Occupation	Education	Land Holding
Categories	- Self-employed in agriculture (n=92) - Self-employed in a non-farm enterprise (n=66) - Labourer (n=66) - Salaried worker (n=16) - Does housework (n=36) - Inactive (n=17)	- Could read in class I (n=162) - Could read from class II to class VI (n=72) - Could read from class VII to class X (n=31) - Received secondary school certificate or more (n=28)	- None : zero *decimals*[i] (n=94) - Small to medium: above zero and below 79 decimals (n=101) - Large: above 79 decimals (n=98)

Table 1b: Socio-economic levels by housing identification options

Housing identification options	Categories
Roofing material	- Material is straw (n=27) - Material differs from straw (n=266)
Type of exterior wall	- Leaves and straw (n=20) - Jute stick (n=25) - Bamboo/wood (n=90) - Tiles or brick/cement (n=19) - CI sheet (n=139) (corrugated tin)
Size of house	- Size of house is small (n=86) - Size of house is medium (n=140) - Size of house is large (n=67)
Main source of lighting	- Kerosene or no source of lighting (n=212) - Electricity (n=81)
Kind of lock on main entrance door	- Door has no lock (n=39) - Use bar to close main entrance door from inside (n=17) - Use key lock to close main entrance door (n=237)
Type of toilet facility	- Toilet facilities (n=70) - Use a pit toilet (n=150) - Use improved latrines (n=73)
Type of flooring	- Type of flooring is dirt (n=278) - Type of flooring contains cement (n=15)
Primary source of drinking water	- Dam, pond, river, or spring (n=6) - Public well with sealed pump (n=128) - Well in residence yard with pump (n=159)

3 Methods

3.1 Design of Field Research

The PWR was carried out in 8 villages located in the divisions Barisal, Dhaka, and Rajshahi. The field research comprised an LSMS-type household expenditure survey and a PWR. The PWR covered all 1660 households (census method) in the eight selected communities. For the expenditure survey, 40 households were randomly selected in each village (i.e., n=320).

Participatory Wealth Ranking is a method whereby communities themselves define who the poorest or the better-off are. Quoting Gibbons et al., 1999, p.43, “We are interested in people’s own ideas about poverty. We want them to tell us what they think and to tell us who in their village are very poor, poor or better off.” The PWR begins with a community-wide meeting convened by the facilitation team. After discussing the meaning and understanding of poverty in the local context, the people draw a map of all the households in the village and fill a card with the name of each household. Three reference groups are then formed in each ranking section, i.e., the hamlet. In Bangladesh, only women were asked to join the groups.[ii] After filling out the cards, each reference group then meets separately and sorts the household cards into piles according to the living standard on a continuum from high to low. Next comes the crosschecking whereupon the results of the ranking done by the three reference groups are brought together and the piles are scored. Scores are calculated according to the number of piles used by the participants, using the following formula: *Score of reference group =[100/(number of piles)] x pile number.*

For instance, if there are four piles, then the poorest pile (number 4) will score 100 by using the formula (100/4 x 4 = 100), and the richest pile (number 1) will score 25 by using the formula (100/4 x 1 = 25). The final score of each household is the average of the scores given by the three reference groups. Thus, the PWR methodology used in the field research closely followed the one developed by Gibbons et al. (1999). To ensure a consistent implementation of the PWR process, the facilitators were trained in a PWR course at the Bangladesh Academy for Rural Development in Comilla, organized by the Microcredit Summit in February, 2004.

3.2 Data Cleaning

Data was entered and cleaned with SPSS (Statistical Package for Social Sciences). Following Gibbons et al. (1999), three main cases can be distinguished when evaluating the internal consistency of the PWR scores. The first case of highly consistent scores is given if the scores by the three reference groups do not deviate more than 25 score points. The second case is defined by a deviation of above 25, but below 50 points, whereas the third case of inconsistent scores shows deviations of 50 points or more. Following the procedure for consistency checks proposed by Gibbons et al. (1999), we discarded 27 households in two hamlets in Chak Shadu where we observed a high number of inconsistent scores. Thus, the sample size for accuracy analysis dropped from 320 to 293 households. We conclude that the overall quality of the remaining data is within the acceptable range as defined by the PWR manual by Gibbons et al. (1999).

3.3 The International Poverty Line

Accuracy is the degree of conformity with a benchmark that is considered to be the generally accepted measure. The benchmark used in our case is the LSMS-type daily per capita expenditure measure, coupled with the absolute poverty line of US $1 per capita per day measured at the purchasing power parity rate. At the time of the survey in March 2004, 1 US-Dollar was equivalent in purchasing power to 23.18 Taka, the currency in Bangladesh (Zeller et al., 2004). Households with per-capita expenditures below this international poverty line are rated as very-poor (VP), otherwise not very-poor (NVP). Using this poverty line, we found 96 households (or 32.8%) of the sample of 293 households to be very-poor. The research task consisted in determining the accuracy of a tool – PWR, for instance – to correctly predict whether the household is very-poor (VP) or not very-poor (NVP).

3.4 Accuracy Process

Initially, the whole sample of 293 households was calibrated to determine the BEST score of 86.67. It is the default cut-off used to rank each socio-economic group except those that comprised at least 100 households and that underwent calibration to find out a special BEST score.

The BEST score is the cut-off (dividing point, poverty line) score which generates a ranking pattern that, when compared with the "true" poverty ranking, yields the highest preferred accuracy criterion, i.e., BPAC in this context (Zeller et al., 2004). To determine BPAC, the difference in the misclassifications from one poverty class to the other is first obtained and then deducted from the accuracy among the VP. All the accuracy measures obtained were calibrated at the BEST score. It takes a few steps to get accuracy measures calibrated at the BEST score. Figure 1 illustrates the stages passed through to generate the BEST score. First, we simulated a cut-off score to perform ranking within the tool. We then repeated several times across the tool's score line by trying other simulated cut-off scores. Second, we compared the ranking pattern of the tool determined by each cut-off and compared it with the "True" poverty's ranking pattern of the benchmark in order to find out the BEST score with respect to the preferred accuracy criterion.

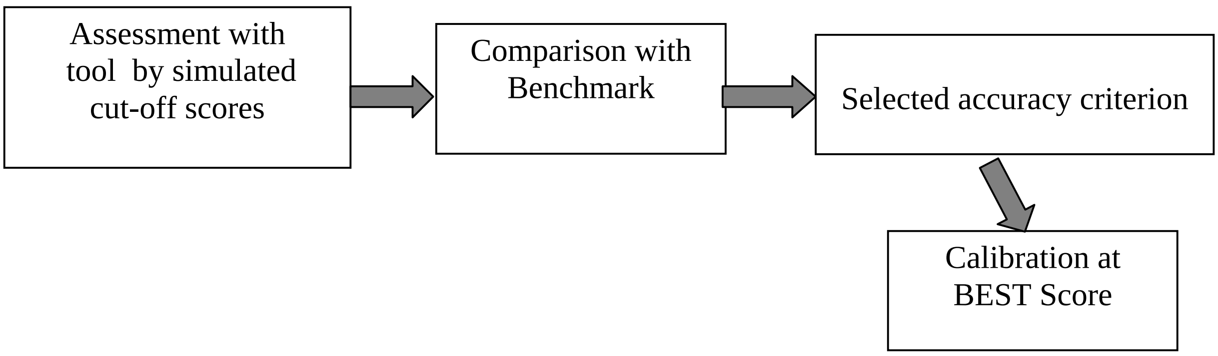

Figure 1: Accuracy process and calculation of the BEST score

4 Accuracy Performance of Socio-economic Descriptors in a PWR Exercise

In this section we begin by examining accuracy performance concerning the main socio-economic characteristics: occupation, education housing, and land holding. We then observe accuracy, on the average, across the main socio-economic description options. Lastly, we draw some partial conclusions.

4.1 Results by Categories of main Socio-economic Characteristics.

4.1.1 Accuracy of PWR

The total accuracy of BEST scores, associated accuracy criteria, and the Balance Poverty Accuracy Performance Criterion (BPAC) are shown in Table 2. Each accuracy figure in this table shows how the PWR tool performs overall given the chosen accuracy measure. When no restriction is made on the entire samples with regard to any group, total accuracy is higher among the NVP compared to the VP. The difference in the rate of misclassifications from one poverty class to the other caused the BPAC value to decrease to 49.03%, i.e., by 5.2 percentage points below its potential value of 54.2%, i.e., the poverty accuracy.

Table 2: Total accuracy and associated parameters for all the socio-economic groups

	BEST score	TA of BEST score (%)	PA (%)	NPA (%)	BPAC (%)
All groups (n=293)	86.7	68.60	54.22	75.16	49.03

BPAC: Balanced Poverty Accuracy Criterion; TA: Total Accuracy
PA: Poverty Accuracy; NPA: Non-poverty Accuracy

4.1.2 Occupation of Household Head

In contrast to the previous paragraph dealing with the overall sample of households, this sub-section and the following ones deal with groups of households defined by socio-economic characteristics. It discloses whether PWR is able to differentiate across such socio-economic classes. In this case, for instance, the criterion is the main occupation of the household head in the past twelve months. We wanted to see what becomes of accuracy measures subject to changes in the main occupation over the said period. We considered the following possible household heads' occupational categories: self-employed in agriculture, self-employed in a non-farm enterprise, labourer, salaried worker, does housework, and inactive people. We then looked especially for the BPAC, TA, PA, and NPA calibrated at the BEST score of 86.67 at the level of the nation as defined in our context. The findings are displayed in Table 3.

Table 3 shows that inaccurate predictions are on the average higher among the VP than the NVP, except for the labourer group wherein PA was above the NPA. Apart from self-employed in agriculture and the inactive groups, all of the other occupational groups achieved a positive BPAC value. A positive value in BPAC suggests that the proportion of the poor correctly identified is above the absolute difference in the rate of misclassifications. The fact that misclassifications are worst among those who are idle and those who are on their own in agriculture in contrast to those earning some salary or wages indicates that monetary indicators play a role in the ranking conducted by local people. Such a role is perceived differently by local people concerning those who work on their own in agriculture or are inactive, which may justify, on the average, the very low accuracy performance among these groups. Accuracy was lower among the VP compared to the NVP in the case of all the occupational categories except among non-farm entrepreneurs and labourers. Because in these categories people are involved in more concrete activities that are easy to monitor, predicting those who are doing better among the very poor is more straightforward.

Table 3: Total accuracy by occupational category

Occupational group	BEST score	TA (%)	PA (%)	NPA (%)	BPAC (%)
Self-employed in agriculture (n=92)	86.67	76.09	18.18	94.29	-45.47
Self-employed in non-farm enterprise (n=66)	86.67	69.70	79.17	64.29	37.51
Labourer (n=66)	86.67	57.58	59.38	55.88	64.65
Salaried worker (n=16)	86.67	75.00	60.00	81.82	60.00
Does housework (n=36)	86.67	69.44	36.36	84.00	9.08
Inactive (n=17)	86.67	76.47	50.00	80.00	-50.00

BPAC: Balanced Poverty Accuracy Criterion TA: Total Accuracy
PA: Poverty Accuracy NPA: Non-Poverty Accuracy

4.1.3 Education of Household Head

We wanted to find out how PWR is able to differentiate within and across the socio-economic groups defined by the highest level passed by the household head. We wanted to assess how total accuracy and related estimates change with respect to the level of the education of the household head. We looked for the accuracy of the BEST score for each educational characteristic. The total accuracy of BEST scores and associated accuracy criteria are shown in Table 4. The average total accuracy is nearly 75% for a cut-off score of 86.67. Inaccurate predictions are on the average always higher among the VP than the NVP. By and large, there were many more wrongly classified true VP than true NVP. There must have been an overestimation of the standard of living among the educated VP. The difference in absolute terms of the misclassification proportions, as a rule, undermined the achievements in poverty accuracy, thereby generally leading to a negative BPAC. The last row of the table requires our attention. It is about those who had received a secondary school certificate or more. Actually there were 27 'true' VP out of 28 members in this category. They had been conferred a secondary school certificate or more but have been *entirely* wrongly predicted by this PWR tool, leading to the very low performance of the tool worth a BPAC of –100% among members identified by this characteristic. There seems to be, following this example, **a positive influence of the level of education on the perceptions of local people, but that totally deviates from the benchmark per capita expenditure ranking. Most people in the village seem to think that those who have achieved a better level of education are doing fine or have a better standard of living.**

Table 4 also reveals some specific trends under PA and NPA. The better the educational level of the household head, the lower the accuracy in prediction among the poor and, conversely, an overall increase among the NVP. It is difficult for reference groups in a PWR exercise to recognize well-educated household heads that are very poor compared to the benchmark per capita expenditure ranking. Conversely, it is easier for them to do it among the "rich" households. We suggest that more vigilance be exercised by facilitators during the discussion of reference groups on which aspects bear more weight when ranking households whose heads have some remarkable level of education.

Table 4: Total accuracy by education characteristic

Education characteristic	BEST score	TA (%)	PA (%)	NPA (%)	BPAC (%)
Could read in class I (n=162)	86.67	64.20	57.35	69.15	57.35
Could read from class II to class VI (n=72)	86.67	73.61	42.11	84.91	26.31
Could read from class VII to class X (n=31)	86.67	64.52	25.00	78.26	12.50
Could pass secondary school certificate or more (n=28)	86.67	96.43	0.00	100	-100

BPAC: Balanced Poverty Accuracy Criterion TA: Total Accuracy
PA: Poverty Accuracy NPA: Non-Poverty Accuracy

4.1.4 Land Holding

We wanted to find out how accurately PWR is able to differentiate within and across the socio-economic classes defined by the total area of land in decimals used for various purposes including agriculture, forest, and orchards.

The total accuracy of BEST scores and associated accuracy criteria are shown in Table 5. The average total accuracy according to the total land use is 69.46% at the BEST score for the cut-off of 86.67 at the national level. Large land size is a relatively, and with respect to per capita daily expenditure, a very accurate indicator in PWR for revealing the poverty status of the NVP. The difference in absolute terms of the misclassification proportions has, on the average, altered the achievements in poverty accuracy, thereby leading to an average BPAC of –6.85% for all the land holding groups. With regard to groups that are formed based on their land holding characteristics, it is very inaccurate to identify who is poor and who is not in such a way that PWR matches with per capita daily expenditure. Based on such characteristics, far more than half of the poor could be wrongly targeted**.** The very low poverty accuracy values attest this fact: nearly 42% on the average. Among the poor who own no land, PWR is able to return 72 households out of 100, while it can return only 40 out of 100 households among those who belong to the limited to medium land use categories and nearly only 12 out of 100 among those in the sizeable land use category. Local people represented by reference groups quite agree with the benchmark that those who own no land are more likely to be poor. In contrast, they are nine out of 10 times wrong, compared to the same benchmark, when they tend to believe that having a large land use area at one’s disposal is equivalent to being better-off. However, they could rightly recognize all the rich households in the benchmark in spite of their belief.

Table 5: Average total accuracy by total land use area

Total land use area	BEST score	TA (%)	PA (%)	NPA (%)	BPAC(%)
None: zero decimals (n=94)	86.67	56.38	72.92	39.13	41.67
Limited to medium: above zero and below 79 decimals (n=101)	86.67	68.32	40.00	80.28	26.67
Sizeable: above 79 decimals (n=98)	86.67	83.67	11.11	100.00	-88.88

BPAC: Balanced Poverty Accuracy Criterion TA: Total Accuracy
PA: Poverty Accuracy NPA: Non-Poverty Accuracy

4.2 Average Accuracy by Main Socio-economic Characteristics

Section 4.1 has examined accuracy from the perspective of each main socio-economic characteristic while this one is to examine accuracy from the viewpoint of all of the characteristics. Table 6 displays the average accuracy estimates with respect to each of the four socio-economic characteristics: housing, land holding, occupation of the household head, and his educational level. Apart from housing characteristics wherein the BEST score varies from 75 to 93.33, all other classes conformed to the normal BEST score of 86.67% at the 'national' level. The variation is specific to socio-economic groups defined by housing descriptors as they responded advantageously to the option of a second step tool. Moreover, across the various main socio-economic characteristics, TA at BEST score is on the average from 69.46% within land holding classes to nearly 75% within those characterized by the educational status of the household head. This range of accuracy shows that, based on indicators chosen from the considered socio-economic characteristics, at least 7 to 8 households out of 10 can be well predicted so that PWR reflects the benchmark best. However, **accuracy among the VP is on the average from slightly above 30% among educational classes to below 51% for occupational groups across all the socio-economic categories. While poverty accuracy is, on the average, nearly 43%, NPA was above 75%.** Hence, despite the relatively comfortable TA, PWR has often wrongly predicted more very poor than the NVP within socio-economic characteristics. For groups defined by occupational and housing characteristics, misclassifications of the 'true' VP were on the average less than that of the 'true' NVP, while in all other socio-economic characteristics, the contrary was possible, i.e., more 'true' VP were always misclassified compared to the 'true' NVP (estimation made in terms of the proportion of the entire population). The situation of those who hold land is of a relatively high standard so that there are more visible signs (as compared to many poor without land) to easily tell about their poverty status.

Figure 2 shows that BPAC values range from above –10% to below 35%. Most values, namely those of three socio-economic descriptors out of the five observed, are negative and, therefore, graphically directed rightwards. The only exception is among land holding and educational descriptors which scored nearly -6.85 and -0.96% respectively. Graphically, they expand leftwards. The nearly -7% BPAC value for land holding indicates how far the nearly 41% poverty accuracy of the PWR tool was weakened by the differences in misclassification proportions among the very poor. Low negative BPAC values signal that there were low accuracy outcomes in predicting the poor compared to the huge gaps existing between the misclassification proportions (i.e., the difference between undercoverages and leakages). Positive values are good signs of successful identification of the very poor, which portends successful outreach and accessibility for the betterment of the entire targeting process. They emphasize that not only does the difference in misclassification proportions balance perfectly the proportion of the total poor predicted correctly but also move forward to achieve an absolute gain in the proportion of the poor identified. In this respect and on the basis of the BPAC values, one may affirm that **– when targeting the poor is the concern – PWR is on average relatively more capable of predicting per capita daily expenditures if the focus is put more on housing and occupations than education and housing characteristics.** This is applicable to the case of Bangladesh.

The above differences in the average total accuracy and average balanced poverty accuracy criteria attest the variations in the ability of socio-economic characteristics to predict per capita daily expenditure ranking in the course of a PWR exercise. More explanations to this issue are given in Table 7 wherein the most remarkable differences in BPAC across the socio-economic classes are found. In this respect, one is acquainted with, say, employment fields, housing types, and other diverse descriptors whose BPAC values were the worst (i.e., below -50) or among the BEST (i.e., above 50). For instance, while sizeable land use may lead to more than 85% loss as well as having received a secondary school certificate or more may lead to a loss of 100% among the very poor in the group, there is a gain of nearly 75% in identifying the very poor among those who use straw as their roofing material. Hence, PWR achieves very different results according to the socio-economic groups: some very good and others very bad.

Table 6: Summary table of average accuracy measures observed at the BEST score by the main socio-economic characteristics

BEST score and accuracy measures		Main socio-economic descriptors				
		Occupation	**Education**	**Housing**	**Land holding**	**Average**
BEST Scores	Min	86.67	86.67	75.00	86.67	84.34
	Max	86.67	86.67	93.33	86.67	88.00
Total accuracy (%)		70.71	74.69	69.82	69.46	**71.17**
Poverty accuracy (%)		50.52	31.12	47.80	41.34	**42.7**
Non-poverty accuracy (%)		76.71	83.08	70.92	73.14	**75.96**
BPAC (%)		12.63	-0.96	32.84	-6.85	**9.41**

BPAC: Balanced Poverty Accuracy Criterion API: Actual Poverty Incidence
PPI: Predicted Poverty Incidence PIE: Poverty Incidence Error = PPI-API

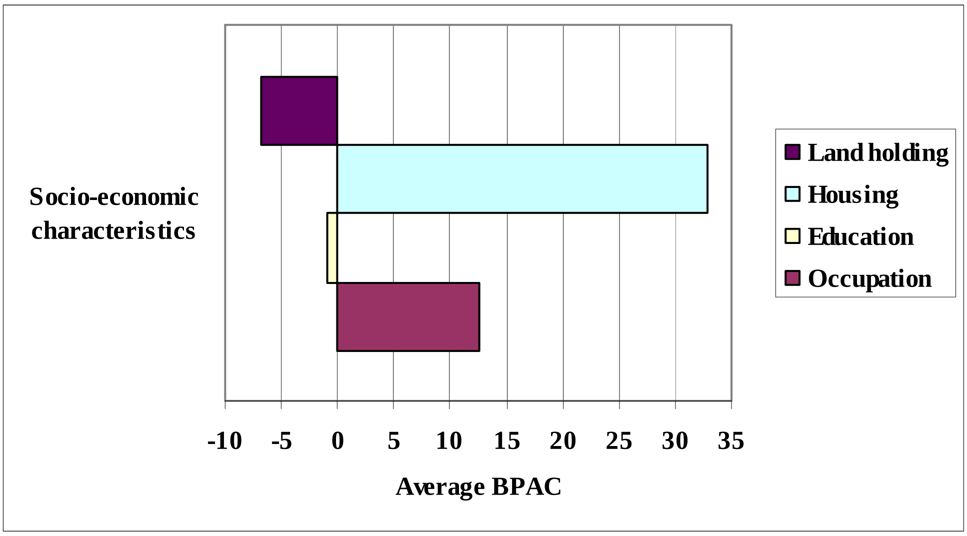

Figure 2: Average BPAC by socio-economic characteristics

Table 7: Socio-economic groups with the least and most prominent BPAC values

Socio-economic group		Accuracy performance (in percent)	
Descriptor	**Category**	**Below -50**	**Above 50**
Employment	Inactive (n=17)	-50	
	Salaried worker (n=16)		60
	Labourers (n=66)		64.65
Education	Could read in class I (n=162)		57.35
	Received secondary school certificate or more (n=28)	-100	
Roofing material	Straw (n=27)		75
Exterior wall	Leaves and straw (n=20)		50
	Bamboo and wood (n=90)		52.17
Type of lock	Main entrance door has no lock (n=39)		52.38
Type of toilet facility	Household without any toilet facility (n=70)		70
Type of flooring	Including cement (n=15)	-100	
Primary source of drinking water	Drinking water from dam, pond, river or spring (n=6)		50
	Drinking water from public well sealed with pump (n=128)*		50.15
	Drinking water from a well in residence yard sealed with pump (n=159)*		52.17
Total land use	Area is large (n=98)	-88.88	

* These groups have their own BEST score different from the regular 86.67 observed at the national level: 93.33 was the BEST score among those who drink from a public well sealed with pump while 75 was among those who use a well with pump in their residence yard.

4.3 Primary Conclusions

i) Considering this PWR in Bangladesh, we see that the average TA values, PIE and BPAC, were each distinct across the socio-economic descriptors. On the average, any gain in targeting performance was achieved among the categories housing and occupational characteristics while a loss was found among education and land holding. These differences attest the variations in the ability of socio-economic characteristics to predict per capita daily expenditures using the PWR tool.

ii) From the perspective of all the socio-economic characteristics considered in this section, it is plausible, given the average total accuracy of nearly 70% at the BEST score, that PWR can, as a rule, correctly predict the poverty status of 8 out of 10 households in regard to per capita daily expenditures. Moreover, given the diversity of the socio-economic variables examined and considering the local perceptions, it can measure a broad dimension of human poverty as well. This corroborates the findings of the previous studies by Van de Ruit and May (2003) which showed at least positive associations in the case of the quality of roofing material, source of drinking water, educational attainment, control over assets, etc. with PWR scores. However, while nearly the ratio of 7 out of 10, on the average, is respected among the NVP, it is unfortunate that, based on socio-economic descriptors, nearly only 5 to 6 out of 10 "truly" poor can, as a rule, be identified: poverty accuracy does not exceed 60%. This issue of reduced accuracy among the VP compared to the NVP has already been mentioned in some previous studies (IRIS, 2005; Zeller et al., 2004b and 2005)

5 Effect of the Combination of Tools on Accuracy Performance

Within some groups that are important in size, further analysing to find out a more accurate BEST score rather than just using the already known BEST score of 86.67 at the 'national' level could help to improve accuracy performance. This can be implemented by asking a question in the first-step to find out whether the household belongs "yes" or "no" to a large-size group in which calibration must be undertaken to find out a special BEST score. If the answer is "no," then we apply the normal BEST score of 86.67. If not, we go to the second step to apply the special BEST score. The tool combination approach has been especially rewarding among the housing categories as explained in the following parts of this section.

5.1 Tool Combination Approach Applied among Housing Categories

Table 8 displays the accuracy measures for the main housing indicators tested using the sample of 293 households. Each housing indicator in the first column of the table is to be understood as the main housing category because it is also comprises sub-categories. For example, the 'type of toilet facility' is the main category of three sub-categories, namely households with 'no toilet', with 'pit toilet,' and those with 'improved latrines.' The minimum and the maximum BEST scores across the sub-categories of the same main category are found in the second main column. Within most of the housing indicators, the BEST score of 86.67 at the national level was respected with the exception of three groups, namely the type of exterior wall, size of house, and primary source of drinking water. Among these socio-economic groups, it would be advisable to apply an additional tool (by setting a different cut-off) in order to achieve better accuracy performance. For instance, among those who own a well in their residence yard with a pump, the BEST score would be 75 for a BPAC value of 52.17; among those whose size of house is medium, it would be 80 for the BPAC value of 46.81; and among those whose exterior wall is made of corrugated tin, the normal BEST score that would apply to it leads to the highest BPAC of 44.46%.

Table 8: Summary table of average total accuracy by housing material groups (n=293)

Housing Indicators	BEST score		TA (%)	PA (%)	NPA (%)	BPAC
	Min	Max				
Roofing material	86.67	86.67	66.63	59.87	54.55	56.58
Type of exterior wall	83.33	86.67	67.95	45.91	65.45	35.17
Size of house	80	86.67	69.33	45.13	69.19	22.46
Main source of lighting	86.67	86.67	75.02	44.45	78.89	41.64
Kind of lock on main entrance door	86.67	86.67	62.04	54.79	65.17	39.51
Type of toilet facility	86.67	86.67	68.77	49.96	72.35	42.40
Type of flooring	86.67	86.67	80.12	27.37	86.61	-25.8
Primary source of drinking water	75.00	93.33	68.73	54.94	75.18	50.77

BPAC: Balanced Poverty Accuracy Criterion TA: Total Accuracy
PA: Poverty Accuracy NPA: Non-poverty Accuracy

5.2 Impact of Tool Combination on some Housing Characteristics

Calibration results within some large-size socio-economic groups are shown in Table 10. The socio-economic descriptors are displayed in the first main column. The second main column presents the situation when we use a tool defined by the standard BEST score at the 'national' level to get accuracy. The third main column (at the extreme right) considers a situation in which we further calibrate within each category to get a more accurate cut-off score. The improvement recorded by BPAC in the latter situation underlines how rewarding using a two-step tool can be to the improvement of balanced accuracy performance. For instance, among those who have a well in their residence yard with a pump, instead of the regular BEST score of 86.67, we define another tool by applying the special BEST score of 75 to gain an increment from -13.05% to 50.17% by 63.22 percentage points. On the average, the improvement among the groups was 11.36 percentage points.

Table 9: Socio-economic groups offering potentials for tool combination

Socio-eonomic characteristic	Standard BEST score at the ‘national’ level		Improved cut-off scores from calibration in large socio-economic groups	
	Score	BPAC (%)	Score	BPAC (%)
Exterior wall material is CI sheet (corrugated tin) (n=139)	86.67	44.42	83.33	44.46
Size of house is medium (n= 140)	86.67	2.13	80	46.81
Those who use public well sealed with pump (n=128)	86.67	39.58	93.33	50.15
Those who use well in residence yard with pump (n=159)	86.67	-13.05	75	50.17
Average BPAC	**-**	**36.54**	**-**	**47.90**

6 Conclusions

Accuracy performance differs in accordance with the socio-economic traits of the groups. The groups formed by housing and occupational descriptors achieve positive performance, whereas those formed by educational and land holding characteristics do not. Inaccuracies are higher among the VP compared with the NVP. For example, the *average* poverty accuracy varies from nearly 45% among the 'poor' to 68.28% among the 'rich.' Accuracy among the NVP was always higher than among the VP: among the former, it varied from 70.92% when housing was stipulated as a group's trait to 83.08% on the average when education was the trait.

Notwithstanding, the accuracy has remained below 51% among the latter. More explicitly, among the VP, taking the occupation of the household head as the descriptor, it varies from an average of 18.18% for the self-employed in agriculture to 59.38% for labourers. The former is very heterogeneous and comprises households with 0.2 hectares and 3 hectares: nobody knows how much land is owned, mortgaged, etc.

Though local people have their own way of judging; they score very differently in accordance with the socio-economic characteristics in such a way that, on the average, they can still recognize 8 out of 10 households determined by a given socio-economic status within the course of a PWR exercise, e.g., 'does housework' for employment or 'owns no land' for land holding.

The local perceptions in Bangladesh often deviated from the benchmark with respect to land holding and the household head's education. Land holding is not, based on our sample, a recommendable housing indicator for targeting the poor that does a good job of portraying the link between PWR and per capita daily expenditure. Furthermore, it appears very inaccurate, based on our example, for reference groups in a PWR exercise to correctly recognize educated household heads that are very poor compared to the benchmark per capita daily expenditure ranking. This calls for more vigilance by facilitators during the field process.

A two-step tool among large-size groups brought about a considerable improvement in the BPAC among some housing categories: namely, those whose exterior wall is made of corrugated tin, those with medium-sized houses, those who use a public well sealed with a pump, and those who use a well in their residence yard with a pump. This leads to the suggestion, based on this case study carried out in Bangladesh, that being more group-specific with regard to the field activities in a given area is likely to improve the accuracy of the PWR. The potential level of accuracy of the PWR tool is not altered, on the average, compared to the situation in which groups are considered from a geographical point of view. However, we recommend that other similar studies be performed elsewhere to confirm our findings.

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Appendices

Appendix I: Demographic characteristics of the divisions of Bangladesh

Division	HASC	ISO	FIPS	Pop-2001	Pop-1981	Area(km.²)
Barisal	BD.BA	1		8,112,435		11,394
Chittagong	BD.CG	2	BG80	23,999,345	22,565,556	32,696
Dhaka	BD.DA	3	BG81	38,677,876	26,248,864	30,772
Khulna	BD.KH	4	BG82	14,468,819	17,149,792	22,181
Rajshahi	BD.RJ	5	BG83	29,992,955	21,087,812	34,235
Sylhet	BD.SY	6		7,899,816		12,718
6 divisions				**123,151,246**	**87,052,024**	**143,996**

- **HASC:** Hierarchical administrative subdivision codes.
- **ISO:** Codes from ISO 3166-2. For full identification in a global context, prefix "BD-" to the code (ex: BD-4 represents Khulna).
- **FIPS:** Codes from FIPS PUB 10-4.
- **Pop-2001:** 2001-01-23 census provisional data. Source: Bangladesh Bureau of Statistics.
- **Pop-1981:** 1981 census.

NB: Capitals have the same name as their divisions.

Source: adapted from (Statoids, http://www.statoids.com/ubd.html, visited on 20.08.2005)

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[i] 100 decimals equal one British acre. One acre equals 0.405 hectares, i.e., 4050 m².

[ii] Mr. Zihad, managing director of the survey firm DATA in Bangladesh, justifies the choice of purely female reference groups as follows. "The reason behind all female groups is twofold: a) If males are in the group they become dominant and it is very hard to get consensus, and; b) especially rural females discussed a lot about wellbeing among themselves and they are very honest about discussing with our female facilitators."