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Developing a Poverty Measurement Scorecard: Predicting MPCE for Microfinance Clients in Urban Delhi

Dr. Vandana Sethi
Associate Professor, Department of Economics, Motilal Nehru College, University of Delhi, New Delhi, India

Corresponding Author: vandanasethidu@gmail.com

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ABSTRACT
A scorecard is a poverty measurement tool (PMT) that helps microfinance institutions (MFI) to measure and track the poverty status of their clients. It uses some verifiable indicators from the national expenditure survey, to get a score that is highly correlated with poverty. In the present study, an attempt has been made to develop a scorecard using the stepwise OLS regression method, to predict the MPCE of MFI's clients. The NSS 68th round (2011-12) data on consumption expenditure for urban Delhi has been used for this purpose. The predictive accuracy of the regression model (scorecard) is assessed by comparing the poverty status predicted by our scorecard with the "true" poverty status as established by the NSSO data. The "Total Accuracy" criterion is used which identified 89.39% of the respondents correctly. Thus, the scorecard appears to be a fairly accurate tool for assessing the poverty status of MFI's clients.

Keywords: *poverty measurement tool (pmt), scorecard development, microfinance institutions (mfi), predictive accuracy, consumption expenditure (mpce)*

I. INTRODUCTION

A scorecard or a short survey is a poverty measurement tool (PMT) that helps microfinance institutions (MFI) to measure and track the poverty status of their clients. According to FORD Foundation and CGAP (2010), "Poverty scoring is a practical way for pro-poor programs to monitor poverty rates, track changes in poverty rates over time, and target services to households". The direct approach of measuring poverty using consumption expenditure surveys is cumbersome, time-consuming, and costly as households are asked about a lengthy list of consumption items. On the other hand, the indirect approach using scorecards is simple, quick, and inexpensive. For developing scorecards, researchers make use of different statistical criteria and some verifiable indicators from the national expenditure survey, to get a score that is highly correlated with poverty. It is used to predict the MPCE and the poverty incidence of the MFI's clients.

In the present study, an attempt has been made to develop a scorecard using the stepwise OLS regression method, to predict the MPCE of MFI's clients. The NSS 68th round (2011-12) data on consumption expenditure for urban Delhi has been used for this purpose. It is hypothesized that a scorecard is an accurate tool for assessing the poverty status of MFI's clients.

Following the introduction, the subsequent section provides an overview of the existing literature on scorecards. Section 3 explains the database and the methodology used. Section 4 presents the scorecard approach to analyze the factors that affect a household's MPCE and the accuracy criteria for the scorecard. The last section concludes.

II. LITERATURE SURVEY ON SCORECARDS

A scorecard or a short survey is a poverty measurement tool (PMT) that helps MFI to measure and track the poverty status of its clients. PPI (progress out of poverty) and PAT (poverty assessment tool) are two examples of scorecards that are gaining ground in the microfinance industry. PPI predicts the probability that the household is poor using the household's data. Then by taking the average of these predicted probabilities across all surveyed households, the poverty incidence of the MFI is estimated. In the case of PAT, the household's data are used to predict the per capita level of expenditures of the household. Then by comparing the predicted expenditure to a particular poverty line, each surveyed household is classified as poor or non-poor. The poverty incidence of the MFI is then estimated by calculating the percentage of surveyed households that are predicted to be poor. Based on the selected indicators and their weights, the tools capture underlying relationships between household characteristics and poverty. These tools are country-specific because this relationship differs across countries. Currently, there are PPIs for 34 countries and PATs for 30 countries. Both these tools use a high-quality, nationally

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representative survey that measures household income or expenditures, such as the World Bank's Living Standard Measurement Survey (LSMS), and National Sample Survey (NSS). These surveys provide data on household-level variables, such as asset holdings, socio-demographic characteristics of household members, and variables describing housing quality. These variables are the potential set of indicators for inclusion in the poverty tool. Both tools use a regression framework to select the indicators and assign weights. The dependent variable is either income per capita or expenditure per capita for each household. In general, expenditure data are preferred as they are a better indicator of household welfare than income. Moreover, income data are difficult to collect in developing countries because of the prevalence of self-employment. Different variables from the household survey are then selected as independent variables in the regression model. For a given set of independent variables, the regression model examines the correlations between the independent variables and the dependent variable and generate a regression coefficient for each independent variable. The regression coefficients, in turn, are then converted into the weights used in the scorecard. "For both tools, a combination of statistical and subjective criteria is used to select the final set of indicators. The statistical criterion consists of examining how the predictive power of the regression model changes when a specific indicator is included. In the case of PPI, the final set of indicators should maximize the probability that households' poverty statuses are correctly predicted. In the case of PAT, the selection of final indicators is based on their ability to explain a higher percentage of variation in household expenditures as well as balancing accuracy at the household level (are truly poor households correctly classified as poor and truly non-poor households classified as non-poor) with accuracy at the aggregate/group level (on average, does the tool deliver the true poverty incidence of a given group of households, such as the clients of an MFI). In general, then, the tools appear fairly accurate, especially considering that a very limited number of indicators are used to predict households' poverty status" (FORD Foundation and CGAP, 2010).

For developing scorecards, various statistical techniques have been used by researchers such as linear probability models (IRIS Centre, 2005), quantile regression method (IRIS Centre, 2010), probit/logit models (Schreiner, 2008), and logit model (IDF, 2011). In PPI, since the weights are explicitly available to the surveyor, there is a scope for manipulation. However, in PAT, the weights are not explicitly available. Therefore, the predicted expenditure of households is not known at the time of the survey. IRIS Center ("IRIS," 2007) used the World Bank's Living Standard Measurement Survey (LSMS) data for 2,250 households in Bihar and Uttar Pradesh for the year 1997-98. To create a scorecard, IRIS used the quantile regression method, taking the log of per capita expenditure as the dependent variable and 17 Indicators as independent variables (selected using stepwise regression). It included household size, age, occupation and marital status of household head, education level of household members, number of rooms, type of latrine used, quality of residential structure, and ownership of durable goods (radio, pressure lamp/petromax, watch, television, camera, thresher, buffalo, cows). Poverty status is determined by whether the estimated expenditure is below the $1/day line. The same data was used for both construction as well as testing of the scorecard. IRIS used Balanced Poverty Assessment Criteria for testing the accuracy of a scorecard.

Schreiner (2008) built a scorecard based on NSS Round 62 expenditure data using Logit regression. Indicator selection uses both judgment and statistics. Around 100 potential indicators were prepared in the areas of family composition, housing, employment and ownership of durable goods (such as TV, automobiles, and land). The entropy-based "uncertainty coefficient" (Goodman and Kruskal, 1979) was used for screening each indicator, to measure how well it predicts poverty on its own. The Logit coefficients were transformed into non-negative integers such that total scores range from 0 (most likely below a poverty line) to 100 (least likely below a poverty line). The single poverty scorecard applies to all of India.

A study by IDF (2011) has used a scorecard approach in assessing the poverty status of MFI's clients. It surveyed over 15,000 households of 27 microfinance institutions and various SHG Bank linkage programmes in 14 states of India for the period 1990-2010. The scorecards were developed using consumption expenditure survey data from NSS's 61st round. To develop the scorecards, they ran logistic regressions and collected the coefficients from the regressions to form the weights for the scorecards. Scores were assigned to the households on the basis of assets possessed by them, both before joining the MFI as well as in the current period. A higher score implies a lower probability of a household being poor (i.e. below the pre-defined consumption threshold). The study found that 12% of all MFI clients have crossed the USD 1.25 a day consumption threshold from below during 1990-2010 and net movement in the model is determined by the assets through the scorecard.

Similar to the scorecard approach, assessing the poverty status based on possession of assets, is now used by the United Nations Development Programme's Human Development Report (UNDP HDR). In 2010, the HDR introduced the Multidimensional Poverty Index or MPI – which directly measures the combination of deprivations that each household experiences. The paper by Alkire and Santos (2010) presents a new MPI for 104 developing countries. The MPI has three dimensions: health, education, and standard of living. These are measured using ten indicators, i.e., child mortality, nutrition, child school attendance, years of schooling, electricity, drinking water, sanitation, flooring, cooking fuel, and assets like a bike, telephone, television, radio, refrigerator, motorbike, and a car or truck. It uses indicators that are related to the Millennium Development Goals (MDGs).

A study by Adjei and Arun (2009) examined the type of poor people served by its leading MFI Sinapi Aba Trust (SAT) in urban centers of Ghana for the year 2007. To capture the multi-dimensional nature of poverty, the study used indicators related to human resources, food security, dwelling, and the ownership of household assets (sewing machines,

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televisions, refrigerators, gas/electric cookers, radios, beds, and mattresses). Out of these six assets, three assets viz. sewing machines, radios, beds, and mattresses were selected for the data analysis as they were found to be significantly correlated with the poverty levels.

III. DATABASE AND METHODOLOGY

In the present study, the NSS 68th round (2011-12) data on consumption expenditure for urban Delhi is used for developing a scorecard. For urban Delhi, this data is available for 887 households. However, for the present study, only those households have been selected whose monthly per capita expenditure based on mixed reference period (MPCE_MRP) is less than or equal to Rs 5000. Thus, data from 706 households have been used for developing scorecards. Households with MPCE higher than this has not much relevance in this context as the scorecard developed here is to be used for predicting the MPCE of MFI's clients, which are low-income group households (comprising of both poor and non-poor).

Different variables from the household survey are selected as independent variables. The choice of the feature universe is limited to the one available in Schedule 1.0: Consumer Expenditure Schedule Type 1 of NSS 68th round. Those features are screened that are likely to be correlated with the welfare measure we use (i.e., consumption expenditure level). To ensure that the scorecard is as broad-based as possible, various assets, the primary source of energy for cooking and lighting, and a few indices based on demographics like social category, religion, household type, household size, education level, housing status, etc. covered in NSS are included in the study.

Using this continuous household expenditure variable (MPCE_MRP) as the dependent variable and different variables from the NSS survey as independent variables, the step-wise OLS regression method is used for the selection of final indicators that best explain the urban Delhi household's MPCE. The regression coefficients of each indicator are used as weights (which represent the relative contribution of a given indicator to the household status) in the scorecard. To check the predictive accuracy of the regression model (scorecard), these coefficients/weights are used to calculate the "estimated (or predicted) MPCE_MRP" for the same households. By taking the value of all the independent variables from the 68th NSS round urban Delhi data and assigning the coefficient values from the above regression model, the MPCE of each household is predicted. The households are then classified as "Poor" or "Non-poor" by comparing the "estimated MPCE_MRP" with the poverty line for urban Delhi. The state-specific poverty lines are given by the Planning Commission, GOI for the year 2011-12. The Urban Delhi poverty line drawn at MPCE of Rs 1134 is used as our consumption threshold. The accuracy of the above set of indicators (scorecard) is assessed by comparing the predicted poverty status of the households (by the scorecard) to the true poverty status for households in the national household survey (NSSO data).

IV. RESULTS

4.1 Scorecard Approach to Analyse the Factors that Affect Household's MPCE

Table 1 presents the parameter estimates for the factors affecting Urban Delhi households' MPCE using the step-wise OLS regression method.

Table 1: Factors affecting Urban Delhi household's MPCE based on stepwise OLS regression

	β- Coefficients	Standard Errors	T-statistics
(Constant)	1801.032	1.090	1.653E3***
Education (mean education of adults)	59.028	.096	614.704***
HH-size	-188.994	.119	-1.583E3***
Motor car	715.465	.813	879.747***
Washing machine	234.454	.550	426.621***
Motor cycle	301.242	.471	640.229***
Personal computer	321.287	.702	457.760***
Dwelling-type	386.837	.449	861.775***
Air conditioner/air cooler	179.530	.535	335.793***
Landline	305.825	.657	463.942***
Purifier	309.421	.641	482.650***
Radio	257.439	.492	522.738***
Refrigerator	232.883	.555	419.333***
Bicycle	-154.007	.412	-373.636***
Age-lessthan15 (no. of children)	-60.064	.174	-346.028***

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Dependent Variable: MPCE_MRP Number of observations = 706 Adjusted R-squared = 71.4% F value = significant			

Source: Author's calculations based on consumption expenditure survey for urban Delhi NSS 68th round (2011-12), NSSO, Government of India. Note: *** p<0.01

Where

"Education" (mean education of adults) is an education index formed by assigning weights in the following way to people aged 15 and above in the households and taking its mean.

General educational level weights: not literate -01, literate without formal schooling: through EGS/NFEC/AEC - 02, through TLC -03, others- 04; literate with formal schooling: below primary -05, primary -06, middle -07, secondary - 08, higher secondary -10, diploma/certificate course -11, graduate -12, postgraduate and above -13.

"HH-size" is the size of the sample household.

"Age-lessthan15" shows the total number of family members whose age is less than 15 years, representing the number of children in the household.

"Dwelling-type" is a housing index. Since the probability of owning a house is higher among the slum dwellers and renting/hiring happen mostly in the formal housing sector, therefore in the housing index, lower weights are assigned to the 'owned dwelling unit' categories, and higher weights are assigned to the 'hired dwelling unit' category. Since 'not owning any dwelling unit' and 'otherwise acquired dwelling unit' are ill-defined categories, they are clubbed together with the 'owned dwelling unit' category for the reason that their MPCE level is lower than the 'hired dwelling unit' category.

The weights are as follows.

Dwelling-type weights: no dwelling unit-1, others-1, owned-1, hired-2.

The results reveal that household MPCE is significantly influenced by 14 variables viz, education (mean education of adults), dwelling-type, HH-size, Age-lessthan15 (no. of children), motor car (i.e. Motor car, jeep), washing machine, motorcycle (i.e. Motor cycle, scooter), pc (i.e. PC/ Laptop/ other peripherals incl. software), ac (i.e. air conditioner, air cooler), landline (i.e. Telephone instrument (landline)), purifier (i.e. Water purifier), radio (i.e. Radio, 2-in-1), refrigerator and bicycle. The regression coefficients of each indicator represent the relative contribution of that indicator to the household MPCE. All these coefficients are statistically significant at a 1 percent level of significance.

The regression coefficients of all the assets (except for bicycles) are positive, indicating that possession of these assets increases MPCE. Our results are consistent with the NSS 61st (2004-05) round report which shows that the percentage of households possessing specific durable goods (radio, television, electric fan, air cooler, refrigerator) increases as we move from lower to higher income quantile groups of both rural and urban households in India. Multidimensional poverty index (MPI) while measuring deprivation of the households, associates an increase in the standard of living with the possession of assets such as radio, car, motorbike, television, telephone, frizz, and truck (Alkire and Santos, 2010).

However, for bicycles, the coefficient is negative, implying that its possession decreases MPCE. A plausible explanation is that the bicycle is used as a means of transportation by lower-income groups only. As per NSS 61st round (2004-05) report, the bicycle is an "inferior" durable. It states that the possession of bicycle falls as one moves from lower to higher fractile groups. It becomes increasingly unwanted as the level of living rises and is replaced by more expensive and comfortable means of travel like motor cars, motorcycles or scooters.

For the variable "education," the regression coefficient is positive, which suggests that as the mean education of the members of a household in the working age group increases, MPCE increases. A plausible explanation is that educated households are likely to have better employment opportunities and thus have higher MPCE.

Also, a positive relationship between dwelling-type and MPCE suggests that households with hired dwellings have higher MPCE than those with owned dwellings. This is consistent with the results of the NSS 50th round (July 93-June 94) report, which states that "the percentage of households with 'owned' type of occupancy shows a decreasing trend whereas the percentage of households with "quarters" & "other hired accommodation" show an increasing trend with the increase in urban MPCE level".

For variables HH-size and Age-less than15, the coefficients are negative suggesting that as household size increases or as the number of dependents (with less than 15 years of age) in the household increases, the MPCE of the household decreases due to the sharing of total expenditure among more people. According to the NSS 68th round report on consumption expenditure, the average number of children in both rural and urban areas falls as the MPCE of the household increases. Richer households have less number of children on average, whereas the average number of adults does not vary substantially with MPCE. Hence the average household size and number of children falls as the MPCE level rises.

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4.2 Accuracy Criteria for Scorecard/Regression Model

The accuracy of the above set of indicators is assessed by comparing the poverty status predicted by our scorecard with the "true" poverty status as established by the NSSO data. Four situations are possible, as summarized in the following table.

Table 2: Comparing the predicted poverty status with "true" poverty status

	Predicted **Poor** by the scorecard	Predicted as **Non-Poor** by the scorecard	
"True" **Poor** (as determined by NSS)	575326 (a)	575313 (b)	1150639
"True" **Non-Poor** (as determined by NSS)	499721 (c)	8482588 (d)	8982309
	1075047	9057901	10132948

The three accuracy criteria are as follows:

1. Total Accuracy = total of correctly predicted Poor and Non-Poor as a percentage of the total sample. From Table 2, Total Accuracy = 100 * (a + d) / (a + b + c + d) = 89.39%.
2. Poverty Accuracy = correctly predicted Poor as a percentage of total "true" Poor. From Table 2, Poverty Accuracy = 100 * a / (a + b) = 50%
3. Non-poverty Accuracy = correctly predicted Non-Poor as a percentage of total "true" Non-Poor. From Table 2, Non-poverty Accuracy = 100 * d / (c + d) = 94.44%

Since the present study is interested in the aggregate assessment of the poverty status of MFI clients who belong to the low-income group (including poor and not very poor), therefore total Accuracy criterion appears to be most relevant for the present study. It identifies 89.39% of the respondents correctly. The tools appear fairly accurate, especially considering that a very limited number of indicators are used to predict households' poverty status. These results accept the postulated hypotheses that a scorecard is an accurate tool for assessing the poverty status of MFI's clients.

V. CONCLUSION

A scorecard is a poverty measurement tool (PMT) that helps microfinance institutions (MFI) assess the poverty status of their clients. In the present study, an attempt has been made to develop a scorecard using the stepwise OLS regression method, to predict the MPCE of MFI's clients. The NSS 68th round (2011-12) data on consumption expenditure for urban Delhi has been used for this purpose. Using this continuous household expenditure variable (MPCE_MRP) as the dependent variable and different variables from the NSS survey as independent variables, the step-wise OLS regression method is used for the selection of final indicators that best explain the urban Delhi household's MPCE.

The results reveal that household MPCE is significantly influenced by the mean education level of adults, dwelling-type, household size, number of children in the family, and ten assets namely motor car, washing machine, motorcycle, personal computer, air conditioner/air cooler, landline, purifier, radio, refrigerator, and bicycle. All these coefficients are statistically significant and bear the expected signs. For the variable "education," the regression coefficient is positive, which suggests that as the mean education of the members of a household in the working age group increases, MPCE increases. Also, a positive relationship between dwelling-type and MPCE suggests that households with hired dwellings have higher MPCE than those with owned dwellings. The regression coefficients of all the assets (except for bicycles) are positive, indicating that possession of these assets increases MPCE. However, for the bicycle, the coefficient is negative, implying that its possession decreases MPCE as the bicycle is an "inferior" durable. For variables HH-size and Age-less than15, the coefficients are negative suggesting that as household size increases, or as the number of dependents (with less than 15 years of age) in the household increases, the MPCE of the household decreases due to the sharing of total expenditure among more people.

The predictive accuracy of the regression model (scorecard) is assessed by comparing the poverty status predicted by our scorecard with the "true" poverty status as established by the NSSO data. The "Total Accuracy" criterion is used which identified 89.39% of the respondents correctly. These results accept the postulated hypotheses that a scorecard is an accurate tool for assessing the poverty status of MFI's clients.

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REFERENCES

1. Adjei, J. K., & Arun, T. (2009). Microfinance programmes and the poor: whom are they reaching? Evidence from Ghana. *Brooks World Poverty Institute Working Paper Series, 7209*, 265-291.
2. Alkire, S., & Santos, M. E. (2010). *Acute multidimensional poverty: A new index for developing countries.* United Nations Development Programme Human Development Report Office Background Paper.
3. Ford Foundation and CGAP. (2010). *Poverty targeting and measurement tools in microfinance, Progress out of Poverty Index and the Poverty Assessment Tool.*
4. Goodman, L. A., & Kruskal, W. H. (1979). *Measures of association for cross classifications. In measures of association for cross classifications,* pp. 2-34. New York: Springer.
5. India Development Foundation (IDF). (February 2011). *Counting the (net) number of people who crossed (from below) the USD 1.25 a day consumption threshold in India between 1990 and 2010.*
6. IRIS Centre (2005). *Note on Assessment and Improvement of Tool Accuracy*, Available at: http://www.povertytools.org/other_documents/AssessingImproving_Accuracy.pdf.
7. IRIS Centre. (2007). *Client Assessment Survey—India*. Available at: http://www.povertytools.org/USAID_documents/Tools/Current_Tools/USAI. D_PAT_India_8-2007.xls, accessed July 7, 2008.
8. IRIS Centre (2010). Accuracy Results for 26 Poverty Assessment Tool Countries, Available at: http://www.povertytools.org/other_documents/Accuracy%20Notes/PAT_26_country_accuracy_result s_Jan2010.pdf.
9. Planning Commission. (2011). *Report of the working group on urban poverty, slums, and service delivery system.* New Delhi: Government of India.
10. Schreiner, M. (2008). *A simple poverty scorecard for India*. Available http://www.microfinance.com/English/Papers/Scoring_Poverty_India.pdf.