Poverty scoring and financial inclusion of the poor[1]

Vitalie Bumacov, Faculty of Business, Oxford Brookes University, UK

Arvind Ashta, CEREN, EA 7477, Burgundy School of Business - Université Bourgogne Franche-Comté

Pritam Singh, Faculty of Business, Oxford Brookes University, UK.

The use of poverty scoring is associated with increased outreach towards poor borrowers only in non-profit microfinance institutions, while in for-profit microfinance institutions poverty scoring is associated with increased availability of financing.

Key points

Poverty scoring allows for-profit microfinance institutions to borrow funds from social investors in addition to funds borrowed from the market.

As long as these social funds do not substitute market funds used in financing poor micro-borrowers, the share of poor clients served increases, so does financial inclusion of the poor.

---

[1] JEL classification codes: G11, G21, I30, I32, O11.

Acknowledgements: Arvind Ashta thanks the Banque Populaire and Conseil Regional de Bourgogne for partially co-financing this research.

Introduction

Microfinance is a development tool that is being accused of mission drift (Aitken, 2013; Bateman, 2012.). Drifting microfinance institutions (MFIs) abandon the poorest clients to serve less poor customers who generate relatively higher revenues for the MFIs. To remain faithful to its social mission, microfinance needs robust instruments for identifying poor people. One such solution is poverty scoring (Schreiner, 2010b.). This paper looks at how the technique of poverty scoring is being incorporated in the microfinance world.

The use of poverty scoring by MFIs is a relatively new trend with possible contradictory implications from the viewpoint of increasing financial inclusion. If credit scoring by using a limited number of a credit applicant's characteristics estimates the creditworthiness of the applicant, the poverty scoring technique estimates the poverty status of the applicant. The main purpose of poverty scoring in financing is to determine the suitability of an applicant from the perspective of poverty to receive well-tailored financial services. This technique of poverty scoring uses about a dozen of characteristics to help in classifying applicants as poor or not poor without measuring their income and wealth (Schreiner, 2010a).

In general, income is an indicator of a person's degree of poverty or prosperity. Any society needs to know about people living in poverty in order to provide them welfare and other benefits such as financial inclusion. Poverty leads to financial exclusion because of several reasons: financial services are too expensive for the poor (Dupas & Robinson, 2013; Prina, 2015); those with modest incomes are denied financial services

(Simpson & Buckland, 2009); and some poor people exercise self-restraint because of the fear and shame of possible refusal (Jennett *et al.*, 2012). Financial exclusion penalizes people, thus contributing to the vicious circle of poverty. Financially excluded people cannot get appropriate financing for making the smallest investment: improve living conditions, pay for education to secure a job; or buy productive assets. It is even more dramatic when a working poor person, who temporarily runs out of money, has no overdraft facility and no possibility to borrow some money for food or medicine.

Although poverty, when measured using income, is a continuous variable, it is commonly dichotomized using a cut-off point. Those with incomes above the cut-off are considered non-poor while the rest are deemed poor. Most developing countries use either a national poverty line – own income cut-off point – or the international extreme poverty line which, from October 2015, is fixed at 1.90 USD per person per day (Ferreira *et al.*, 2015). These 1.90 USD are 2011 US dollars and have to be adjusted by inflation and corresponding purchasing power parity (PPP) when applied to different countries and different years. The international extreme poverty line assumes that the very basic daily needs of a person could be procured in 2011 with 1.90 USD or its equivalent in other currencies accounting for the local purchasing power parity. World Bank estimates that just over 900 million people were experiencing extreme poverty in 2012 (Ferreira *et al.*, 2015) – a consistent decline from 1.93 billion in 1981 and 1.3 billion in 2008 (Chen & Ravallion, 2010).

The measurement of poverty and identification of the poor in developing countries poses several problems because of the widespread existence of informal and semiformal sectors (Schneider & Enste, 2000), which can both underestimate as well as overestimate the scale of poverty (Harriss-White, 2003). Underestimation of poverty can result from corrupt bureaucrats and businessmen registering property and banking accounts on poor nominee persons. Overestimation of poverty can result from entrepreneurs underreporting income in order to diminish tax liability and avoid drawing attention of corrupt bureaucrats. It can also result from business entities not formally hiring employees or reporting in the payroll only fractions of their effective salaries in order to reduce employer contributions (Dabla-Norris *et al.*, 2008). Under conditions of overestimation of poverty, considerable proportions of the population qualify for social benefits, including those who are non-poor due to their reported incomes being small.

Many families in developing economies live on remittances sent by migrant workers. Such remittances, if sent through informal channels or if not verifiable by tax authorities, do not get reported as income in spite of their important contribution to the family budget (Singh & Velásquez, 2013). The chances are high that such families are not poor by local standards, but for the state authority they qualify as poor or extremely poor. Such information asymmetry entitles non-poor families to claim welfare.

These complexities do not imply that there is no widespread poverty and extreme poverty in developing countries. In fact many of those who are not currently poor are vulnerably to being poor due to internal or external shocks (Bhusal, 2012). Nevertheless, these complexities hinder the process of identification of the real poor who desperately need access to welfare benefits and financial inclusion.

Institutions involved in providing welfare benefits and financial inclusion, such as the MFIs, therefore need robust mechanisms to identify the real poor. The best technique to identify the poor would certainly be to assess each household separately using financial diaries such as those implemented by Collins *et al.,* (2009) or long questionnaires to estimate different income sources of applicants, but this is expensive and time consuming. The costs of estimating poverty and identifying the poor can be reduced by using poverty scoring algorithms. An algorithm is built by using structured data resulting from an initial investment in large numbers of extensive income and wealth assessments. The algorithm will distill the few characteristics of households that predict poverty and will isolate their relative weights. In consequence, only a few specific questions need to be answered by applicants seeking welfare benefits and financial inclusion for the purpose of an institution to estimate accurately if they are poor or not.

In this paper we empirically test if the use of poverty scoring by MFIs is associated with increased social outreach – that is provision of financial inclusion to a larger share of poor clients. Since microfinance services are provided by both non-profit organizations and for-profit businesses, we segregate the analysis for both types of organizations. We further test if the use of poverty scoring by MFIs is associated with lower financial cost that MFIs pay for borrowing funds. Such an association would indicate that social investors financing MFIs value the use of poverty scoring by MFIs and are, therefore, willing to provide them cheaper financing.

The structure of the paper is as follows: section 2 describes the theoretical importance of poverty scoring for financial inclusion; section 3 describes the construction of poverty scoring algorithms and associated issues; section 4 provides information about the selected sample used to test our hypothesis; section 5 details the empirical analysis dealing with the aspects of financial inclusion mentioned above; section 6 examines the results; and section 7 concludes.

Who needs poverty scoring and why?

Using a representative sample of surveyed households, one can extrapolate the poverty level and income distribution in a country. But this does not identify exactly who in the country is poor and who is not, it only provides a general picture. This is where poverty scoring comes in. It can be used to identify rapidly, with a certain degree of accuracy, poor households which need to be targeted for welfare benefits or financial inclusion.

It is in the interest of institutions that provide welfare benefits or subsidized services that without spending a major part of their budget on extensively surveying their applicants, to reach the really poor. People who are not poor by the local standards may often apply for welfare benefits. In conditions of information asymmetry, institutions that cannot verify each individual claim can use poverty scoring for screening the poor from the non-poor or, if exclusion is not desirable, measure the real share of poor beneficiaries and adjust, if necessary, the outreach strategy to target bigger shares of poor people.

Some easily observable characteristics of a household can be helpful in differentiating a poor family from a non-poor one without performing a full income assessment of the household (Schreiner, 2010b). For example, if in a village a house has walls made of clay instead of stone or bricks, a tin roof instead of tiled or concrete roof, one common room instead of many, and does not own any cattle, it seems to be good evidence of the household being poor. Therefore, using statistical procedures and structured data of such type, one can construct an algorithm which estimates the chances of a person with a certain profile to have revenues below an established poverty line.

Based on an initial sample of responses to a questionnaire, the poverty scoring developer identifies the characteristics which differentiate the poor from the non-poor, isolating the importance of each characteristic. This individual importance is usually expressed with a number – the characteristic's score. All the characteristics and their scores form the scorecard. Using the poverty scoring algorithm supposes checking the profile of a subject against the scorecard. When a subject's characteristic matches one from the scorecard, the subject gets the associated score. The aggregate score is associated with a probability of the subject being poor. For example if the aggregate score of a person applying to receive subsidized services is eighty in a particular algorithm, it may be associated with 90 per cent chance that the applicant is poor. If the score was ninety-five in the same algorithm, it may be associated with 70 per cent (lower) chance that the applicant is poor. Dichotomization – poor or not – is made by applying a cut-off score.

It is worth mentioning that poverty scoring algorithms ca be developed using different techniques of multivariate statistical analysis. Not all of these techniques imply the use of a scorecard, but all of them should result in a probability that the subject is poor.

There are costs associated with the use of poverty scoring tool as with any tool. Some costs are operational, related to the implementation, use and maintenance of the scoring tool. Others are opportunity costs relating to some non-poor applicants being characterized as poor (the false positives) while others who are poor being categorized as non-poor (the false negatives). If no tool were to be used, there would be no operational costs, but there would still be such opportunity costs.

Many microfinance institutions do not deny credit based on the poverty score, but screen non-creditworthy applicants. The use of poverty scoring allows the institutions to estimate the proportion of poor subjects among the applicants and loan recipients. These metrics, if outreach towards the poor is high in the MFI, might represent an intangible asset for the microfinance institution. The MFI can signal to social investors interested in poverty reduction to get funding from them.

One other big advantage of poverty scoring is the ability to track recipients' scores over time and thus measure their progress out of poverty. If the average poverty score of long term clients increases with time (the probability of poverty decreases), it would demonstrate that the average income of loan recipients increased and some are no longer poor or are less poor than before. An MFI may attribute this poverty reduction to the impact of financial inclusion it facilitated.

To summarize, microfinance institutions may need poverty scoring to: screen applicants – refuse some clients if their profiles indicate low probability of being poor; evaluate post-factum the percentage of poor micro-borrowers; and track the progress out of poverty of microloan recipients – an indicator of possible social impact.

Potentialities and limitations of poverty scorecards

Construction of poverty scoring algorithms requires statistical modelling and appropriate data comprising of a training sample and a test sample. The training sample is used to model the poverty scoring algorithm, while the test sample is used to make sure it works – assigns systematically high probabilities of being poor to poor subjects and low probabilities of being poor to non-poor subjects without previously knowing their incomes.

Obtaining the training sample demands a lot of effort since poor and non-poor households have to be extensively surveyed, first to determine accurately their income, and second, to collect various poverty-related characteristics out of which a manageable number, say a dozen, can be identified for the purpose of composing the poverty scoring algorithms.

Some MFIs might already have collected their own data needed for development of poverty scoring algorithms because when loan officers evaluate loan applications they make detailed assessment of income and expenditure of applicants. Loan application forms require, and thus collect, social, business and demographic information. If the

MFIs can get complete data about a few hundred confirmed poor loan applicants and a few hundred confirmed non-poor applicants and if this sample is representative of the population that applies for MFI’s loans, then this data can be used for statistical modelling. It is important to mention here that there are limitations to the use of poverty scoring algorithms because the availability of data does not guarantee that the algorithms will have sufficient discrimination power to justify their use. That is an unavoidable risk which any scoring technique has to bear.

Governments of many developing countries systematically organize national household income and expenditure surveys. Data from such surveys are used for developing poverty scorecards (Schreiner, 2011).

The choice of indicators to be included in national poverty scorecards can have social implications, since those classified as non-poor would not have access to welfare benefits. For example, in 2013 there were media reports (Puiu, 2013) about social tensions which led the Government of Moldova to amend the official poverty scorecard by excluding 3 out of 17 characteristics, which seemed unjust or unclear to different segments of population for the use of these characteristics for classifying households as poor or non-poor. These characteristics were: possession of a black and white television in rural area; possession of bicycle in rural area; and possession of a telephone.

Martinelli & Parker (2009) found that applicants in a poverty alleviation program in Mexico were systematically underreporting certain household characteristics to appear poorer than they actually were in order to increase their chances of getting into the

program. It was also noted that they were reporting certain non-existent characteristics, such as availability of sanitation infrastructure, in order to not appear embarrassingly poor for social reasons. This example of contradictory behavior on the part of the poor in underreporting some and over-reporting other characteristics highlights the difficulty in constructing robust poverty scoring algorithms and their use. Therefore the developers of poverty scoring algorithms and their users have to be vigilant. For example, it may appear that observing whether a household owns a television is an easy task, but it may turn out to be very difficult if the householder hides the television.
Societal changes also affect the usefulness of a scorecard for classifying households as poor or non-poor (Desiere *et al.*, 2015). For example, in many developing countries the possession of a mobile phone a few years ago signified a well-off economic status, while currently the advances in telecommunication technologies, by reducing costs, have enabled many poor households to get access to mobile phones. Therefore each poverty scoring algorithm needs to evolve with social changes.

Since statistical modelling is a scarce and expensive skill, several open-source initiatives have emerged. We can cite here the internet portals microfinance.com and progressoutofpoverty.org. In 2016 these combined provided free reliable poverty scorecards for more than 60 developing countries where extreme poverty is concentrated.

From this discussion one would expect that: hypothesis 1 – MFIs that use poverty scoring show increased social outreach; and hypothesis 2 – MFIs that use poverty scoring have lower financing costs than similar MFIs by attracting social investors and donors that provide them cheap financing.

The sample

The sample we used for our data analysis was constructed through the following stages. A survey conducted from 2012 to 2015 identified MFIs that use poverty scoring, poverty rating or do not use any poverty assessment tool. Poverty rating is defined as a poverty assessment tool which is not empiric but rather based on the subjective experience of professionals. In the survey the MFIs were asked to define the poverty assessment tool they use. Rater MFIs were identified and separated from the scorers.

Secondary data came from progressoutofpoverty.org. The internet portal maintains a list of MFIs which use certified poverty scoring algorithms. The names of other MFIs that use poverty scoring (Grameen Foundation USA, 2014) complemented the primary data. The combined data contains the information about whether the MFIs were using poverty scoring or not at a certain point in time.

We complemented this data with the concurrent financial and business indicators of these MFIs available on the MIX Market internet portal (Microfinance Information Exchange, Inc., 2016). MIX Market collects annually standardized business and financial information from MFIs that volunteer it. The portal provides most of the data in a form which is suitable for comparative analysis. We matched MFIs' business and finance indicators with their status of users or non-users of poverty soring.

We complemented the database with concurrent country specific indicators to capture also the external environment of the MFIs (World Bank Group, 2016). We excluded outliers – MFIs with less than 100 and more that 1 million borrowers. The dataset contains 1.683 data entries, some with missing variables. We did not treat missing data.

The regression models

Hypothesis 1 – poverty scoring is associated with increased social outreach

To test if the use of poverty scoring in MFIs is associated with increased outreach towards the poor, we construct a linear regression model using ordinary least squares. Since only MFIs that use poverty scoring can estimate the number of poor borrowers they serve, while non-users cannot, we use a proxy which estimates the depth of the outreach level towards poor borrowers. This proxy measures the average loan balance per borrower expressed in PPP dollars – *AVGLoanPPP*. We calculated this variable using MFIs' average loan balance per borrower provided by MIX Market (Microfinance Information Exchange, Inc., 2016) and PPP conversion rates which are used for calculating the PPP gross domestic product of countries (World Bank Group, 2016b). The lower the average loan balance expressed in PPP dollars in the MFI, the poorer are its borrowers. This proxy is suitable for cross-country comparison. The biggest advantage of this proxy is that it is expressed in dollars considering each country's purchasing power parity. One such dollar buys in the same year the same amount of goods and services in each country.

A set of parameters describing MFI's internal affairs and external environment are the independent variables. In order to observe the behavior of variables which measure the use of poverty scoring, we construct two dummy variables for identifying the type of poverty assessment MFIs use. Dummy *Scorer* identifies MFIs that use poverty scoring and dummy *Rater* identifies MFIs that use poverty rating. Control variables concern legal status, region, MFI's financial indicators and some macroeconomic indicators of the country. We selected the control variables based on availability and judgement.

The regression model is applied in two iterations. The first iteration considers non-profit MFIs only and the second iteration considers only for-profit MFIs. Regression coefficients are presented in *B* columns and the significance of these coefficients are presented in *Sig.* columns of Table 1. For each iteration, values of R squared and number of degrees of freedom are presented at the bottom of the table. This structure of presenting the regression results is common to all regression models in this paper.

The robustness of each regression model was tested using data from different time periods. The regression coefficients of our dummy variables maintained their sign and statistical significance when incorporating different control variables. In the regression models we chose our variables to balance a high R squared with a high number of degrees of freedom.

[Table 1 here]

We note that in non-profit MFIs the dummies indicating the use of poverty scoring *Scorer* and poverty rating *Rater* show negative statistically significant regression coefficients. We observe just the opposite in for-profit MFIs. The dummy *Scorer* shows a positive statistically significant regression coefficient in for-profit MFIs. We conclude, without implying any causality that, non-profit MFIs which use poverty scoring reach to more poor borrowers. We also conclude that for-profit MFIs which use poverty scoring reach to wealthier borrowers. Hypothesis 1 is validated for non-profit MFIs only. In the case of for-profit MFIs we find a counter-intuitive observation.

Other statistically significant coefficients confirm the validity of the model. For example: larger MFIs – high *Loan portfolio in PPP dollars* – serve richer borrowers; reaching to poorer borrowers is associated with having more employees – *Personnel*; reaching to poorer borrowers is associated with higher operating expense – *Operating expense / Assets*; reaching to poorer borrowers is associated with higher return on assets – *ROA*; Number of *automated teller machines per 100,000 adults*, which is a proxy for the development of the financial sector in the country, is associated with serving richer borrowers in non-profit MFIs – as financial sector develops and small overdraft facilities become available to all applicants, non-profit MFIs have to increase their level of financing to provide appropriate financial inclusion.

Hypothesis 2 – poverty scoring is associated with reduced financial expense

We expect to observe that MFIs which use poverty scoring have lower financial expense compared to their peers because they attract or retain social investors and donors. Poverty-reduction oriented financiers should be willing to supply MFIs with cheaper financing in exchange for MFIs attaining certain social objectives. The use of poverty scoring by MFIs facilitates the reinforcement of the character of MFIs as contributing to the achievement of such social objectives as poverty reduction.

We construct a second linear regression model in which *Financial Expense* – financial charges divided by the value of assets – depends on several factors, including the use of poverty scoring. Table 2 presents the regression results of the model. We control also for the social outreach level – *AVGLoanPPP*, noticing that good social outreach performance is not associated with reduced financial expense of MFIs.

[Table 2 here]

We observe that the use of poverty scoring is not associated with lower financial expense in both non-profit and for-profit MFIs. We can reject hypothesis 2. MFIs do not attract cheaper financing from social investors when using poverty scoring. The question remains why MFIs use poverty scoring?

Resolving the paradox

On one hand, we observed that the use of poverty scoring is associated with increased outreach towards poorer borrowers only in non-profit MFIs, while in for-profit MFIs we observed just the opposite – the use of poverty scoring is associated with better-off borrowers. On the other hand, MFIs that use poverty scoring do not register lower cost of financing. Why then MFIs use poverty scoring? Non-profit MFIs might decide on their own to implement poverty scoring or be influenced by their socially oriented stakeholders, but why for-profit MFIs use poverty scoring if they cannot lower their cost of financing?

We believe it is not about the costs MFIs pay for borrowed funds, but it is about the availability of funds coming from social investors. Poverty scoring allows for-profit MFIs to borrow funds from social investors. With poverty scoring MFIs can measure and possibly guarantee a certain social outcome in exchange for the funds. For-profit MFIs that serve a wide range of customers with diverse poverty levels will see their average loan size being much higher than in other non-profit MFIs that target only poor borrowers. Nevertheless, such MFIs can reach naturally to as many poor borrowers as non-profit MFIs with loans at similar interest rates. Poverty scoring allows for-profit MFIs to signal to social investors that the MFIs can commit to certain social objectives if financing is made available for them. Already being able to operate in the market by borrowing funds at market prices, such MFIs do not seek cheap limited funding for which there is strong competition. These MFIs need more funding at reasonable prices.

Our database does not allow us to observe the structure of borrowed funds in MFIs. However, we can detect if MFIs have access to increased financing by observing the share of non-earning liquid assets MFIs hold. MFIs that have access to extra financing will be inclined to draw down funds in excess of their current needs. Excess funds will appear in MFIs' accounts as non-earning liquid assets. Similarly, if social investors provide funding that is reserved for poor borrowers which can be identified with poverty scoring, these funds will be disbursed to the MFI, but will be further lent to poor borrowers only when the appropriate candidates will apply for loans. In the meantime, the reserved funds will appear in MFIs' accounts as non-earning liquid assets.

We construct a regression model in which the dependent variable is *Non-earning liquid assets* – the value of non-earning liquid assets divided by the value of total assets. The regression results are presented in Table 3.

[Table 3 here].

Results of the regression show clearly that the use of poverty scoring by for-profit MFIs is associated with higher shares of non-earning liquid assets. We conclude that, regardless of the direction of the causality, poverty scoring is a technique and a signal that allows for-profit MFIs to borrow funds from social investors. In exchange for providing funds, social investors have the guaranty that their money will reach poor borrowers.

Discussion and future research directions

Our research confirms that poverty scoring is a technique and a signaling tool that allows for-profit MFIs to borrow funds from social investors. These funds can have for the borrowing MFI a marginal utility above the market prices if mainstream investors do not provide the MFI with enough debt. Social investors get in exchange the certainty that provided funds will serve the aimed poor borrowers. Any mission drift will be detected when measuring the poverty score of clients serviced with the funds provided by the social investors.

Future research should focus on observing if such social funds do not substitute market funds that are used to finance poor borrowers. If substitution happens, the net social outcome resulting from lending to poor borrowers might decrease even if MFIs increase borrowing from social investors.

Results of the regression show that only the use of poverty rating by non-profit MFIs is associated with higher shares of non-earning liquid assets, while this is not true for non-profit MFIs that use poverty scoring. Future research should investigate the reasons of this difference.

Conclusions

This is the first scholarly investigation into the use of poverty scoring for financial inclusion by MFIs. We find that non-profit MFIs that use poverty scoring reach to more poor borrowers than non-profit MFIs that do not use any poverty assessment technique. We conclude that poverty scoring is a technique and a signal that allows for-profit MFIs to borrow funds from social investors. As long as these funds do not substitute market funds that are used by for-profit MFIs to finance poor borrowers, the share of poor borrowers served will increase, so will increase the financial inclusion of the poor.

Our findings have the following policy implication: social investors should make disbursal of funding to MFIs, especially for-profit MFIs, conditional on the implementation of poverty scoring. Poverty scoring will guarantee that funds reach poor borrowers. Substitution might reduce the impact of funds lent by social investors if these replace market funds that previously were used to finance poor borrowers. To avoid substitution, social investors should check that the share of poor borrowers served increases with the receipt of funding from social investors.

References

Aitken, R. (2013). The Financialization of Micro-Credit. *Development and Change, 44(3)*, 473–499.

Bateman, M. (2012). How Lending to the Poor Began, Grew and Almost Destroyed a Generation in India. *Development and Change, 43(6)*, 1385–1402.

Bhusal, L.N. (2012). Poverty Estimates and the Welfare State: the case of Nepal. *Contemporary South Asia, 20 (1)*, 45–59.

Chen, S., & Ravallion, M. (2010). The Developing World is Poorer than we Thought, but no Less Successful in the Fight Against Poverty. *Quarterly Journal of Economics, 125 (4)*, 1577–1625.

Collins, D., Morduch, J., Rutherford, S., & Ruthven, O. (2009). *Portfolios of the Poor: How the World's Poor Live on $2 a Day.* Princeton: Princeton University Press.

Dabla-Norris, E., Gradstein, M., & Inchauste, G. (2008). What causes firms to hide output? The determinants of informality. *Journal of Development Economics, 85 (1-2)*, 1–27.

Desiere, S., Vellema, W., & D'Haese, M. (2015). A validity assessment of the Progress out of Poverty Index (PPI)™. *Evaluation and Program Planning 49*, 10–18.

Dupas, P., & Robinson, J. (2013). Savings Constraints and Microenterprise Development: Evidence from a Field Experiment in Kenya. *American Economic Journal: Applied Economics 5*, 163–192.

Ferreira, F.H.G., Chen, S., Dabalen, A.L., Dikhanov, Y.M., Hamadeh, N., Jolliffe, D.M., Narayan, A., Prydz, E.B., Revenga, A.L., Sangraula, P., Serajuddin, U., & Yoshida, N. (2015). *A global count of the extreme poor in 2012: data issues,* *methodology and initial results. Policy Research working paper; no. WPS 7432*. Washington, D.C.: World Bank Group.

Grameen Foundation USA (2014) *Organizations that Use the PPI.* http://www.progressoutofpoverty.org/ (accessed 29 August 2014).

Harriss-White, B. (2003). *India Working: Essays on Society and Economy*. Cambridge: Cambridge University Press.

Jennett, C., Brostoff, S., Malheiros, M., & Sasse, M.A. (2012). Adding insult to injury: consumer experiences of being denied credit. *International Journal of Consumer Studies, 36 (5)*, 549–555.

Martinelli, C. & Parker, S.W. (2009). Deception and Misreporting in a Social Program. *Journal of the European Economic Association, 7 (4),* 886–908.

Microfinance Information Exchange Inc. (2016) *Basic MIX MFI Data Set.* http://www.mixmarket.org/ (accessed 11 April 2016).

Prina, S. (2015). Banking the poor via savings accounts: Evidence from a field experiment. *Journal of Development Economics, 115*, 16–31.

Puiu, V. (2013, April 01). Televizorul alb-negru, telefonul și bicicleta vor fi excluse de pe lista bunurilor. *Timpul de dimineață,* Retrieved from http://www.timpul.md.

Schneider, F., & Enste, D.H. (2000). Shadow Economies: Size, Causes, and Consequences. *Journal of Economic Literature, 38 (1)*, 77–115.

Schreiner, M. (2010a). A simple poverty scorecard for Pakistan. *Journal of Asian and African Studies, 45(3)*, 326–349.

Schreiner, M. (2010b). Seven extremely simple poverty scorecards. *Enterprise Development and Microfinance, 21(2),* 118–136.

Schreiner, M. (2011). Estimating Expenditure-Based Poverty from the Bangladesh Demographic and Health Survey. *Bangladesh Development Studies, 14 (4)*, 65–95.

Simpson, W., & Buckland, J. (2009). Examining evidence of financial and credit exclusion in Canada from 1999 to 2005. *The Journal of Socio-Economics, 38*, 966–976.

Singh, P., & Velásquez, S. (2013). Remittances and poverty alleviation, Ecuador and Bangladesh', in I. Ness (Ed) *The Encyclopedia of Global Human Migration,* Blackwell Publishing Ltd.

World Bank Group. (2016) *World Bank Data*. http://data.worldbank.org/ (accessed 11 April 2016).

Vitalie Bumacov is conducting a doctoral research with the Faculty of Business at Oxford Brookes University on the use of poverty scoring and credit scoring in microfinance. He is an entrepreneur and consultant in access to small finance.

Dr. Arvind Ashta is professor of Accounting, Finance and Law at CEREN, EA 7477, Burgundy School of Business - Université Bourgogne Franche-Comté in Dijon, France. He has taught Microfinance as visiting faculty in Brussels, Chicago, New Delhi, Pforzheim and Winterthur, and provided student seminars in Barcelona, Hertfordshire, Kathmandu, Mysore and Nancy. He is a member of research associations (CERMi, ISEE, RRI) and professional associations (European Microfinance Platform).

Pritam Singh is a professor in economics at the department of accounting, finance and economics, Faculty of Business, Oxford Brookes University, UK. His area of specialization is development and environmental economics. He is Federalism Advisor to the Government of Punjab India and has been Economic Advisor to the British House of Commons' Parliamentary Group on Punjabis in Britain. He has been a visiting professor at Jawaharlal Nehru University in Delhi and Moscow State University.

Correspondence to:

Vitalie Bumacov

Tudor Panfile 38, MD2049, Chisinau, Moldova

Email: bumacov@hotmail.com.

Table 1. Regression which models the depth of social outreach (hypothesis 1).

Dependent variable: AVGLoanPPP	**non-profit MFIs**		**for-profit MFIs**	
Independent variables are:	**B**	**Sig.**	**B**	**Sig.**
(Constant)	-6741.21	.000	-4432.64	.324
Scorer	-638.49	.009	1650.80	.012
Rater	-884.99	.048	1184.54	.288
Loan portfolio in PPP dollars (in logarithm)	518.80	.000	407.10	.100
Personnel	-.59	.041	-1.42	.003
Equity / Assets	10.76	.071	-15.78	.266
Administrative expense / Assets	16.43	.573	-21.80	.821
Financial expense / Assets	-76.08	.019	-91.59	.163
Operating expense / Assets	-70.44	.000	-140.05	.004
ROA	-67.85	.000	-71.73	.067
From Africa	798.04	.090	3241.20	.008
From East Asia and the Pacific	321.49	.546	2086.06	.069
From Eastern Europe and Central Asia	477.73	.439	6227.73	.000
From Latin America and the Caribbean	914.57	.018	4944.73	.000
From Middle East and North Africa	-583.05	.304	-151.29	.936
Is bank	-874.49	.376	4693.40	.001
Is cooperative	862.10	.009	1350.71	.539
Is non-bank financial institution	425.14	.339	812.83	.471
Is rural bank	493.35	.832	2810.87	.190
Population density	.81	.117	-1.26	.202
Per capita GDP (in PPP dollars)	-.01	.487	-.03	.450
Automated teller machines (per 100,000 adults)	41.94	.000	6.25	.673
degrees of freedom	***493***		***428***	
R^2	***.395***		***.355***	

Table 2. Regression which models financial expense of MFIs (hypothesis 2).

Dependent variable: Financial expense	**non-profit MFIs**		**for-profit MFIs**	
Independent variables are:	**B**	**Sig.**	**B**	**Sig.**
(Constant)	5.18	.002	4.65	.033
Scorer	0.32	.285	-0.35	.400
Rater	0.79	.148	0.13	.855
Loan portfolio in PPP dollars (in logarithm)	0.00	.998	-0.12	.305
Equity / Assets	-0.06	.000	-0.06	.000
Deposits / Assets	-.02	.029	-0.00	.762
Administrative expense / Assets	-0.28	.000	-0.49	.000
Financial revenue / Assets	0.15	.000	0.25	.000
ROA	-0.13	.000	-0.22	.000
From Africa	-1.27	.017	-1.68	.010
From East Asia and the Pacific	-2.00	.001	1.56	.025
From Eastern Europe and Central Asia	1.19	.049	1.71	.000
From Middle East and North Africa	-0.66	.287	-0.86	.478
From South Asia	0.37	.369	2.11	.000
Is bank	1.72	.173	1.44	.090
Is cooperative	0.31	.519	2.87	.036
Is non-bank financial institution	-0.64	.274	2.17	.002
Is rural bank	1.49	.630	-0.90	.482
AVGLoanPPP (proxy for outreach towards the poor)	0.00	.321	0.00	.854
degrees of freedom	***562***		***427***	
R^2	***.367***		***.535***	

Table 3. Regression which models non-earning liquid assets.

Dependent variable: Non-earning liquid assets	**non-profit MFIs**		**for-profit MFIs**	
Independent variables are:	**B**	**Sig.**	**B**	**Sig.**
(Constant)	11.27	.025	-0.89	.897
Scorer	0.20	.823	4.99	.000
Rater	7.55	.000	0.56	.799
Loan portfolio in PPP dollars (in logarithm)	-0.27	.320	0.32	.370
Equity / Assets	0.01	.481	0.08	.022
Deposits / Assets	.03	.226	0.11	.000
Financial expense / Assets	-0.09	.447	0.07	.635
Yield on gross portfolio (real)	0.07	.048	0.08	.019
From Africa	7.64	.000	5.58	.004
From East Asia and the Pacific	6.62	.001	0.91	.685
From Eastern Europe and Central Asia	0.17	.924	3.32	.015
From Middle East and North Africa	1.33	.480	36.13	.000
From South Asia	5.38	.000	7.78	.000
Is bank	1.13	.768	0.06	.982
Is cooperative	0.87	.543	-4.90	.216
Is non-bank financial institution	0.64	.720	-1.75	.444
Is rural bank	2.38	.803	0.32	.940
degrees of freedom	***584***		***455***	
R^2	***.169***		***.294***	