THE PROGRESS OUT OF POVERTY INDEX

A Detailed Analysis of MFI Implementation

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EXECUTIVE SUMMARY

The Progress Out of Poverty Index (PPI) is a tool that allows a microfinance institution (MFI) to estimate the poverty rate of its clients. This document provides an in-depth analysis of the implementation and utilization of the PPI by MFIs in Latin America. The analysis is based on interviews with five MFIs in Peru and Ecuador that have adopted the PPI as well as interviews with a range of other relevant institutions including rating agencies, social investors and the PPI designer.

The PPI is a high quality poverty measurement tool that has the *potential* to provide significant value to MFIs seeking to adopt quantitative, evidence-based strategies for monitoring the poverty outreach objectives identified in their social mission. The PPI also allows MFIs to provide quantitative evidence of their poverty outreach to external donors and lenders who may base their funding decisions on this evidence. Critical evaluation and internal monitoring of the social mission and communicating poverty outreach to external funders were the two most common uses made of the PPI by the interviewed MFIs.

The PPI is particularly attractive because of its relative simplicity and low cost. The PPI developer has made significant investments to make data collection and the conversion from raw data to poverty estimates intuitive and simple. In addition, the developer has created and made freely available in-depth documentation of the statistical methodology underlying the PPI as well as training material for PPI implementation. The simplicity, transparency and documentation all contribute to promoting adoption and effective use of the tool.

The PPI also has strong potential for use outside of microfinance. Its relative simplicity and low-cost make the PPI potentially attractive to a wide range of institutions seeking to monitor and deliver accurate, quantitative estimates of poverty outreach. The PPI would be most appropriate for institutions with a clearly defined client or beneficiary population and whose clients/beneficiaries can easily be visited in the home. Because the PPI was designed with visual confirmation of certain housing characteristics and assets, the PPI may be inappropriate for institutions that cannot easily visit the beneficiaries' homes.

In spite of this simplicity and transparency, effective implementation of the PPI faces several challenges. First, adoption and effective use of the PPI require a non-trivial investment of human resources by the MFI. MFIs that have internal capacity to carry out quantitative analysis and that have experience participating in social science research are best positioned to take full advantage of the opportunities presented by the PPI. Second, the accuracy of the PPI may be compromised by challenges to implementation. These challenges include insufficient training and incentive problems when loan officers collect the PPI data and insufficient understanding of sampling by the MFI leading to the drawing of an improper PPI sample. Both of these issues suggest that strengthening of regional training capacity and the transfer of knowledge and technical capacity from MFIs that have successfully implemented the PPI to those that are either new or potential adopters would be important.

The primary challenge to accuracy of the PPI stems from improper implementation by MFIs. The PPI faces two additional challenges which are related to statistical design. First, construction of the PPI requires nationally representative household data that allows the designer to identify the 10 household indicators that are the best predictor of consumption-based poverty. If the predictive power of these indicators erodes over time then, unless the PPI is updated with more recent national household data, the accuracy of the PPI will decline. Second, if the relationship between poverty and the indicators varies significantly across regions, then the accuracy of the PPI when applied to MFIs that occupy a small geographic area may also be reduced.

In order to promote more widespread uptake of the PPI by MFIs in Latin America, we suggest the following potential roles for donors such as the Multilateral Investment Fund (MIF).

First, strengthen (or create) national and regional network support institutions. It is useful to think about the PPI as a new technology that MFIs consider adopting. One of the primary barriers to adoption and effective use of the PPI is lack of information. Regional support institutions can provide and promote workshops and serve as a clearing house for information and sharing of experiences across MFIs.

Second, promote increased communication and consultation with national governments regarding the design and use of the PPI. Potential synergies exist with respect to evaluating indicators for inclusion in the PPI, updating the PPI and comparing government targeting methodologies with the PPI. The more informed are national governments about the PPI and the potential uses of the PPI for their own anti-poverty programs, the easier it will be to scale-up the use of the PPI in the region.

Third, in order to improve the performance of the PPI and reduce uncertainty about the PPIS accuracy, we recommend that the MIF support three types of accuracy-related research:

- **Accuracy of PPI implementation:** A random re-survey of the PPI samples of a set of MFIs by a qualified third party would provide evidence on the degree of implementation error. This type of analysis should be carried out on both MFIs that use their own loan officers and those that use third parties to collect PPI data in order to compare the frequency of errors across the two data collection methods.
- **Direct test of accuracy of PPI predictions:** Given the regional and inter-temporal concerns discussed above, a direct test of the accuracy of the PPI would be useful. This would require administering both the PPI and the full consumption module of the national household survey upon which the PPI is based to an appropriate sized sample of MFI clients. Poverty rates predicted by the PPI could then be compared to the "true" poverty rates.
- **Additional tests of regional and inter-temporal accuracy:** Certain national household surveys (with sufficient frequency and observations) could be used to extend the analysis that the PPI designer has already conducted regarding the erosion of accuracy over time and when applied to small regions.

TABLE OF CONTENTS

INTRODUCTION:
OBJECTIVES AND METHODOLOGY

The Progress out of Poverty Index (PPI) is a method for estimating the poverty rates of any well-defined population of households. The relative simplicity, transparency and ease of use and interpretation of the PPI has resulted in it becoming the most popular method for generating quantitative poverty estimates of microfinance institutions (MFIs) in the region. The primary goal of this report is to document and critically evaluate the heterogeneous ways by which MFIs implement the PPI. The use of the PPI involves a large number of choices including the specific questions the MFI seeks to answer, the method used to collect and manage the household-level data, and the way that poverty estimates generated by the PPI are incorporated into the MFI's strategies and activities. This report identifies the key areas of decision making, with a particular emphasis on how different choices taken by the MFI, may affect the reliability of the poverty estimates. The report also identifies potential areas of support by the Multilateral Investment Fund (MIF) to improve the effectiveness of PPI implementation as well as to promote more widespread adoption by MFIs in the region.

The methodology underlying this report is straightforward. First, during the last half of March 2012, interviews were conducted with leadership of five MFIs in Peru and Ecuador. Each of these MFIs currently receives support either directly or indirectly (via microfinance investment funds) from the MIF. The MFIs in Peru included: Prisma, Fondesurco and Arariwa. The MFIs in Ecuador were Fodemi and Espoir.[1] The structured interviews focused on the following topics: A) History of adoption and implementation of the MFI; B) Method of implementation; C) Primary uses made of the PPI results and; D) Challenges faced in PPI implementation.

Furthermore, interviews were carried out with two social-performance rating agencies: Planet Finance in Lima and Microfinanzas Rating in Ecuador. Both of these agencies operate at a regional level. In-person interviews were also carried out with OikoCredit, a social investor that works closely with the Grameen Foundation to promote the implementation of the PPI in Latin America and the Red Financiera Rural, an umbrella institution for a large number of rural financial institutions in Ecuador.

In addition to these interviews, documentation of the PPIs in Peru and Ecuador was reviewed. Detailed documents describing the construction of the PPIs and guidelines for its use are available through Progress Out of Poverty website ***(http://www.progressoutofpoverty.org/)***. Documents provided by

1. These MFIs are not meant to be representative of the MFI sector in Latin America. This, combined with the small sample size, imply that the discussion in this document should not be generalized to the MFI sector in Latin America.

the individual MFIs detailing their use of the PPI were also reviewed (Alvarado Guerrero, 2011; Fernandez Concha, 2011). Finally, phone interviews were conducted with five social investors in order to discuss their views on the PPI.

With the exception of Espoir, I was accompanied by Claudia Gutierrez and/or Tetsuro Narita, from the MIF, on visits to each institution. While I am responsible for any errors and omissions, I would like to acknowledge the important contributions and insights provided by Claudia and Tetsuro. Nobuyuki Otsuka, MIF Specialist, Mark Schreiner, the developer of the PPI, and Mary Jo Kochendorfer, the Manager of Grameen Foundation's Social Performance Management Center reviewed an initial draft of this report. I thank them for the careful and detailed feedback they provided, much of which is reflected in this report.

The remainder of the report is organized as follows. The first section introduces the PPI and its underlying methodology and ends with a critical discussion of several factors that may affect the degree of accuracy. Section 2 provides a conceptual framework to help think about the major challenges to effective implementation of the PPI. Section 3 describes the different types of questions the MFIs tend to answer with the aid of the PPI. Section 4 then turns to implementation and outlines the primary sources of variation in data-collection methodologies. Section 5 provides a more in-depth description of PPI implementation by two of the MFIs, including poverty measurement results from PPI implementation. The costs and benefits of the different methodologies are also discussed. Sections 6 and 7 turn to methods for ensuring data quality and the integration (or lack thereof) of PPI and client data bases. Section 8 briefly describes the role of external auditors. Section 9 discusses potential roles of the PPI outside of microfinance. Section 10 provides an evaluation of social investors' perception of the PPI and the role it plays in their evaluation of social performance. Finally, section 11 concludes and provides several recommendations.

1.
OVERVIEW OF THE PPI

1.1. WHAT IS THE PPI?

The PPI is a tool that allows MFIs and other institutions to estimate poverty rates for groups of individuals (such as new clients).[2] The PPI is based on a statistical and institutional approach developed by Mark Schreiner.[3] The development and diffusion of the PPI has been supported by a number of institutions, including the Grameen Foundation, CGAP, and the Ford Foundation. We begin with a brief description of the main components of the PPI. A more in-depth discussion of the statistical methodology follows.

The PPI is an example of an *indirect* poverty measurement methodology. Instead of directly measuring a household's income or expenditures to determine whether the household falls below a poverty line, the PPI requires the measurement of only 10 household characteristics, or indicators, that are strongly correlated with income or expenditures.[4] These indicators are selected using a statistical model that identifies the best predictors of poverty in the most recent nationally representative household income or expenditure survey. Weights from the statistical model are then applied to the values of each of the indicators to predict the probability that a household's income or expenditures are below the poverty line. The PPI developers have made the algorithm that converts indicator values into predicted poverty probabilities transparent and simple, thus facilitating adoption by MFIs.

The primary advantage of indirect methodologies such as the PPI is low cost.[5] Directly measuring household income in developing countries is highly complicated due, among other factors, to the prevalence of agriculture, self-employment, informality and lack of record-keeping. Directly measuring expenditures is also complicated as it requires lengthy interviews with carefully constructed consumption modules and price information. High time, personnel, and other costs imply that direct measurement of income or expenditures is prohibitively costly for the vast majorities of MFIs and NGOs.

2. The PPI may also be used for targeting as it generates an estimate of the probability that an individual or household is poor. Since MFIs rarely use the PPI for targeting, the remainder of this report will focus on the use of the PPI for estimating poverty rates for groups.

3. Mark Schreiner is the Director of Microfinance Risk Management, L.L.C. (www.microfinance.com) and a Senior Scholar in the Center for Social Development at Washington University in Saint Louis.

4. The PPIs for all countries except Ethiopia require collection of only 10 household indicators. The Ethiopian PPI requires 11 indicators.

5. The Poverty Mapping or Small Area Estimation techniques developed by the World Bank is the other main example of indirect income or poverty measurement methodology. While the World Bank provides a free software program (PovMap) to implement poverty mapping, implementation of Poverty Mapping is several orders of magnitude more complex than the PPI and, at least at this point, it is not feasible for MFIs to implement. A large literature on the methodology and applications of poverty mapping can be found at the following World Bank website: http://web.worldbank.org/WBSITE/EXTERNAL/TOPICS/EXTPOVERTY/EXTPA/0,,contentMDK:20219777~menuPK:462078~pagePK:148956~piPK:216618~theSitePK:430367,00.html.

In contrast, with the PPI, the MFI need only collect information on the 10 indicators. In addition, the PPI developers select indicators that are relatively easy for enumerators to collect with just a small amount of training. When selecting the indicators, the PPI developers also place weight on indicators that are verifiable and that will likely not embarrass respondents. These two characteristics of indicators increase accuracy and, importantly, the likelihood that MFIs will be willing to adopt the PPI.

Implementation of the PPI by an MFI requires two simple-to-use documents. The first is the *Poverty Scorecard*, the questionnaire form on which the enumerator records the values of the household indicators. Based on the underlying statistical model, the Scorecard also converts the response to each question into "points" that when summed up over the 10 questions (one for each indicator) generate the household's "poverty score." Appendix B shows the Scorecard for Mexico. A unique Scorecard exists for each country with a PPI.

The second document is the *Lookup Table*. As mentioned above, the Poverty Scorecard generates a poverty score for each household. This score ranges from 0 to 100. By consulting the Lookup Table, the enumerator can convert the household's poverty score into a probability that the household falls below a given poverty line. The poverty rate of the group is then simply the average of these poverty probabilities across all households in the sample. An important feature of the Lookup Table is that it reports poverty probabilities for a wide range of poverty line. In the case of Mexico, for example, the Lookup Table converts poverty scores into poverty probabilities for eight separate poverty lines. The Lookup Table for Mexico is included in Appendix B.[6] This is an important innovation because different MFIs may use different lines to define the poverty outreach goals of their social mission. In addition, a given MFI may be interested in reporting poverty rates for different poverty lines; for example using the national poverty line for their internal social mission while providing poverty rates based on an absolute and internationally comparable poverty line such as the $1 per day line to external investors.

The PPI designer provides extensive documentation for MFIs interested in adopting the PPI. A detailed document describing the statistical methodology, the selection of the indicators, and an in-depth analysis of the tool's accuracy is available for each of the country-specific PPIs on the Progress Out of Poverty website: ***http://www.progressoutofpoverty.org***. The documentation for each country also includes a discussion of other poverty measurement tools available for the specific country. A critical comparison of the PPI versus other available tools is provided so that the institution can take an informed decision about which tool is best for its particular needs and circumstances.

Finally, in some countries, the Grameen Foundation provides support and training for MFIs interested in adopting the PPI. This support, including a certification program, is discussed in greater detail later in this report.

1.2. HISTORY AND UPTAKE

By the end of the 1990's, significant demand arose by MFIs for a method of quantifying poverty levels of their clients. On one hand, donors, including governments and social investors, sought a means to con-

6. For brevity, only the first three poverty lines are included in the Appendix. The Scorecards, Lookup Tables, and documentation for the PPIs in each country are available at the Progress Out of Poverty website: ***http://www.progressoutofpoverty.org***. The Poverty Scorecard and complete documentation for the PPI in Mexico is available at: ***http://www.progressoutofpoverty.org/country/mexico***. Access to the documents requires creating a free user account.

firm that the funds they were providing to MFIs were indeed being channeled to the poor. In 2000, the U.S. government passed legislation requiring micro-enterprise supporting institutions, including MFIs, that received U.S. government support via USAID to report the percentage of beneficiaries (i.e., MFI clients) that were poor. In addition, the legislation required MFIs to use an approved poverty measurement methodology. On the other hand, MFIs have increasingly adopted poverty measurement tools for their own internal uses. Most important among internal uses is the ability to evaluate whether the MFI is meeting its social mission.

The two primary methodologies used by MFIs to generate quantitative poverty estimates are the PPI and the Poverty Assessment Tool (PAT), developed by the IRIS Center at the University of Maryland. For further information on the PAT, visit: ***http://www.povertytools.org/***.

Currently, PPIs exist for about 50 countries throughout the developing world and Eastern Europe, including 13 in the Latin America and Caribbean region. Table 1 provides additional detail on the PPIs of the 13 Latin American countries, including the national household survey (and survey year) upon which it is based and the year the current PPI was created. The year of the national survey is relevant because the accuracy of the PPI may be reduced over time if it is not updated on the basis of new household data.

TABLE 1. LATIN AMERICAN AND CARIBBEAN COUNTRIES WITH PPIs

Country	National Household Survey Source	Year of Latest PPI
BOLIVIA	2007 Encuesta de Hogares	2009
BRAZIL	2008 Pesquisa Nacional por Amostra de Domicilios	2010
COLOMBIA	2009 Gran Encuesta Integrada de Hogares	2011
DOMINICAN REPUBLIC	2007 Encuesta Nacional de Ingresos y Gastos de los Hogares	2010
ECUADOR	2005 Encuesta de Condiciones de Vida	2008
EL SALVADOR	2008 Encuesta de Hogares de Propósitos Múltiples	2010
GUATEMALA	2006 Encuesta Nacional de Condiciones de Vida	2010
HAITI	2001 Enquete sur les Conditions de Vie en Haiti	2006
HONDURAS	2007 Encuesta Permanente de Hogares de Propósitos Múltiples	2010
MEXICO	2008 Encuesta Nacional de Ingresos y Gastos	2009
NICARAGUA	2005 Encuesta Nacional de Hogares sobre Medición de Nivel de Vida	2010
PARAGUAY	2011 Encuesta Permanente de Hogares	2012
PERU	2010 Encuesta Nacional de Hogares	2012

Source: Schreiner 2012a, 2012b, 2012c, 2010a, 2010b, 2010c, 2010d, 2010e, 2010f, 2009a, 2009b, 2009c, 2008.

1.3. CONSTRUCTION OF THE PPI/STATISTICAL METHODOLOGY

In this section we provide a more detailed description of the statistical methodology and construction of the PPI.

The first step in the construction of the PPI is the identification of the most recent, high quality, nationally representative survey that measures either household income and/or expenditures. Table 1 lists the national household surveys used in the construction of the PPI. The surveys include both multi-purpose surveys modeled after the World Bank's Living Standard Measurement Surveys (LSMS) as well as more directed surveys focusing specifically on income or consumption. These large, specialized surveys have sample sizes ranging from just under 5,000 in the case of Paraguay (Schreiner, 2012b) to over 220,000 households in the case of Colombia (Schreiner, 2012a). In addition to collecting detailed consumption and/or income data, these surveys collect information on a large number (typically between 100–300) of household characteristics.

The most recently available, national household survey thus provides the raw material for constructing the country-specific PPI. These data are used to select the 10 indicators that ultimately appear on the PPI Scorecard. The Scorecard points are derived through estimation of the statistical model of the relationship between household poverty status and the 10 indicators in these data. The points are scaled so that, when summed across the 10 indicators, the household's score falls between 0 and 100, with lower scores corresponding to higher probabilities of falling below the poverty line. A separate non-parametric, statistical technique is used to estimate the probabilities that households with PPI scores within a given range have income or expenditures below a range of different poverty lines. The Lookup Table presents these "Category Likelihoods."[7]

Once the national household data set has been identified and acquired, the total sample is randomly divided into two equal sized sub-samples:

Construction/Calibration Sample: This sample is used to identify the 10 best predictors of poverty status and estimate the parameters of the statistical model.[8] The statistical model utilized is the logit model, which takes the following form:

$$P(Y_i = 1 | X_1, X_2, \ldots, X_{10}) = F(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_{10} X_{10}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_{10} X_{10})}}$$

In the above equation, Y_i is the observed poverty status of household i, and takes value 1 if the household is poor and 0 if it is not poor; the X_i are the observed values of the 10 household indicators; and the β_k are the parameters to be estimated. The function *F(.)* is the Logistic function. The logit parameter estimates, $\widehat{\beta_k}$, are then scaled and rounded into integer values such that when they are summed up, the maximum "score" is 100 and the minimum "score" is 0. In order to make adding-up to get the final PPI score easier, the points for each possible answer for the indicators are non-negative integers.

Placing the PPI score on an integer scale from 1 to 100 is an important innovation, because it places the household's score on a scale that is familiar with MFI management and staff. The household's PPI score is

7. As seen in the Lookup Table for Mexico in Appendix B, poverty probabilities are provided for twenty PPI five-point score ranges beginning with 0 – 4 and ending with 95 – 100.

8. Clear details of indicator selection are provided in the methodological document for each country's PPI.

not, however, the probability that the household is poor. Instead, an additional step is required to identify the poverty probability. This step is to consult the Lookup Table, which converts the PPI score into a poverty probability.

The probabilities in the Lookup Table are calculated using an intuitive and straightforward statistical procedure with the Construction/Calibration sample. Specifically, the PPI is "applied" to and a PPI score is generated for each household in the Construction/Calibration sample. Households are then grouped together by their PPI score. The poverty probability associated with each score is simply the percentage of households with that score whose true income or expenditure (as measured by the national household survey) falls below the selected poverty line. These poverty probabilities are then reported in the Lookup Table. Consider, for example, the top left entry in the Lookup Table for Mexico in Appendix B. We see that a household that has a score between 0 – 4 would have an estimated 83.9% probability of being poor as defined by Mexico's National Food Poverty Line. This is because 83.9% of the households in the Construction/Calibration Sample that had PPI scores between 0 – 4 had incomes below the National Food Poverty Line.

So how does the developer select the 10 household indicators for inclusion in the PPI? The specific methodology for selecting the 10 "best" indicators includes both objective and subjective criteria. The key objective criteria used is the Concordance Statistic, or "C-Statistic". The C-Statistic is a conventional test statistic used to evaluate the predictive power of models of binary outcomes, such as the logit model. The C-Statistic measures the ability of the model to correctly classify households as poor versus non-poor.[9] The PPI developer selects the 10 indicators in order to maximize the C-Statistic, and thus maximize the probability of correctly classifying households as poor and non-poor. In addition to this statistical criterion, the PPI developer also uses a range of subjective criteria to select the 10 indicators. These additional criteria include a range of factors that affect the ease of applying the PPI Scorecard and the accuracy of the responses. For example, the developer considers how easy the question is to communicate to the respondent, whether the indicator can be easily verified visually, and the degree to which the question may make the respondent uneasy. In addition, the developer seeks to include some indicators that are likely to change over time and thus will allow the PPI to capture changes in poverty rates over time.

Validation Sample: This second sub-sample of the national household survey is used to evaluate the accuracy – including bias and precision – of the Poverty Scorecard. This is done by drawing 1,000 random samples of households from the Validation Sample, using the Poverty Scorecard to estimate the percentage of poor (i.e., the poverty incidence) in each of these samples, and then examining the empirical distribution of the difference between these estimates and the true values. Specifically, the mean of the poverty incidence over the 1,000 samples is compared to the true mean in order to examine the degree of bias. The 90% confidence interval of the poverty rate is given by the 50th and 950th poverty incidence estimates ordered from smallest to largest. The design documentation for each country-specific PPI presents an analysis of the bias and precision for each of the poverty lines for which poverty probabilities are reported in the Lookup Table.

9. The basic idea behind the C-Statistic is as follows. Assume we have grouped households from the nationally representative survey into their true categories of poor or non-poor. Now, randomly pick one household from the poor group and one from the non-poor group and apply the PPI to both households. The household with the largest PPI value should be the one from the non-poor group. The C-Statistic is the percentage of randomly drawn pairs for which this is true (that is, the PPI correctly classifies the two households in the random pair). The primary objective criteria is thus to select the 10 indicators that maximize the C-Statistic.

1.4. DISCUSSION OF ACCURACY OF THE PPI

There are two broad concerns relating to accuracy of poverty measurement tools such as the PPI. The first set of concerns relates to the design of the tool; the second relate to implementation. We discuss implementation in detail in subsequent sections. Here we identify several issues relating to design.

As discussed above, the statistical model underlying the PPI captures the relationships between the selected indicators and household poverty (i.e., the β_Ks above) across all households in the nationally representative household survey sample at a given point in time (the year that the national survey was administered). This raises two immediate concerns, both of which are acknowledged and discussed in the PPI design documentation for each country. First, if these relationships change significantly over time but the PPI is not updated to reflect these changes, then the accuracy of the PPI may be reduced. Second, if the relationships vary significantly across sub-groups in the population, and if the MFI's clients tend to fall within a single sub-group (which they usually do), then some bias may be introduced in the poverty estimates generated by the PPI.

The first concern, namely potential bias resulting from PPIs becoming outdated, can be put into context by examining Table 1 above. Consider MFIs in the LAC region implementing PPIs in 2012. The most recent national survey upon which a PPI is based is that of Paraguay, which is based on a 2011 national survey. Haiti is at the other extreme with its PPI based on a 2001 national survey. This gives a range of at least 1 and at most 11 years between the application of the PPI and the year in which the underlying relationships were estimated. The developers of the PPI acknowledge this issue and, when possible, provide evidence on the degree to which (and the likely direction of) bias may occur. Consider, for example, the case of Peru. Nationally representative household consumption surveys are administered on an annual basis in Peru. The current PPI is based on the 2010 household survey. Thus one can gauge the loss in accuracy due to this first inter-temporal concern by "applying" the PPI to random samples of households in earlier years of the national household survey and comparing the poverty rate estimated by the PPI to the true poverty rate. This approach is followed by the developers. Specifically, the developers compare estimates of the change in poverty rate over time as estimated by the PPI to the true change as measured by the national household surveys. Returning to the Peru example, the developers find that between 2004 and 2009, the true change in the poverty rate (using the national poverty line) was a decrease of 25.4 percentage points. The PPI, in contrast, predicts that the poverty rate fell by only 21.9 percentage points. The PPI thus underreports the change by 3.5 percentage points, or about 14 percent of the true value (Schreiner 2012c, p. 41).

Whether this is a large or small bias depends on the criteria of the user. Here we make the following three observations.

- First, the PPI developers do not try to hide issues of potential bias due to this inter-temporal concern. Instead, when possible, they provide transparent and in-depth analysis of the likely size of this bias. This rigor and transparency is a clear indication of the high quality of the PPI; the self-critique demonstrates that the developers are open to improving the tool so that it can be as useful as possible to the MFI sector.
- Second, while the developers have taken important strides in examining the size of potential bias, additional research would be welcomed. In particular, instead of analyzing bias in change in poverty rates, the analysis could focus on a more direct object of interest, namely the bias in the level of poverty rates as a function of the number of years since the most recent PPI was created. A comparison of accuracy decay rates across countries, and specific sub-groups (urban versus rural) with countries would also be important. Exploring patterns in the time path of PPI bias is important as it would provide additional

evidence to determine the optimal time to update the PPI. This would be a highly useful and focused area of research that could be supported by the MIF or other donors.

- Third, in some countries, updating the PPI is not possible because reliable, more recent nationally representative household survey data is simply not available. In addition, even when national surveys are conducted at a higher frequency, they often are not available to the public for one to two years after the data are collected.
- Fourth, although updating the PPI based on more recent national household data will reduce bias, one must weigh the benefit of reduced bias against the costs of updating the PPI. The costs, in turn come in multiple forms. On one hand, the design of an updated PPI – as described above – implies significant human and time resources. On the other hand, updating the PPI implies costs for MFIs, as they must invest time and money in the conversion to the new PPI. This includes understanding the new indicators and, depending on how the MFI implements the PPI, modifying client databases and re-training loan officers or enumerators in the application of the PPI.

The second concern, namely that the relationships between poverty probabilities and indicators may vary across different sub-groups, such as rural-urban or across provinces, is also acknowledged by the PPI developers and discussed in the documentation. In contrast to the potential for bias introduced over time, the developers do not provide systematic evidence regarding the existence or not of sub-group bias. This would appear to be an area of important future research. Specifically, accuracy analysis using a range of sub-groups that would appear relevant for the particular country could be conducted with the Validation Sub-Sample. In Peru, for example, due to different government policies, infrastructural development and cultural patterns of consumption, one might expect significant differences in the relationships between poverty and the 10 indicators on the PPI across regions. By drawing repeated samples from these sub-groups and comparing the sampling distribution of poverty incidences, evidence on this type of sub-group bias could be generated.[10]

Again, however, both the benefits and the costs of defining sub-groups must be acknowledged. One of the most attractive features of the PPI is its simplicity. If significant sub-group differences are found, then either sub-group specific PPIs would have to be developed (thereby allowing all the $\beta_k s$ and X*s* from the logit regression to vary by sub-group) or sub-group control variables would have to be introduced. While the latter may appear straightforward, implementation may be complicated depending on the sub-group definition. Consider the introduction of an urban versus rural indicator. As many MFIs have both urban and rural clients, correctly classifying a household as urban versus rural would add additional complexity to the data-collection process. The complexity would be even greater if a separate PPI existed for urban versus rural households as the enumerator would need to select the correct Scorecard for each client.

A related concern is that the population of MFI clients in a country may itself be a sub-group for whom the relationships between poverty and PPI indicators is systematically different from the average relationships captured in the national survey data or even in the geographic area where the MFI operates. To take an extreme example, consider the case of MFIs in Colombia working with internally displaced families. The relationship between poverty and indicators such as education of the household head or possession of certain durable goods is likely to be very different for this sub-population compared to the average relationship across all Colombian households. While this is perhaps an extreme example, it makes the point that the MFI client population may be systematically different (in ways that matter for the estimates

10. As pointed out by Mark Schreiner in comments on this document, this type of analysis, which requires sub-dividing the Validation Sample into sub-groups would be most feasible in those countries whose national household surveys have relatively large samples.

generated by the PPI) from the national average. This issue is more difficult to address in the design of the PPI because nationally household surveys often do not contain information on credit access. Even if they did, the size of the sample that are MFI clients would likely be too small to carry out a meaningful analysis.

A final design issue, related to the above discussion, is that of clustering. Clients of many MFIs—especially smaller ones with a narrow geographic coverage—tend to be clustered in a relatively small number of districts, municipalities or provinces. Again, if within these clusters the relationship between the indicators and poverty is different from the "average" relationship, then bias could be introduced. In addition, if a significant amount of the total variation in income is driven by shocks at the cluster level – for example municipal floods or a provincial drought that reduce income (consumption) but do not necessarily affect the PPI indicators -- then again bias may be introduced. This again suggests the need for conducting accuracy analysis using samples drawn from regional clusters, as opposed to drawing simple random samples. For example, when evaluating the accuracy of samples of size n = 350, these samples could be drawn with replacement from the same sub-region, such as a province or a group of districts, as opposed to the current practice of drawing random samples from the entire accuracy evaluation sub-sample.

Overall, the PPI developers do an excellent job at identifying challenges to and evaluating the accuracy of the PPI estimates in the design stage. They acknowledge and discuss, in the PPI documentation, almost all the potential sources of bias noted here. The accuracy evaluation for each PPI is well documented and extensively described in the country-specific PPI reports that are all publicly available. Some additional analysis would be welcomed, in particular evaluating the potential gains in accuracy from accounting for sub-regions. Remaining questions, such as implementation error (which we discuss in the upcoming sections) and the potential differences in the MFI sub-population relative to the national household survey sample cannot be addressed without additional fieldwork.[11]

11. The ideal design would be to apply the national income or expenditure survey to a sample of MFI clients to whom the PPI is also administered and directly compare poverty estimates.

2.

PRIMARY CHALLENGES TO EFFECTIVE IMPLEMENTATION OF THE PPI

We begin by describing the two main challenges that PPI implementation faces in order to generate high-quality poverty estimates. It is important to note that these two challenges are conditional on the statistical quality of the PPI itself. Of course a PPI that is poorly designed or based on low quality or old data, will generate poor poverty estimates even if MFIs overcome all implementation challenges. The two challenges are cost and adverse incentives.

2.1. CHALLENGE 1: COST

To get a handle on costs, it is useful to divide overall PPI implementation into roughly three stages:

- **Adoption:** This includes the process of management learning about the PPI; training of management and staff about the general methodology underlying the PPI and how the PPI will be used by the MFI; specific training of loan officers about data collection (if data collection is not outsourced); establishment and management of a PPI data base and potential integration of the PPI data base with the existing client data base.
- **Execution:** This includes the definition of the client population of interest (new clients, all clients, etc.), the drawing of the sample, and the collection and entry of the PPI data.
- **Analysis and dissemination:** This includes the calculation of poverty rates, writing of reports, and communication of results internally and externally. This final step may also include the contracting of an external auditing institution to verify the implementation process.

Within each stage, costs come in multiple forms, none of which are trivial:

- **Monetary costs:** The good news for end-users is that the PPI is freely and publicly available. In many countries, technical assistance is also available for some MFIs, especially those who work with the Grameen Foundation, OikoCredit, or have support from international development institutions such as IDB to support adoption of the PPI. This dramatically lowers the cost of adoption. The bad news is that, even with this cost reduction, adoption, execution and analysis are not costless. If the MFI chooses to integrate the PPI data into the client data base, programmers must be hired or, at a minimum, significant time of existing staff must be used.[12] Based on interviews with MFIs, the monetary costs to execute a sample-based PPI of approximately 350 clients, which is a common sample size used by MFIs consulted for this report, ranges between $2,000 – $10,000. For a large MFI, this may be a relatively minor cost, but for smaller MFIs this may represent a substantial outlay. This cost does not include additional costs of acquiring or adapting existing software; establishing, managing or merging the PPI data base with the client data base; or time and personnel costs of analyzing the PPI data. Analysis requires staff time, thus raising the salary costs of the MFI. Finally, based on interviews with Microfinanzas Rating and Planet Finance, an external audit of Social Performance Indicators, of which the PPI is one component, can cost between $3,000 – $10,000.[13]

- **Time costs:** The time dimension of costs is multi-faceted and non-trivial. Learning about the PPI by management, training of staff, and participation in local and regional workshops all take the time of MFI management. The time required for execution varies greatly depending on the method used for data collection. If the data collection is outsourced to a third party, then the time cost is relatively low for the MFI (although the MFI must be involved defining the relevant client population and drawing the sample). If instead, the data is collected by loan officers, either as part of the loan application process or as a separate survey, then the time costs may be significantly higher, in particular if the PPI is applied as a separate survey. Perhaps most importantly, developing the internal human capital—if it does not already exist—required for the MFI to correctly implement and effectively utilize the PPI requires significant investment in time. If this human capital is not developed, it is likely that the institution will not "buy in" to the PPI process, thereby raising the likelihood that the PPI will not be implemented well. It is also important to note that the investment in time, if it is made, may result in benefits beyond the PPI itself. Specifically, serious implementation and use of the PPI may result in a change in the organizational culture of the MFI, with greater emphasis placed on quantitative, evidence-based decision-making which, arguably, would strengthen the MFI.

2.2. CHALLENGE 2: ADVERSE INCENTIVES

Why do MFIs use the PPI? This is a logical starting point of our analysis of PPI implementation as it will suggest both the expected benefits derived by MFIs and the some of the potential incentive-related concerns with respect to appropriate implementation. In general, we can identify two main motivations: Internal and External.

- **Internal Motivation:** By internal motivation, we mean the reasons that the MFI uses the PPI to adjust business or management practices or, in the words of numerous MFI managers, *"para la gestión interna"*. Internal motivation is crucial for the PPI 's sustainability for, without it – or if the MFI does not perceive any value to integrating the PPI into the business model of the institution – then it is unlikely that the MFI will continue to use the PPI over time. Internal motivation, in turn, can be separated into two further categories: 1) Identifying whether the poverty level of the MFIs client base is consistent with the MFIs mission and 2) Modifying or developing new products. When used for internal motives, the MFI wants

12. Note that the PPI data need not be integrated into the MFI's client data base. The PPI developer provides a stand-alone Excel spreadsheet that may be used to independently store and analyze the PPI data.

13. External audits, of course, are by no means required for MFIs implementing the PPI. If one primary objective of the MFI is to present client poverty rates to external funders, then an external audit may be sensible. If, however, the primary objectives are internal to the institution, then internal auditing procedures may be sufficient to provide quality control.

to learn the true poverty rates of their clients as revealed by the PPI and, if appropriate, adjust policies or practices. As such, the scope for morally hazardous behavior (intentional mis-use or mis-reporting of the results of the PPI) is reduced. Moral hazard may still exist internally if, for example, incentives of the MFIs management are not completely aligned with the incentives of the individual field agents applying the PPI. For example, loan officers who are required to apply the PPI to clients may derive no direct benefit from asking the additional 10 questions, but they do perceive a cost as asking these questions implies additional time. This misalignment of incentives may lead the loan officer to apply the PPI in a quicker and less rigorous manner, thereby reducing the reliability of the poverty rate estimate generated by the PPI.

- **External motivation:** By external motivations, we mean the reasons that the MFI uses the PPI to present the poverty profile of its clients to the outside world, in particular national and international donors and investors. External motives are associated with two separate concerns. First, external motives generate the potential for incentive and moral-hazard issues. If MFIs derive benefits, say in the form of cheaper lines of credit, if they can demonstrate minimum poverty rates of clients, then MFIs may have an incentive to either over-state the "true" poverty rate as revealed by the PPI or to implement the PPI in a way that generates an artificially high estimate. Second, if the primary motivation for implementing the PPI is external, then minimal effort may be made to apply the PPI in a rigorous way; again potentially jeopardizing the quality of the poverty estimates generated by the PPI. It is important to note that vulnerability to intentional mis-reporting is not a criticism of the PPI *per-se*. Indeed any quantitative poverty measurement tool would be subject to the same challenges. The transparency and extensive documentation provided by the PPI designers, in fact, help to reduce the scope for "bad behavior".

We now turn to more specific aspects that highlight the variation in the ways that MFIs implement and utilize the PPI.

3.

WHAT QUESTIONS DO MFIS TRY TO ANSWER WITH THE PPI?

We begin with the most basic question: When an MFI implements a PPI, what is it trying to learn? While at first glance, the answer seems straightforward – the poverty rate of clients – at second glance, the answer is somewhat more complicated and, indeed, MFIs use the PPI to answer fairly different questions. More in-depth descriptions of specific questions will be provided in the in-depth case studies in Section 5.

The first source of heterogeneity derives from the population of interest defined by the MFI. In other words, the first step in the execution of the PPI is to answer the question: For whom do we want to estimate the poverty rate? The primary target populations defined by the visited MFIs include:

- **All Clients:** This group is typically defined as any individual who either took a loan or had an active loan in the previous 12 months.

- **New Clients:** This group is typically defined as any individual who took their first loan in the previous 12 months.

- **Clients of Specific Regions or Branches:** In this case, data is only collected from clients in a subset of the MFIs operating areas or branches.

The second source of heterogeneity derives from whether the MFI seeks to answer *dynamic* questions. These potential dynamic questions include:

- How did the percentage of poor clients (for any of the target populations defined above) change over a given period of time? Answering this question requires applying a survey to a randomly selected sample from the same target population (but not necessarily the same individuals) over time. As we will see in more detail in a subsequent section, Prisma, for example, sought to see how the poverty rates of new clients changed from 2009 to 2010. To do so, in 2009 they applied the PPI to a random sample of clients that entered in 2009, and in 2010 applied the PPI to a random sample of clients that entered in 2010.

- What is the average change in poverty rates of cohorts, or particular groups of individuals over time? Continuing with the example of Prisma, management wanted to track over time the poverty rates of clients who had entered in 2009. To do so, they applied the PPI to the same sample of clients who entered in 2009 in 2010 and 2011. This is a more difficult question to implement because it implies administering the PPI to the same sample of individuals over time. It also is complicated by attrition, as some clients originally interviewed will leave the institution. The specific question answered is then, "What is that change in poverty rates of the individual clients over time, *conditional on remaining a client?*" The attritors themselves raise a host of interesting questions including, do clients leave because they have become wealthier and have graduated to the formal financial sector? Or are they poorer than those who continue to be clients, perhaps because they were hit by shocks or were simply not good entrepreneurs and were unable to repay the loan? Answering these questions would require applying the PPI to the attritors. While these questions may be of business interest to the MFI, the additional cost may prevent MFIs from designing the PPI sample to permit answering them. In order to answer these questions, additional resources from sources such as the MIF may be required.

A final important issue to address in this section is that of statistical significance of results (i.e., answers to the questions being asked). While the PPI documentation is quite clear about margins of errors for the point estimate of poverty rate for the target population upon which the sample is drawn, the MFIs typically seek to compare poverty rates for sub-groups within the sample. For example, in its 2011 PPI report, Prisma reports comparisons of poverty rates by: gender, principal economic activity, and branch. As these are sub-groups, however, the same margins of error are not applicable. Instead the margins of error will be larger and, in most cases, substantially so.

The lack of understanding of the relationship between margins of error when making poverty rate comparisons on sub-samples is a potential problem. First, it may give a false sense of the poverty profile of the MFI to the external world. Second, and more importantly, if the MFI is making any internal adjustments to policy based on these sub-group comparisons, they would be making these decisions based on a false sense of precision.

A recommendation of this report is that greater attention should be placed on the interpretation of results and on notions of statistical significance in PPI training. Emphasis should be placed on the notion of confidence interval around the point estimate of the poverty rate of the overall target population. Caution should be urged on any sub-group comparison.

4.

HOW ARE THE DATA COLLECTED?

MFIs enjoy (or are faced with) several important choices in the means by which they collect the PPI data from clients. Different choices taken by MFIs with respect to data collection lead to widely varying experiences with the PPI across MFIs. Figure 1 summarizes two of the main dimensions of choice and provides a stylized categorization of MFI approaches to the PPI.

FIGURE 1. HETEROGENEITY IN PPI DATA COLLECTION METHODOLOGY

WHO ADMINISTERS THE SURVEY?

		Internal	Third Party
TO WHOM IS THE SURVEY APPLIED?	Sample	A Arariwa (future) Espoir, Fodemi (current) Fondesurco (initial)	B Arariwa (initial) Prisma
	Population	C Arariwa (current) Fodemi (current, initial) Fondesurco (current)	D

Once the target population has been defined (i.e., new clients, all clients, clients in certain regions, etc.), the MFI must decide if they will administer the PPI to a randomly selected sample from that target population or instead to the entire target population. This choice is represented by the rows in Table 1. In addition, the MFI must decide if it will use its own personnel to administer the PPI or instead contract an independent, third party for this task. The term in parentheses denotes when the MFI was located in the specific cell. For example, Arariwa appears both in cell A and B because in the initial year of adoption, Arariwa hired a third party firm to administer the PPI (cell B) but the institution plans on implementing the PPI in future years with in-house personnel (cell A).

Consider each of the MFIs visited listed above:

- **Prisma:** Prisma adopted the PPI in 2008 after participating in a training program provided and partially funded by the Grameen Foundation and OikoCredit. Since adopting the PPI in 2008, Prisma has contracted a third-party survey firm to carry out the data collection. Prisma defines the target population, draws the sample, and carries out data entry after receiving the paper PPI survey forms. The sole responsibility of the third party firm is to do the data collection. As discussed above, Prisma defines a number of different target populations for poverty measurement. For each of these populations, Prisma selects a random sample of clients. Prisma uses the PPI user manual to select the appropriate sample size in order to achieve a desired level of precision. The sample sizes for each target population are typically around 350 clients.

- **Fondesurco:** In 2008, Fondesurco implemented the PPI on a pilot basis. Training and implementation of the initial pilot was provided by the Programa Misión, a project aimed at strengthening social performance measurement and reporting and supported by the Ford Foundation and CGAP with local support from Catholic Relief Services (CRS) and COPEME (the Peruvian microfinance association) in Peru. In this pilot, Fondesurco loan officers and a group of individuals from the target communities were trained to apply the survey to a sample of 353 clients. When Fondesurco initially adopted the PPI, they were thus in cell A of Table 1. Beginning in 2009, management decided to implement the PPI to the entire population of clients. Specifically, the PPI is administered at the moment of loan application for new clients and loan renewal *(renovación de crédito)* for existing clients. The PPI variables have been added to the first part of the loan application form. Loan officers thus collect the PPI data at the same moment of filling out the loan application form. Fondesurco is thus currently placed in cell C in Table 1.

- **Arariwa:** In 2010, Arariwa applied the PPI to a sample of 2,400 client families. This pilot application was a part of a broader research program funded by CGAP and implemented by Innovations for Poverty Action (IPA) on the role of MFIs in promoting mobility of households out of extreme poverty (*graduación de la extrema pobreza)*. In this initial pilot phase, Arariwa is thus placed in cell B, since IPA carried out the survey which was administered to a random sample. In 2011, Arariwa sought to establish a "baseline" snapshot of poverty rates of the entire institution and thus applied the PPI on the entire population of clients. In this baseline, loan officers applied the PPI at the moment the loan was distributed to the client *(al momento del primer desembolso)*. We thus place Arariwa in cell C for their current situation. Finally, moving forward, Arariwa plans on following up with the PPI on a 10 – 20% sample of all clients in order to track changes in poverty rates of the overall client base over time. As the plan is for loan officers to again administer the PPI to the future sample, we expect Arariwa to be in cell A in the future.

- **Fodemi:** In 2010, Fodemi management and loan officers participated in a PPI training workshop funded by OikoCredit. After this training, Fodemi applied the PPI to the population of new clients, defined as those who took their first loan in 2010. Loan officers applied the PPI during the same visit in which they fill out the loan application *(solicitud de crédito)*. In contrast to Fondesurco, which has integrated the PPI questions into the loan application, Fodemi administers the two forms separately. Currently, Fodemi continues to apply the PPI to the population of new clients. In addition, beginning in the second half of 2012, Fodemi began administering the PPI to a 10% sample of the new clients from 2010. The goal is to measure the change in poverty rates after two years for those who joined in 2010. As loan officers will again administer this sample-based PPI, we also place Fodemi in Cell A of Figure 1.

- **Espoir:** In 2009, Espoir participated in a PPI training workshop funded and run by OikoCredit. After this training, Espoir applied the PPI to a sample of about 680 households drawn from the target population of all clients. In 2011, Espoir again applied the PPI to a sample of the same size, this time drawn from the target population of new clients. Espoir uses its own staff, although the individuals who implement the PPI are health workers *(promotores de salud)* from another unit within Espoir. Espoir is thus classified in cell A in Figure 1.

Finally, there are no institutions in cell D. This is because it would be prohibitively costly to hire a third party to independently collect the PPI data on the entire target population.

Discussion

The classification above suggests a somewhat surprising result; namely that, even within this relatively small group of MFIs, we observe a lot of variation in data collection methodologies. In addition, this variation exists both across MFIs and, in some cases, within a given MFI.

First, consider heterogeneity across MFIs. At one extreme, Prisma relies on a third party firm and thus maintains separation between the institution and the data-collection process. Prisma cites two reasons for this choice. First and foremost, using a high-quality, independent firm to carry out the data collection yields the highest quality of data; both because the independent enumerators have no incentive to manipulate the data and because specialized personnel are more qualified and less apt to make data-collection errors. In addition, Prisma prefers to avoid placing any additional burdens of data collection on loan officers. At the other extreme, Fondesurco uses its own loan officers to apply the PPI to the entire population of clients. Fondesurco has not sought to maintain separation between the PPI and the day-to-day operations; instead they have fully integrated the tool into the normal operations of the institution.

Even when we consider a single MFI, we observe heterogeneity in the data collection methodology. This is due, on one hand, to the testing and learning process. Fondesurco, for example, tested the PPI with a sample-based application. Based on this experience, the institution felt that the PPI could indeed generate not only external, but—especially—internal benefits, and thus decided to more fully adopt the tool and move toward a population based, internal methodology (i.e., move from cell A to C). On the other hand, MFIs seeking to answer multiple types of questions may use multiple approaches even at a given point in time. Fodemi provides one example, as in 2012 they began applying the PPI to the entire population of new clients as well as to a randomly drawn sample of clients who joined the institution in 2010.

Should the high degree of heterogeneity raise a concern in terms of quality of data collected? This is a difficult question as there important tradeoffs associated with these choices, in particular, with the use of a third party for data collection.

On one hand, one may argue that the use of a third party raises the quality of the data collected for a number of reasons. First, as discussed above, the third party (if appropriately chosen) is independent of the MFI and thus has no incentive for manipulating the data. Second, again if appropriately chosen, the third party should be specialists in the application of household surveys and would be likely to do a better job at collecting household data. Similarly, loan officers typically have, at best, little incentive to carefully collect the PPI data. In nearly all MFIs, loan officers' primary incentives are to increase the volume of loans and to ensure loan repayment. As the PPI adds time to the loan application process without adding information that is relevant to predict credit-worthiness, it may be seen as a nuisance to loan officers. This was indeed confirmed by loan officers from both Fondesurco and Fodemi who claimed that when the PPI was first introduced the loan officers were upset and viewed the PPI questions as an imposition and impediment to effectively performing their job. Even though management and the loan officers from Fondesurco and Fodemi stated that once the loan officers became accustomed to having to ask the PPI questions they no longer viewed them as an imposition, it is easy to imagine that the quality of PPI data collected by loan officers is lower than that collected by qualified third-party survey institutions. Contracting a third party also eliminates the (potentially large) fixed time cost to management to train loan officers and the marginal costs of supervising and monitoring loan officers in their application of the PPI.

Weighed against this likely benefit of higher data quality from third-party data collection is the monetary cost. Prisma, the only MFI here that consistently uses a third party, paid its third-party service provider about $13,000 to carry out the 1,200 surveys implemented in 2012. One way to think about the cost-benefit trade-off of internal versus external application of the PPI is through fixed versus marginal costs. The marginal costs of external application are high; each additional survey may cost as much as $10 - $15.[14] The fixed costs, however, are relatively low as there is no need to train loan officers. In contrast, when the PPI is applied by loan officers who are already collecting information via a loan application, internal application implies relatively low marginal costs. These marginal costs come in the form of the extra few minutes required for the loan officer to ask the additional 10 PPI questions and for management to monitor the loan officer. If, however, a visit to the client's home was not previously a requirement of the loan application process, then the marginal costs would be significantly higher as a visit to the home is (at least in theory) required for PPI application. Compared to external application, the fixed costs of internal application are likely to be significantly greater as internal application requires lengthy, time intensive training of loan officers.

One undeniable, and potentially very important, advantage of internal application of the form followed by Fondesurco, i.e. applying the PPI as a census to all clients when they apply or re-apply for loans, is that the range of questions that can be examined by the MFI is much greater. As Fondesurco applies the PPI to the population of all clients each year, they are able to compare poverty rates across sub-groups and track poverty rates of specific groups over time. Of course the range of questions that can be answered via external, sample-based application is not any less than with internal application; however, the number of different questions that may be answered is significantly less because a separate sample must be drawn from each target population corresponding to the question being asked. Thus, in practice, the range of questions that will be answered by the PPI will be reduced under external than internal application and, as a result, the usefulness of the PPI to the MFI may also be reduced.

14. Note that Prisma was the only institution that provided information about the cost of third party implementation. As such, this should not be taken as representative of other third parties.

5.

IMPLEMENTATION CASE STUDIES

This section provides additional detail regarding implementation and findings for two of the MFIs, Prisma and Fondesurco. These two are chosen as they demonstrate significantly different approaches to implementation, as reflected in their positions in Figure 1, which describes data collection methodologies.

5.1. PRISMA: SAMPLE BASED, DYNAMIC USE OF THE PPI

Prisma is an MFI with a total of just under 21,000 clients spread across 19 branches throughout Peru. Within Latin America, Prisma is one of the earliest adopters of poverty measurement tools. They participated in pilot applications of both the PPI and USAID's alternative tool, the PAT, in 2008. Subsequently, Prisma has continued with annual applications of the PPI to different sub-populations of their overall clients. As described above, Prisma uses a third party to collect the PPI data on randomly drawn client samples. Prisma defines a range of questions it seeks to answer, which in turn define the appropriate sub-populations from which samples must be drawn. Prisma has in-house personnel to carry out the sample design and sample selection. The third party receives the list of sample clients and is responsible solely for data collection.

Table 2 summarizes these sub-populations, the sample sizes and the estimated percentage of each sub-population found to be below the Peruvian national poverty line.

TABLE 2. PPI IMPLEMENTATION AND POVERTY RESULTS FOR PRISMA*

Year	Sub-Population	Sample Size	% Below National Poverty Line
2008	All clients (in 2 branches)	349	36.5%
2009	New clients in 2009	357	35.3%
2009	All clients	375	31.8%
2010	New clients from 2009	302	33.6%
2010	New clients in 2010	346	31.1%
2010	All clients	376	30.4%
2011	New clients from 2009	229	30.8%
2011	New clients from 2010	N/A	28.5%
2011	New clients in 2011	347	32.0%
2011	All clients	377	23.6%

Source: *This table is based on Fernández Concha (2011).

In 2008, Prisma participated in a pilot implementation of the PPI in two of their 19 branches. The third party applied the PPI to a random sample of 349 clients in these two branches. The specific question Prisma sought to answer in this pilot program was: "What percentage of all clients in the two selected branches were poor?" The answer, according to the PPI, was 36.5%.

Based on this pilot experience, the managers of Prisma decided to apply the PPI on an annual basis. According to Diego Fernández, Director of Prisma's microfinance operations, the institution felt that the PPI yielded sufficiently accurate poverty estimates and was sufficiently easy to implement to justify continued use. One particularly attractive feature of the PPI to Prisma is the ease of generating poverty comparisons across a range of sub-groups, such as across branches, across male versus female clients and across rural versus urban clients.

Prisma also took a decision to apply the PPI to different sub-groups in order to answer a range of different question. This is made clear with reference to Table 2. In 2009, Prisma applied to PPI to two separate sub-groups: 1) All clients and 2) New clients (who had become first-time Prisma borrowers during 2009). This required drawing two separate random samples; a sample of size 357 new clients and a separate sample of size 375 from the entire client population. This use of the PPI allowed Prisma to answer the question: How does the poverty rate of new clients compare to the poverty rate of all clients in the institution? The results, reported in the last column of Table 2, show that the poverty rate among new clients was slightly higher than the overall client population (35.3% versus 31.8%).

In 2010, Prisma added an additional level of complexity of PPI use. Specifically, they decided to answer the following dynamic question: "How did the poverty rate change from 2009 to 2010 for those clients who had entered in 2009?" In order to answer this question, Prisma sought to apply the PPI to the 302 new clients from 2009. In Table 2, we see that the poverty rate of this group fell slightly from 35.3% to 33.6% after one year. In 2010, Prisma applied the PPI to random samples from two additional sub-groups: 1) New clients that entered in 2010 and 2) The entire client population.

Finally, in 2011, Prisma applied to PPI to four separate sub-samples: 1) The new clients from 2009, 2) The new clients from 2010; 3) The new clients from 2011 and 4) The entire client population.

Table 2 shows that Prisma has identified a range of questions, including static and dynamic, that it is interested in answering via the PPI. Beginning in 2009, Prisma has annually applied the PPI to samples from both the entire client population and to the sub-population of new clients, or those that took a first loan in that year. Within a given year, this allows Prisma to compare the poverty rates of new to existing clients. We see, for example, that in each year the poverty rate of new clients is slightly higher than that of existing clients (35.3% versus 31.8% in 2009, 31.1% versus 30.4% in 2010, 32.0% versus 23.6% in 2011). This information may be particularly valuable to the institution in assessing whether it is meeting its social mission of poverty outreach.

The repeated cross-sectional samples (i.e., new random samples of existing and newly entering clients) over multiple years also provide a view of the evolution of the poverty profile of the institution's clients. The most notable result here is the large decline in poverty of the overall client group from 2010 to 2011 (from 30.4% to 23.6%). Given that Prisma applied the PPI to multiple sub-samples, we can also form an idea of where among the overall client base this decrease is coming from. We see, for example, that the poverty rate of new clients in 2011 was 32%. This implies that the reduction in the overall poverty rate of clients was not due to attracting a relatively wealthier clientele; instead the reduction reflects lower poverty rates of older clients.

Prisma has made significant efforts to track the poverty of specific cohorts of clients over time. The same 2009 "new client" sample was re-surveyed in both 2010 and 2011. For that group, the poverty rate fell slightly, from 35.3% to 33.6% to 30.8%. Similarly, the 2010 "new client" sample was re-surveyed in 2011, and showed a decrease in poverty rate from 31.1% to 28.5%. By re-applying the PPI to the same set of households over time, Prisma is able to literally track clients' progress (or lack thereof) out of poverty.

Of course Prisma must be cautious in the interpretation of these "dynamic" results. First, since the change in poverty rate may be due to many factors, such as general changes in the local or regional economic situation, that are independent of the MFI, the change cannot be interpreted as causal. As discussed previously, the documentation provided by PPI developers is very clear on this point. Indeed, based on both discussions with Prisma management and the poverty status reports generated by Prisma (Fernández Concha 2011), Prisma has clearly internalized this point, and they make no claim that the reduction in poverty rates were *caused by* the MFI.

Finally, it is worth mentioning a specific challenge in Prisma's dynamic use of the PPI; namely attrition, or the inability to re-survey some of the same households over time. Note in Table 2, that the sample size of new clients in 2009 was 357. However, of these 357 households, Prisma only applied the PPI to 302 in 2010 and 229 in 2011. This declining sample size is due to the exit of clients from Prisma over time. With this attrition, it becomes difficult to answer the question: "How did poverty rates of the new clients in 2009 change over time?" For example, if the 55 (= 357 – 302) clients that left Prisma between 2009 and 2010 were the most successful (relative to those that remained clients) then the reduction in poverty from 35.3% to 33.6% would understate the true reduction in poverty of the original new clients. The attrition problem becomes even more severe in 2011 as the sample size falls further to only 229 of the original "new clients" from 2009.

For MFI's that seek to use the PPI for this type of dynamic analysis in which they re-survey the same sample over time, we make two recommendations. First, the original sample size should be increased so that, even after attrition, the sample size in subsequent years is large enough to maintain desired levels of statistical significance. Second, the MFI should report the poverty rate of a consistent sample over time. For example, in Table 2 we see that 229 of the new clients from 2009 were re-interviewed in both 2010 and 2011. It would be useful to report the poverty rate for these 229 households in each of the three years. This would require, for example, separating these 229 from the full 357 households in 2009. While this reduces the sample, it allows a clear answer to the following question: "How have poverty rates of households that entered in 2009 *and continued to be clients* changed over time?" An alternative, and perhaps preferable method, would be to simply draw in subsequent years a new random sample of the cohort of clients that entered in 2009. In other words, there is no need to re-interview precisely the same sample. As attrition would not be a concern, this alternative method would avoid the need to increase the sample size of the new clients in the year they become new clients.

Finally, we briefly comment on Prisma's reporting of poverty results. First, we note that since Prisma collects PPI data on an annual basis, the reporting is also done annually. Second, because Prisma has merged the PPI data base with the client data base, it is able to compare poverty rates by a range of variables that it collects in the loan application. For example, the 2011 report (Fernández Concha 2011) compares poverty rates by: Principal economic activity of the households; gender of the client; branch of the institution, and rural versus urban. One interesting comparison, for example, is the poverty rates of male versus female clients. In Prisma, the poverty rate is consistently higher for men than women. In 2011, the poverty rate among new clients was 32% for men versus 30% for women. The difference is much larger among the full client population, with 19.6% of all women clients estimated as poor while 33.9% of all male clients are estimated to be poor.

It is important to note that the sample selected by Prisma is designed to generate poverty estimates of a given degree of statistical reliability, for example plus or minus 3% points, for the initially defined subpopulations (i.e., those identified in Table 2). Comparisons across more disaggregated groups, such as men versus women within a given sub-population, will no longer have the same degree of statistical reliability. The more disaggregated the comparison, the less reliable the poverty comparisons. For example, Prisma compares poverty rates across the 19 branches. But since the total sample is less than 400 clients, each branch has an average of less than 20 clients. With such small sample sizes, this type of comparison may not provide useful information, and management should be cautious in basing new policies or decisions on this type of sub-group comparison.

5.2. FONDESURCO: POPULATION-BASED USE OF PPI

Fondesurco is an MFI located in southern Peru with just under 11,000 clients spread across 16 branches. With support from Copeme and the Proyecto Misión, Fondesurco implemented the PPI on a pilot basis in 2008. In this first effort, Fondesurco implemented the PPI on a randomly selected sample of 353 clients that were representative of the full client population. Fondesurco hired external enumerators to apply the PPI survey. The initial PPI application generated an estimated poverty rate of 25% among clients.

The results of this pilot application of the PPI surprised Fondesurco's management, as they were expecting a significantly higher poverty rate. This expectation was based on the fact that Fondesurco draws clients from some of the poorest rural areas in Peru, with poverty rates significantly higher than 25%. Instead of rejecting the PPI results, they instead critically re-evaluated the institution's mission. Part of that re-evaluation led to the recent partitioning of Fondesurco into three separate institutions: an NGO that will focus on business development and micro-lending to the extreme poor; a regulated MFI that will maintain a goal of a clientele with 20% poverty rate and; a regulated venture capital firm for wealthier entrepreneurs.

In 2009, after the initial pilot offering of the PPI, Fondesurco decided to institutionalize the application of the PPI to all clients. Loan officers apply the PPI at the same time the client fills out the loan application. Thus the PPI is applied to the population of clients (where client is defined as an individual with an active loan).

Since it collects the PPI data at the same time it fills out the loan application, Fondesurco has expanded its client data base to include the PPI variables. Thus, like Prisma, Fondesurco can easily generate poverty reports that compare poverty rates by any of the variables in the client data base. Fondesurco generates a monthly poverty report that gives poverty rates by the following variables: Gender of client; Age of client (elderly, adult, youth); Rural versus Urban; Economic sector; Branch; Type of loan; Interest rate and; Late payment status.

Table 3 below replicates a portion of the end of year report, generated in December 2011. Note that the overall poverty rate increased slightly from 20.8% to 22.6% between December 2010 and December 2011. In addition to the poverty rates for all clients and each sub-group, the relative proportions of each sub-group are reported. Thus in December 2010, women *(mujeres)* accounted for 45.4% of clients with outstanding loans while men *(hombres)* accounted for 54.6%. In 2010, households of women clients were slightly more likely to be poor (21.3%) compared to households of male clients (20.5%).

TABLE 3. END OF YEAR PPI REPORT FROM FONDESURCO

	FONDESURCO'S CLIENTS' POVERTY LEVEL FROM DECEMBER 2010 TO 2011 (PPI METHODOLOGY)					
			2010		2011	
	Variable	Indicator	Participation/No of Credits	PPI - 100% (% of Poor)	Participation/ No of Credits	PPI - 100% (% of Poor)
1	Gender		100.0%	20.8	100.0%	22.6
		Women	45.4%	21.3	43.8%	22.2
		Men	54.6%	20.5	56.2%	23.0
2	Age		100.0%	20.8	100.0%	22.6
		Children	19.8%	16.8	20.5%	19.0
		Adult	69.6%	23.0	68.5%	24.8
		Older Adult	10.6%	14.7	11.0%	16.2
3	Zone		100.0%	20.8	100.0%	22.6
		Rural	92.6%	21.3	92.4%	22.6
		Urban	7.4%	15.4	7.6%	23.5
4	Economic Sector		100.0%	20.8	100.0%	22.6
		Agriculture	34.3%	19.6	33.9%	21.9
		Ranching	19.6%	27.6	18.1%	28.6
		Commercial	21.2%	18.3	20.9%	19.9
		Services	11.4%	19.8	11.2%	21.3
		Public Admin.	0.5%	11.6	0.6%	14.3
		Banking and finances	0.1%	1.4	0.1%	14.6
		Construction	4.4%	26.5	6.1%	28.2
		Education	1.1%	11.2	0.9%	8.9
		Industry	1.2%	21.6	1.1%	21.2
		Mining	1.0%	23.0	1.6%	24.1
		Fishing	0.9%	17.1	0.7%	20.2
		Social and health	0.3%	5.7	0.4%	10.6
		Supply electricity gas water	0.0%	12.4	0.0%	7.5
		Transportation	2.9%	15.4	3.4%	19.4
		Tourism	0.9%	13.3	1.0%	15.5

As in the case of Prisma, Fondesurco can use the PPI to answer a wide range of questions, including poverty comparisons across types of clients and the evolution of poverty over time for the overall clientele and specific sub-groups. One of the most important internal uses of the PPI for Fondesurco is what they call "regional targeting". When Fondesurco opens a new branch, they examine government statistics on poverty rates of the municipalities in which the branch is located. The PPI is used to compare poverty rates of clients to the government rates. The government statistics thus generate a "rough guide" or expectation for the poverty rates of clients in the new branches relative to other branches. If the PPI shows that the poverty rates are relatively high or low compared to the expectations, management meets to discuss whether an adjustment in client outreach is necessary.

One thing apparent in conversations with Fondesurco was that they are generating far more data than they are using. For example, the value of generating monthly reports is not clear. Since Fondesurco reports the PPI based on clients with outstanding loans, poverty rates could potentially change throughout the year if there are strong seasonal patterns in loan applications. For example, assume that maize farmers are, on average, poorer than dairy farmers and that maize farmers' loan cycles run from January through June while dairy farmers' loan cycles run from July through December. In this (artificial) case, we would anticipate significant changes in poverty in the June versus July reports. While this type of seasonality of poverty rates might be of some interest, it might also give a misleading impression. For example, following the example above, if Fondesurco used the December report to present its poverty rates to external donors, it would understate the true poverty rate of its clients (because only dairy farmers, the relative wealthy clients, have loans in December). A more satisfactory approach might be to generate a single PPI report that gives the poverty rate of all clients that had a loan outstanding at some point during the year.

This is a relatively minor concern that is, in fact, more indicative of the "excess of riches" enjoyed by Fondesurco in the form of a very large amount of poverty data. As a final point of interest, we note that Fondesurco is indeed in search of additional ways of utilizing the poverty data. Fondesurco management suggested that national or regional workshops in which MFIs shared experiences of how they use PPI data would be very useful.

6.

HOW DO MFIS ENSURE DATA QUALITY?

As with any survey, the quality of the data collected depends on a range of factors. Even though the PPI contains only a small number of what appear to be straightforward questions, there is still significant scope for the data to be marred by low quality. Based on the MFI interviews, the following points stood out.

First, the PPI developer and Grameen Foundation provide extensive and systematic training documentation for the PPI in each country. The design documentation provides in-depth description of the construction of the PPI, the uses to which the PPI can be put, and a range of other topics, including sampling. Second, a series of "Help Docs" is freely available for download on the PPI country websites. These Help Docs provide checklists for each stage of PPI implementation including: Sampling Strategy, Operational Readiness; PPI Interviews and; Data Integrity. In addition, the Grameen Foundation provides periodic training and implementation workshops throughout the region.

In spite of the existence of these training resources, though, there is a lack of systematic, uniform training for enumerators across the MFIs consulted in this report. As a result, the PPI may not be applied uniformly across MFIs. Although the PPI questions may seem straightforward, in practice the concepts involved may be quite complex and thus subject to multiple interpretations. A clear example is the definition of *household*. Should it be defined as: A) The nuclear family? B) The individuals living under the same roof? C) The individuals living under the same roof and sharing food? The correct answer, according to the PPI documentation, is that the household should be defined in exactly the same way that it was defined in the National Household Survey upon which the PPI was based. The PPI documentation provides a reproduction of this definition, for the convenience of users. This importance of applying the PPI survey in exactly the same way that it was applied in the National Survey was not sufficiently understood by the MFIs. One exception was Prisma, who fully understood this and, in fact, this was one of the reasons they prefer to use a third party instead of their own personnel.

A second concern for data quality was in the rigor with which the PPI survey was applied. Again, this concern primarily applies to those MFIs using loan officers to carry out data collection. A first concern relating to loan officers as data collectors is that, in order to reduce the time of data collection, the loan officer may not visit the household at the homestead. For example, he may ask the client the questions when the client comes in to the MFIs office or when he is inspecting the client's farm or business. This may reduce the reliability of the PPI as it would prevent the enumerator from visually confirming certain questions such as housing materials. This issue is of particular concern for village banking *(bancos comunales)*, and group lending technologies more generally, in which loan applications may be filled out in a group meeting, instead of at the individual members' homes. While all of the MFI managers interviewed acknowledged that this could be a problem, they insisted that their loan officers were instructed to always visit the client's home to administer the PPI. It is thus difficult to assess the degree to which this is an issue.

Third and potentially more important, is the possibility that, for reasons mentioned above, loan officers may simply not ask some of the questions and instead make assumptions about the answer. One specific example of concern mentioned by several MFIs was the possibility that the loan officer would assume that the number of color televisions would not have changed since last year for repeat clients. Again, as mentioned above, loan officers have multiple incentives to shirk on the application of the PPI. Reducing time is first and foremost. In addition, the client may perceive the PPI questions as unrelated to the loan application and thus could be made uneasy by the questions. As loan officers have incentives to maintain positive relationships with clients, they may be reluctant to ask certain PPI questions and instead prefer to make assumptions about the answers.

In summary, the following issues are of potential concern for data quality, in particular when loan officers are used to collect the data:

- Do enumerators follow the precise methodology of the National Household Survey? Indeed, what is the precise methodology that the national survey followed?
- Do enumerators actually visit the household and visually confirm data?
- Do enumerators "assume" too much? E.g., If they only rely on visual confirmation, they may not capture a recently acquired color TV.

Finally, there exists a lot of variation in the quality-control protocols followed by the MFIs. In our opinion, the most systematic and rigorous auditing protocol was implemented by Fodemi who has hired an employee who is dedicated 100% to quality control of the MFIs data bases (PPI and client data base). The quality control supervisor re-visits 5% of all clients of the MFI. Of this 5%, 20% must be new clients. As FODEMI applies the PPI to the population of new clients (but not to all clients), this ensures that the supervisor re-visits a significant number to whom the PPI was applied. During the re-visit, the supervisor re-applies the PPI. The data are entered and compared to the original PPI. According to FODEMI, an inconsistency requiring a change in the data base is discovered in about 40% of audited PPIs. Even though the change is typically restricted to a single variable, this would appear to be a fairly high rate of error, suggesting that a lot of additional noise is being introduced in the data.

Based on these observations, additional evidence on the quality of data collected, in particular by loan officers, would be a high priority. One possible method for doing so would be for a donor to fund a project the mimics Fodemi's internal quality control auditing method across a range of MFIs. This approach, accompanied by critical analysis, could generate highly valuable learning about the relative frequencies and causes of different types of enumeration errors and suggest methods for reducing these errors. Carrying out this approach systematically across a range of MFIs would be important as it would help determine which errors are specific to an MFI versus errors that are being systematically committed across multiple MFIs.

Finally, it is important to note that the variation in the care or rigor of PPI implementation across MFIs is not an indictment of the PPI methodology per-se. Ultimately, the MFI must be responsible for using the training materials and carrying out the PPI in a rigorous form. The PPI developers have provided a significant amount of useful training materials; whether or not and how they are used is ultimately determined by the MFI.

7.

HOW ARE THE DATA STORED?

An important determinant of the usefulness of the PPI data to the MFI is the degree to which the PPI data are integrated with the client data base. If highly integrated, then additional analysis such as poverty rate comparisons by sub-groups can be carried out. Of course, we recall the caveat that caution should be exercised by MFIs when making sub-group comparisons when the sub-group sample sizes are small (as a rough rule of thumb, less than 60), as these comparisons would have a lower level of statistical power.

Significant variation exists in the degree of integration of the five MFIs interviewed. Fodemi and Fondesurco lie at one extreme. Both have fully integrated the PPI data into the client data base. Fodemi management indicated that the process of integration was far from seamless or costless. As the PPI was initially carried out on a separate paper form from the loan application, there existed problems in matching the PPI data base to the client data base. This issue has been subsequently addressed with the move to a single loan application/PPI form. Fondesurco also has a single paper form that collects both the PPI and the loan application data together. This information is entered simultaneously into a single client data base. This greatly facilitates the generation of PPI reports such as the one replicated in Appendix C.

Arariwa and Espoir lie at the other end of the spectrum. They each maintain completely separate data bases for PPI data and client loan application and loan repayment data. According to Arariwa management, the institution will likely move towards integrating the two bases in the next year or two.

The management of Espoir does not have plans for integrating the data bases even though the institution implemented the PPI pilot in 2009. Espoir has some reservations with the PPI. First, they do not believe the 10 indicators can generate a sufficiently accurate estimate of poverty rates. Specifically, they felt that the estimated poverty rate of 22% that emerged from their pilot use of the PPI was significantly below the true level. Second, they felt that the PPI calculation done during the pilot phase was not fully accurate.

As described above, the correct method of generating the poverty rate is to first convert the PPI score of each household into a poverty probability and then to take the average of these probabilities across all households in the sample. Espoir management believed that during the pilot, the average of the PPI scores across households was first calculated then the poverty rate as the poverty probability associated with that average score was consequently calculated. Since the poverty probability is a non-linear function of the PPI score, these two methods will, in general, not give the same poverty rate.[15] Finally, Espoir

15. Consider the following simple example using the Lookup Table from Mexico in the appendix. Suppose the PPI sample consists of two households. The first has PPI score of 20 and thus poverty probability (with respect to the national poverty line) of 46.9%. The second has PPI score of 40 and thus 27.8% poverty probability. The correct poverty rate estimate for this MFI would be 37.35%, which is the average of 46.9% and 27.8%. In contrast, the poverty rate of the average PPI score is 9.9%, which is the poverty probability corresponding to a PPI score of 30, which is the average of the two households' PPI scores.

management felt that recent policy changes in Ecuador had altered the cost-benefit calculation against use of the PPI. Specifically, in 2012, the government of Ecuador passed legislation making available lines of credit to qualified MFIs that carry an interest rate lower than most external funding sources. As such, the value of using to PPI to attract cheaper lines of international credit was reduced. In sum, while Espoir continues to implement the PPI, they have decided that the costs of dedicating a programmer's time to restructure the data bases is not worth the potential benefits.

8.

EXTERNAL AUDITING

Recall from section 2 that one of the external motivations for implementing the PPI is to demonstrate that the MFI is reaching poor clients. This may allow the MFI to attract new funds from socially responsible investors or to receive lower interest rates from existing investors. The potential for incorrect application of the PPI or mis-reporting /manipulation of PPI results creates the need for independent, external verification for those MFIs for whom reporting to external funders is a primary reason for implementing the PPI.

Due to the increased emphasis on "social performance" amongst MFIs, in recent years, a market has emerged to meet this auditing need. Specifically, several non-profit institutions exist to audit a range of MFI social-performance indicators. The two auditing institutions interviewed for this report have, since 2010, added the PPI to the set of indicators of social performance that they evaluate. In addition, the MixMarket has recently provided an updated format that allows MFIs to report details of their PPI implementation.

Two auditing agencies were interviewed regarding their roles as PPI auditors. These two agencies are Planet Rating (Lima office) and Microfinanzas Rating (Quito office). These agencies carry out in-depth interviews with MFI management regarding sample selection, enumerator training, survey implementation, data entry, and data analysis. Based on these interviews and examination of the MFIs' data bases, the rater gives an opinion on whether or not the MFI is following correct procedures in generating poverty estimates of its clients. The auditing agencies do not re-apply the PPI questionnaire to MFI clients. The audit is thus process-based; the auditors identify whether the MFI followed the correct process of PPI implementation. The cost of the social rating is non-trivial, ranging from $3,000 - $10,000. Planet Rating also offers the service of PPI implementation, including designing the sample, applying the PPI Scorecard and calculating the poverty incidence at a cost of $15,000.

Given the potential for implementation error and manipulation, the emergence of external rating agencies that examine the PPI would certainly appear to be a positive step. However, the degree to which a process-based auditing process can detect intentional or un-intentional errors in estimates of poverty incidence is questionable. On one hand, an in-depth and critical evaluation of the PPI implementation process based on interviews with MFI management and loan officers and examination of documents and data bases can detect obvious errors, such as a non-random selection of the sample or alterations (or additions and omissions) of the questions associated with each of the 10 indicators. On the other hand, this process-based auditing is unlikely to uncover voluntary manipulation of data enumerators or management. Increasing the rigor of the auditing process by random re-visits of sampled households would go a long way in overcoming this challenge. Since only a small number of randomly selected repeat visits would likely be needed to provide incentives not to cheat and detect errors, we recommend exploring this addition to the auditing methodology.

9. APPLICATION OF THE PPI OUTSIDE THE MFI SECTOR

Currently, the PPIS primary use is within the microfinance sector. Nonetheless, the PPI is a general tool that could be used by a wide range of institutions with a wide range of objectives relating to poverty measurement. We begin by discussing two concrete examples of non-MFI institutions using the PPI. The first is Marie Stopes International, a global health care NGO. The second is PT Ruma, a for-profit social enterprise that provides mobile technologies to rural businesses and households in Indonesia. The discussion below draws from case studies available on the PPI website: ***http://www.progressoutofpoverty.org*** as well as information available from both institutions' websites.[16]

9.1. MARIE STOPES INTERNATIONAL: MEASURING POVERTY OUTREACH OF A GLOBAL HEALTHCARE PROVIDER

Marie Stopes International (MSI) is a UK-based NGO that provides family planning and reproductive health care services to under-served families in 42 countries. MSI delivers services through three main institutional forms: MSI fixed health care centers, social franchising with private clinics and, mobile clinical outreach teams that provide healthcare services in remote locations.

One of MSI's primary missions is to deliver healthcare services to under-served families, including the poor. In 2010, in an effort to systematically estimate poverty rates of clients, and thus to monitor the degree to which they were complying with their mission, MSI introduced the PPI to programs in seven countries. In 2011, MSI expanded the use of the PPI to an additional 15 countries. In their applications, the MSI reports poverty rates based on the $1.25 poverty line as this allows a comparison of absolute poverty across the wide range of countries in which they work.

The implementation of the PPI was greatly facilitated by MSI's existing human capital and research capacity and its strong emphasis on quantitative monitoring and evaluation. MSI collects a small number of basic demographic variables on all clients at the time of service provision and enters the data into a client data base. Second, and more relevant for the PPI, each MSI country office administers an annual client survey which collects more in-depth information on client satisfaction and service quality. MSI takes advantage of the existence of the client survey to administer the PPI; adding it as an additional section to the existing survey.

16. The PPI website is: http://www.progressoutofpoverty.org. The Marie Stopes International Website is: ***http://www.mariestopes.org/. PT Ruma's website is: http://ruma.co.id/.***

The MSI home office has developed instructional material for the implementation of the PPI for the country programs. MSI in-country monitoring and evaluation officers plan, coordinate and execute the PPI. In the case of Ghana, for example, a random sample of the three types of institutional delivery forms was first drawn: 5/5 fixed service centers, 44/89 social franchises and, 24/36 remote outreach teams were selected for inclusion. Sample sizes were then defined for each of these three types of primary sampling unit and a simple method for drawing random samples of individual clients (such as selecting every fourth client) was used to draw the client samples. The MSI country officer hired and trained local residents, typically healthcare workers and volunteers, as enumerators. After data collection was completed, data entry was carried out by a local contractor, with the MSI country officer responsible for quality control. Finally, the client survey (including the PPI) data base is merged with the client data base to permit detailed analysis of the PPI data.

9.2. PT RUMA: MEASURING POVERTY LEVELS OF MICRO-FRANCHISEES

PT Ruma is an Indonesian for-profit social enterprise that was created in 2009. PT Ruma offers a pre-packaged micro-franchise business to potential entrepreneurs, or "agents". Once established, these agents sell mobile services, including pre-paid mobile phone minutes and mobile electricity bill payment, to rural businesses and residents. The entrepreneurial "package" provided to the agents includes a cell-phone, marketing materials, training and access to airtime through PT Ruma to the main mobile operators in Indonesia.

While PT Ruma is a for-profit business, it has a strong social mission to provide entrepreneurial opportunities to under-served Indonesians. Specifically, its bylaws state that PT Ruma should draw 80% of its agents from the poor (below the $2.50/day poverty line). The bylaws further state that if this goal is not met, all dividends must be re-invested in the business instead of being distributed to shareholders.

Given these quantitative, poverty-related objectives, PT Ruma adopted the PPI in 2009. PT Ruma field staff administer the PPI to all agents (1,550 in 2009) on an annual basis. With support from the Grameen Foundation, PT Ruma has integrated the PPI data base into a large data base generated by each transaction between the agents and their clients. This data base allows PT Ruma to characterize entrepreneurial performance of the agents (revenues generated, frequency of transactions, etc.) by poverty levels. For example, PT Ruma found that the drop-out rate of agents was higher among agents with the lowest PPI scores. Of those agents that did not drop out (after one month), the success of agents – as measured by revenues and transaction density – did not significantly differ by PPI score. Based on this finding, PT Ruma increased support during the start-up period to the lowest scoring PPI agents.

In addition to the internal use of the PPI mentioned above, PT Ruma also uses the PPI for attracting funds from socially oriented outside investors. In 2009, the results of the PPI showed that 65% of PT Ruma's agents were below the $2.50/day poverty line. Although this fell below their own objective (80% poverty rate), the ability to provide a rigorous and quantitative poverty estimate helped PT Ruma secure support from both the Grameen Foundation and the telecommunications company Qualcomm.

9.3. DISCUSSION: EXTERNAL USES OF THE PPI

The two examples above demonstrate that the PPI can be successfully adopted and implemented by a range of institutions seeking to measure poverty outreach outside of the MFI sector. It is, however, important to identify several common features of the above institutions that are likely crucial for successful PPI adoption and implementation.

First, an institution requires *sufficient human and institutional capital* to effectively implement the PPI. As discussed above, although the PPI Scorecard itself is simple to administer, implementation and effective use of the PPI requires sufficient human and institutional capacity. In particular, the institution must have the capacity to understand and manage the sampling, training, monitoring, quality control and subsequent analysis of data generated by the PPI. Both PT Ruma and especially MSI were well positioned to make effective use of the PPI. Institutions such as MSI, that place a strong emphasis on evidenced-based learning and that have a significant dedicated staff responsible for monitoring and evaluation, are the best positioned to make effective use of the PPI. Institutions that have less experience with quantitative research and data-base management or those that have insufficient personnel to manage the adoption and implementation can still successfully and effectively use the PPI, but they may require additional support and will likely be less sophisticated in their use of the PPI.

Second, effective use of the PPI requires a clearly defined client or beneficiary population to whom the institution can administer the PPI in a straightforward manner. To make this point clear, consider the following two examples that do not easily lend themselves to the PPI. A development institution investing in physical infrastructure, such as roads, wells or sewage lines, may seek to measure the poverty rate of beneficiaries of its investment; however they may find it difficult to identify the entire population that directly benefits from its investment. Disaster relief efforts may also face difficulty in using the PPI as the urgent demands of delivering resources may preclude the planning and time required to administer the PPI.

In theory, any intervention or program should be able to clearly define its beneficiary population. The resources requires to gain access to that population, however, may be significant for certain types of programs such as those mentioned above. A careful cost-benefit analysis would need to be carried out (in addition to going through the exercise of carefully defining the beneficiary population) in order to determine whether using the PPI makes sense.

In addition to government, NGO and private sector institutions, one additional type of institution that could potentially benefit from using the PPI are researchers. Precisely because the PPI offers a low-cost means of measuring poverty rates, researchers interested in estimating poverty rates, tracking poverty over time or measuring the causal impact of interventions on poverty rates could consider using the PPI. Compared to conventional household income or consumption surveys, which typically require between one to three hours to administer, a carefully designed survey that includes a few key individual or household characteristics of interest plus the PPI could be administered in less than 30 minutes. As with most decisions, use of the PPI for research purposes would require evaluating a tradeoff. On one hand, for a given research budget, the reduced time-per-survey would allow the researcher to expand the sample size. On the other hand, relative to directly measuring income or expenditure, the PPI would introduce additional measurement error, thereby raising the sample size needed in order to achieve a given level of statistical precision. While exploring this tradeoff is beyond the scope of this report, we note that the cost-savings of the PPI makes its research use potentially quite attractive.

We conclude this section with one important caveat to the use of the PPI outside of the MFI sector. Recall that, within the MFI sector, the PPI is meant to be applied *in the client's household*. Indeed one of the primary advantages of the PPI is that it includes some variables, such as housing material, that can be easily verified visually by the enumerator during the household visit. The household visit is important because the visual confirmation raises the accuracy of data collection. If the PPI is to be extended outside of the MFI sector, it is quite possible that the PPI survey would not be administered in the household. Indeed, this is the case of the two case studies discussed above; MSI applied the PPI during an exit survey at the clinics, while PT Ruma applied the PPI to agents at PT Ruma facilities during meetings with PT Ruma staff. While no empirical evidence exists to gauge the decline in accuracy due to remote application of the PPI versus application in the household, it is important to note this difference from the recommended MFI application. While conducting the survey at the household is not necessary for successful implementation of the PPI, training material should emphasize that non-household applications would require additional training to ensure high quality data collection.

10. SOCIAL INVESTORS' PERSPECTIVES

In this section, we provide a brief discussion of how social investors view and incorporate the PPI in their fund allocation process.

10.1. METHODOLOGY

This section is based on phone interviews conducted with the following five social investment institutions:

- **Locfund** is an investment fund managed by Bolivian Investment Management Ltd. With offices in Bolivia, Costa Rica and Peru, Locfund provides local currency loans and technical assistance to MFIs throughout Latin America. Locfund was started in 2007 and currently has a loan portfolio of approximately $30 million spread across 30 MFIs in the region. The phone interview was conducted with Fernando Sánchez, General Manager, and Verónica Céspedes, Portfolio Manager.
- **Blue Orchard** is a commercial microfinance investment management company with headquarters in Geneva and offices in New York, Phnom Penh, and Lima. Blue Orchard was founded in 2001 and maintains a portfolio of loan and equity investments of over $350 million to over 80 MFIs in 42 countries across Asia, Africa and Latin America. The phone interview was conducted with Yolanda Chenet and Alfredo Ebentreich, Senior Investment Analyst and Investment Analyst, respectively, in the Lima office.
- **Global Partnerships** is a non-profit impact investor with headquarters in Seattle and Managua. Global Partnerships was founded in 1994 and invests in MFIs and cooperatives. In 2011, Global Partnerships managed a portfolio of approximately $36 million in loans to 30 institutions across seven countries in Central America. The phone interview was conducted with Mark Coffey, Chief Investment and Operating Officer, and Tara Murphy Forde, Director of Fund Performance.
- **responsAbility** is a Swiss-based asset management company that invests in a range of development institutions including MFIs, fair trade enterprises, health care institutions and independent media. Currently, responsAbility manages an investment portfolio of approximately $1.2 billion with 392 institutions in 77 countries across Asia, Africa and Latin America. The interview was conducted with Martín Barragan, Senior Investment Officer for Latin America.

Prior to the interview, a list of questions was sent to the social investors. The questions focused on the social investors' familiarity with the PPI, their perceptions of the accuracy of the PPI and the role that the PPI plays in the social investor's evaluation of the MFI's social performance.

We summarize the main impressions to these three main areas.

10.2. FAMILIARITY WITH THE PPI AND PERCEPTIONS OF PPI ACCURACY

Each of the social investors knew of the existence of the PPI and, with the exception of Locfund, each incorporates the PPI, when it is adopted by an MFI, into their evaluation of social performance. Each of the investors, including Locfund, had a good working knowledge of the PPI. Specifically, all investors understood that a single PPI exists per country, and that the PPI is based on a large, nationally representative household data set, and uses a small number of variables from the data set to predict poverty status. More diversity exists with respect to the investors' understanding of the statistical methodology underlying the PPI. On one extreme, one of the investors was aware of and has a good understanding of the logit model used to predict poverty status. More commonly, the investors had not taken the time to familiarize themselves with the underlying methodology, but all assumed the methodology was sound.

All investors perceived a sufficiently high level of accuracy that they were comfortable incorporating the PPI in their social performance evaluation. In general, the social investors felt that the PPIS accuracy was, at least potentially, on the same level as that of the national expenditure surveys upon which it is based.

A general consensus exists among the social investors that the PPI is a more accurate and preferable measure of client poverty rates than the commonly used alternative indicators, such as the percent of clients that are rural, the percent of clients that are women, and, most commonly, average loan size. For example, while loan size may be correlated with poverty status, it is certainly not a perfect predictor. As pointed out by Locfund, loan size may be a particularly poor measure of poverty for an MFI with a mixed farm and non-farm clientele. This is because, even though farm households tend to be poorer than non-farm entrepreneurial households, their working capital needs, and thus loan sizes, are greater than those of non-farm entrepreneurs.

While the social investors were unanimously positive regarding the potential accuracy of the PPI, several also raised concerns regarding accuracy. Four of the investors expressed a concern that accuracy might be reduced when the PPI is not regularly updated. One investor felt that PPIs that were based on national data set over five years old would be particularly unreliable. A second concern voiced by two of the investors was that, although in principal the PPI has a very high potential for delivering a quantitatively rigorous measure of clients' poverty, there is a possibility that MFI would not correctly implement the PPI. The Blue Orchard managers, for example, felt that a PPI administered by loan officers (instead of independent, third party enumerators) would be particularly unreliable if the loan officers do not receive sufficient training or are not provided with sufficient incentives (such as salary penalties for discovered errors) to implement the PPI well.

10.3. ROLE OF PPI IN SOCIAL PERFORMANCE EVALUATION

With the exception of Locfund, each of the social investors incorporates the PPI into their evaluation of an MFI's social performance, *when it is available*. That said, none of the social investors requires the MFIs they work with to use the PPI or, for that matter, any other quantitative poverty measurement tool.

While the use made of the PPI varied slightly across each investor, several commonalities emerged.

First, the investors are more interested in the *process* of PPI implementation, as opposed to the quantitative poverty estimate generated by the PPI. In other words, the investors are less concerned with the poverty rates reported by the MFIs than they are with the signal generated by the MFI's use of the PPI. When evaluating social performance, social investors evaluate whether the MFI has a clearly identified social mission, whether the MFI is committed to that mission and, whether the MFI implements a strategy to evaluate the success in meeting the mission. Since most MFIs identify serving poor and under-served populations as an important part of their mission, the social investors seek evidence that this component of the mission is being achieved. The social investors are also interested in knowing how the information generated by the PPI influences decisions within the MFI. In particular, they are interested in knowing if PPI information is used in a meaningful way to evaluate if the MFI is meeting their poverty outreach objectives and, if not, what actions are taken to better meet the mission.

Second, poverty outreach is just one of many components considered by social investors when evaluating social performance. For example, Blue Orchard identifies five key areas of social Performance measurement: 1) Outreach; 2) Client Protection; 3) Human Resource Policy; 4) Corporate Social Responsibility; and 5) Measurement of Social Performance and Impact. Each of these main categories, in turn, is evaluated based on a number of sub-indicators. The PPI, when it is used by the MFI, is thus just a small component in the social investors' overall evaluation of social performance.

Third, just as poverty outreach is only one of many components of social performance evaluated by social investors, the PPI, in turn, is just one of many potential indicators of poverty outreach. Global Partnerships, for example, estimates that less than 20% of the MFIs they work with use the PPI. Each of the social investors uses a range of alternative indicators for poverty outreach including, as mentioned above, the percent of clients that are women, the percent of clients that are rural and, most commonly, average loan size. Still, the general impression that emerged in conversations with the social investors is that while the PPI is welcomed as a serious measure of poverty outreach, there exists a range of, albeit inferior, alternatives to estimate poverty rates of clients.

10.4. ADDITIONAL CONCERNS AND SUGGESTIONS

In the course of the interviews, several additional concerns and suggestions stood out.

Need for Increased Reporting Transparency. Several social investors were frustrated with the lack of clarity in PPI reporting. For example, Global Partnerships expressed concern that there does not exist a standard, transparent method for MFIs to report results of the PPI. Specifically, some PPIs do not provide sufficient information to identify the specific client sub-group (for example, all clients, new clients or clients of specific branches) of whom the PPI sample is representative. Similarly, when the PPI is applied over time, they felt that MFIs often do not provide sufficient information to determine whether the MFI is following the same sample over time or is drawing new random samples in each year. Global Partnerships thus identifies improved communication regarding the application of the PPI and the group for whom the PPI is representative as an important area of improvement. The MixMarket has recently taken a positive step in this direction by creating a standardized Excel form for reporting PPI results, including the specific poverty line being used and a description of the sample to whom the PPI (or other poverty measurement tool) was applied.[17]

17. The spreadsheet is part of the Social Performance Task Force's efforts to homogenize reporting of social performance measures. For a given MFI, the report is available under the "Profiles and Reports/Files" tab for a specific institution. One can then download the Excel file identified under the "Social Performance Report" category. Finally, the poverty measurement information is reported in the "Medida de Pobreza" worksheet.

More Emphasis on "Progress" Needed. Several social investors felt that most of the MFIs that use the PPI do not take advantage of the range of questions that the PPI can help them answer. In particular, they felt that the PPI should be used more to answer dynamic questions such as the rate at which clients are "progressing" out of poverty. Global Partnerships went a step further and suggested that, in order to make full use of the quantitative rigor of the PPI, MFIs should make more effort to explain the changes in poverty rates measured by the PPI. Acknowledging that expenditures are just one component of poverty, Global Partnerships also suggested that –in order to be a more valuable yardstick for "development" – the PPI should be complemented by tracking other key indicators, such as health and education. This would allow MFIs and social investors to examine whether progress out of expenditure-based poverty is accompanied by progress out of low-education and progress out of poor health.

Critical Role of Multilaterals. Several social investors voiced concern that the fixed costs and high human capital requirements prevent small MFIs from adopting and effectively using the PPI. On the human capital side, MFIs that do not have personnel trained in social sciences or with a research background, are likely to find it much more difficult to know how to effectively implement the PPI and, as noted in particular by responsAbility, incorporate results from the PPI into their business strategies. Several social investors suggested that multilaterals and development finance institutions could play a critical role in promoting more widespread adoption and more effective use of the PPI by: A) providing subsidies for the adoption; B) funding workshops to facilitate exchange of information and uses made of the PPI and, C) creating and strengthening associations and networks of MFIs who will then serve as the technology transfer and support agents for MFIs in their use of the PPI.

responsAbility raised an additional possibility. They posed the question: Why haven't industry leaders such as Banco Pichincha and Banco Solidario adopted the PPI? Since smaller MFIs tend to look to these leaders for ideas, responsAbility felt that a strategy of promoting adoption and use of the PPI by such a leader could have a far greater positive impact on PPI adoption than direct support to MFIs.

11.
SUMMARY AND RECOMMENDATIONS

We conclude by offering the following summary.

1. **The PPI is a high quality poverty measurement tool that has the potential to provide significant value both to the individual MFIs who adopt it and to the MFI sector in general.** Most importantly, the PPI represents a valuable tool for any MFI that seeks (and has the human capital) to adopt more quantitative, evidence-based strategies for evaluating the degree to which they are meeting their social mission. This conclusion of high quality is based on assessments of three main aspects of the PPI. First, the statistical methodology underlying the PPI is sound and, *if implemented correctly*, delivers quantitative poverty estimates with levels of accuracy such that both MFIs and external donors and investors can be confident in basing decisions on PPI results. Second, the developers have made significant investment and innovation that make the PPI relatively easy and low cost to use. These innovations include simplicity (the Scorecard and Lookup Table are intuitive and easy to use and interpret) and resources to support implementation and use (training documents and "Help Docs" exist for each country). Third, the developers provide transparent and in-depth documentation for the PPI in each country. The "design documentation" provided for each country on the PPI website provides a clear and detailed description of the construction of the PPI, a discussion of PPI accuracy, a discussion of alternative poverty measurement tools and findings, as well as instructions on how to implement the PPI. It also provides a critical evaluation of the PPI itself, pointing out the limitations and uses for which the PPI is not appropriate. This careful documentation, transparency and self-criticism inspire confidence in the tool. Any potential user of the PPI will know exactly how it was constructed, its potential uses and limitations. The combination of sound statistical methodology, innovation to provide simplicity and careful and transparent documentation is critical for promoting adoption of the tool throughout the MFI sector.

2. **Substantial homogeneity exists in the basic objectives of PPI use across MFIs.** Each of the MFIs interviewed stated that the primary value added by the PPI is the generation of a rigorous, quantitative evaluation of the degree to which the MFI is meeting the poverty outreach targets in their social mission. This "internal" use of the PPI by each of the MFIs suggests that, among this sample of MFIs, the PPI has become an important component of the MFIs' internal evaluation of their social mission. Each of the MFIs also acknowledged that the PPI is useful for "external" purposes, such as attracting lines of credit from social investors or simply signaling that the MFI is a "player" in that it is keeping abreast of innovations in the broader world of microfinance.

3. **Significant heterogeneity exists in use of the PPI beyond the basics.** Some of the MFIs interviewed, most notably Prisma and Fondesurco, use the PPI to analyze a range of poverty-related questions about their clients including poverty comparisons across sub-groups and changes in poverty profiles over time. Others, including Arariwa and Espoir, use the PPI to answer a more limited range of ques-

tions. Differences in human capital, in particular the presence of in-house capacity for data analysis and experience in social science research, would appear to explain these differences.

4. **Significant variability exists among MFIs in the method of implementing the PPI.** The main dividing line is whether the MFI applies the PPI to the entire client population via incorporating the PPI into the loan application process or instead maintains a sample-based PPI approach, typically with a third party collecting the data. Each method has its pros and cons. The population approach obviously provides significantly more data and thus allows the institution to given questions with greater confidence (because of the larger sample size) and to answer a wider range of questions. On the other hand, requiring loan officers to apply the PPI questions both adds time (which is loan officers' most scarce resource) and raises questions about the quality of the PPI data. We do not recommend that MFIs adopt a particular methodology, rather we acknowledge that the PPI is sufficiently flexible to accommodate the style and objectives of the specific MFI. Promoting interaction and exchange of experiences across MFIs that use different methodologies would, however, likely be a valuable exercise.

5. **In general, most institutions feel confident in the potential accuracy of the PPI.** The general impression provided by MFI management is that, while the PPI is not perfect, the poverty estimates that it generate give a picture of poverty rates that is reliable enough for the institutions' goals. Several concerns about accuracy were also voiced. The two main concerns were: a) The 10 indicators are insufficient to measure poverty, especially to distinguish between urban versus rural poverty and b) The national household data upon which the PPI is based are themselves of low quality or too old.

6. **The human capital level of the MFI is an important determinant of the degree to which the MFI can take advantage of the potential benefits of the PPI.** Those institutions with a strong social science/research component appear to be much more able to take advantage of the PPI. This is not surprising as effective use of the PPI requires the ability to clearly define questions and hypotheses; draw samples; and carry out data analysis. Prisma is a clear example. This institution is far more than an MFI; as it also runs educational and health interventions. The institution is run by social scientists and has its own statistical-analysis office. With this background, Prisma has easily adopted the PPI with a primary objective of generating quantitative measures of impact of the institution in the socio-economic development of its target population. Institutions with less background in research and less of a social science orientation are more limited in their ability to take advantage of the PPI. Again, exchange of ideas and experiences across MFIs about their use of the PPI would be a potentially useful exercise, especially if MFIs with less human capital are paired with those with more.

7. **The PPI is not the most important component of social investors' evaluation of MFIs social performance.** While all but one of the social investors interviewed for this report consider the PPI when evaluating an MFI's social performance, they focus on process not results. In terms of social performance, the social investors are concerned about whether the MFI has a clearly defined social mission and a strategy for achieving that mission. Social investors thus examine whether or not the MFI uses the PPI – or other quantitative indicators of poverty outreach – and how the MFI uses the results of the PPI to adjust modify actions to better meet the social mission. None of the social investors require PPI use, nor do they prioritize the actual poverty levels reported by the MFI.

8. **The PPI has high potential for use outside of microfinance.** The same characteristics that make the PPI attractive as a poverty measurement tool for MFIs – simplicity, low cost and reasonable accuracy – make it potentially attractive to a wide range of other institutions. The most obvious candidates are institutions that have an easily identifiable client or beneficiary population and whose clients/beneficiaries are easy to visit in their home. We urge caution, however, if the institution proposes to apply the PPI in contexts other than the client/beneficiaries' homes as the PPI is currently designed with the

expectation that some variables will be confirmed via visual inspection in the home. The PPI may also be inappropriate for institutions working with displaced or migrant populations as the definition of the household and the residence for these populations is complicated.

Finally, we turn to a series of suggestions and recommendations regarding the PPI.

9. **Additional analysis on PPI accuracy should be carried out.** Specifically, the following three types of analysis would be particularly useful:

   Accuracy of PPI implementation. The most important question with respect to PPI accuracy is the degree to which MFIs correctly implement the PPI Scorecard questions. As discussed above, both insufficient training and incentives to manipulate data can lead to systematic errors in data collection. A random re-survey of sub-samples of the PPI samples by a highly qualified third party would provide evidence on the degree of implementation error. It would be useful to carry out this exercise in MFIs that use loan officers and those that use third parties to see if significant differences exist across the methods.

   Direct test of accuracy of PPI predictions. The second main issue related to accuracy is, assuming no implementation errors, the accuracy of the PPI indicators themselves. As discussed above, since the relationship between the indicators may vary both across time and space, the PPIs accuracy may be reduced as the number of years since the PPI is updated with new national data increases. A direct test of accuracy would thus be useful. This direct test would require applying both the full household expenditure model from the national survey and the PPI to a random sample of MFI clients and comparing the "true" versus PPI predicted poverty rates. While this would be the most direct evaluation of PPI accuracy, it would also require significant resources as applying the expenditure modules requires highly trained enumerators and a minimum of one hour per household.

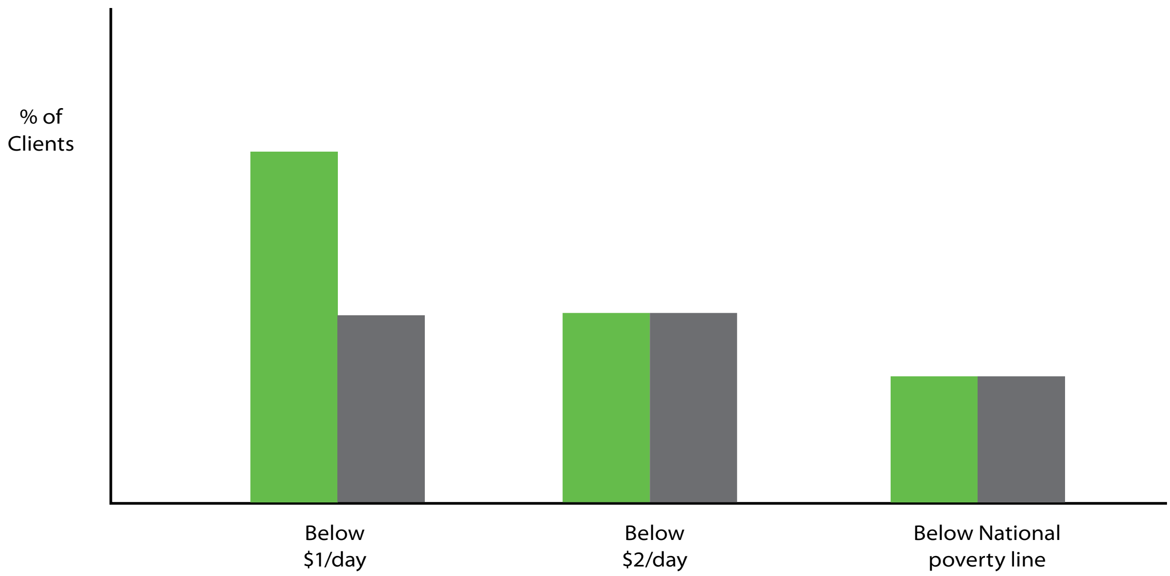
   Additional tests of regional and inter-temporal accuracy issues. Additional analysis could be carried out using existing national household data (in some countries) to evaluate both of the fundamental challenges to PPI accuracy. First, in countries that have multiple years of household expenditure surveys, additional analysis could be carried out to evaluate how the PPI accuracy changes over time (in the absence of updating). Second, in countries with sufficiently large national household survey samples, additional analysis should be carried out on the potential bias associated with spatially concentrated samples such as those that would be typical of small MFIs that have a small geographic area of operation. This suggestion would extend the analysis that the PPI developer has already carried out in the design documentation.

10. **Strengthen regional "aggregating" and network support institutions.** Given the complexity of adopting the PPI, an institution that provides training and support at a national or regional level appears critical. In the case of Peru and Ecuador, the Grameen Foundation, OikoCredit and, to a lesser degree, COPEME – in the case of Peru specifically – have played this role. If the PPI is to be effectively scaled up to a large number of institutions, the role of regional support institutions will be even more important. The provision of training workshops to promote the homogeneous and high quality implementation of the PPI would be especially critical. The regional support institution could also play a critical role in the sharing of information across MFIs. Returning to the analogy of PPI as a new technology to be adopted, we know that "learning from others" can be a very important means of promoting technology adoption. The regional coordinator could be place special emphasis on sharing experiences, both positive and negative, relating to many of the issues discussed above – such as quality control, integration of PPI and client data bases, and examples of PPI uses for business practices (gestión) – across MFIs.

11. **Promote increased communication and consultation with national governments.** Given that the PPI is based on data collected by national governments, it seems strange (and inefficient) that there is minimum involvement by the government, and the statistics bureau more specifically, in the design and uses of the PPI. At a minimum, it would seem that the statistics bureau should be consulted about the choice of indicators and the ex-ante precision analysis conducted by the PPI developers. It would also be useful to explore additional synergies between the PPI developers and national governments. For example, how does the PPI compare to the current method used for regional targeting of social protection programs? Could the government's method be improved by adopting aspects of the PPI? What about the reverse? In addition, given that one of the constraints to the PPI is the challenge of updating when new data is available, it would seem that greater collaboration with national statistics bureaus could promote updating at a higher frequency. At an extreme, the national statistics bureau could be responsible for the development of PPI updates. While this clearly raises issues such as intellectual property rights over the PPI methodology and how to maintain the high standard of quality currently characteristic of the PPI, significant expansion of the PPI to MFIs and beyond MFIs to other development projects would likely benefit from and perhaps even require a greater role of national governments.
12. **Expand reporting options of the PPI.** Two concerns voiced by MFIs suggest two possible means of enhancing the reporting of PPI results.

Increased granularity

The first concern voiced by MFI managers was that the MFI does not capture the "true" poverty profile of their clients. One way to interpret this concern is that the MFIs expectations of poverty rates were higher than the true value revealed by the PPI and, as a result, the MFI is simply unhappy with the result. This undoubtedly occurs in some instances. Another interpretation is that the MFI would like greater information about the overall distribution of income (expenditure) of their clients. One straightforward way to address this concern would be to develop an "app" that would generate something like the following figure:



The figure presents the poverty profiles of two different institutions; MFI A is represented by the shaded bars and B by the green bars. The height of each bar represents the percentage of clients with income below a given poverty line. In this hypothetical example, the two MFIs look exactly the same at the higher two poverty lines. But when the lowest poverty line is considered, the two institutions look quite different;

with MFI B having a significantly higher fraction of its clients below this lower line. By depicting simultaneously the percentage of clients below all of the poverty lines, one is able to gain a clearer idea of the shape the distribution function over certain ranges. A similar picture could be used to more effectively show changes over time (in this case the different color bars would represent points in time instead of different MFIs).

The main point here is simply that, because the PPI generates estimates of poverty rates at a number of different poverty lines, this information could be more effectively combined to partially overcome a limitation of the PPI; namely the binary nature of the dependent variable of the underlying regressions, and partially move to a depiction of the continuous distribution.

The PPI developers have recently taken a step towards permitting the depiction of the underlying continuous income distribution. Specifically, the documentation reports now include not just the probability that a household's income falls below a given poverty, but also the probabilities that the household's income falls between the different poverty lines. For example, the PPI for Mexico is calibrated for seven poverty lines.[18] In addition, the documentation includes a Lookup Table that gives the probability that, for any given score, the household's income falls within the eight ranges defined by the seven poverty lines. As the poverty lines range from just under 10 Pesos/day to just over 70 Pesos/day, the Mexican PPI would allow a fairly good depiction of a given MFIs income distribution relative to the overall income distribution in Mexico. By simply taking the sample mean of the probability that clients fall within a given range, the following table could be easily generated:

TABLE 4. INCOME DISTRIBUTION OF MFI CLIENTS

Income Range (in Pesos)	% of MFI Clients in Income Range	% of Mexican Households in Income Range
y < 9.94		
9.94 < y < 19.88		
19.88 < y < 24.23		
24.23 < y < 29.42		
29.42 < y < 47.32		
47.32 < y < 59.15		
59.15 < y < 70.97		
70.97 < y		

The PPI developers would, of course, need to provide the data for the third column (which would be straightforward using the national household survey upon which the PPI is based).

18. See Figure 7, page 89 of "A Simple Poverty Scorecard for Mexico", by Mark Schreiner, 23 November, 2009, available at: http://www.microfinance.come/#Mexico.

Donors, such as the IDB, who are interested in acquiring a more detailed view of the income distribution of the MFI could also request that the developers include additional cutoff points or ranges. Potentially interesting points might include: A) Between zero and the median income level of individuals below the national poverty line or; B) Between the national poverty line and the overall median income levels.

Until now at least, generating this type of more granular or fine tuned view of the income distribution has not been a major motivation of MFIs in adopting the PPI. Whether or not it makes sense to add the type of "app" depicted in the table above is not clear. One possibility would be to present this type of information to MFIs and donors on a pilot basis and see if they find it useful. The main point is that, the PPI methodology is sufficiently flexible to allow as detailed a depiction of the income distribution as one may want. Whether the additional detail in income distribution portrayal becomes a "standard" feature of the PPI or instead remains available "on-demand" to interested parties is left for future discussion.

Comparison relative to local poverty rates

A second concern came from MFIs that considered the relatively low poverty rate of clients should not be "held against them" because they were operating in areas that had relatively fewer poor. This raises the point that the (or at least a) relevant question is how does the poverty rate of MFI clients compare to the poverty rates of the communities in which they operate? This suggests that the MFI (or the regional aggregator such as OikoCredit) could report both PPI results and poverty rates according to national government for most disaggregated level available. For example, poverty rates in Peru are available at the municipality level from National Statistics Office. PPI results could thus be compared to the poverty rates of the relevant population. For example, if an MFI reports that 30% of its clients are poor, we might interpret this quite differently if the municipality in which the MFI works has a poverty rate of 30% versus 80%.

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APPENDIX A
LIST OF MFI INTERVIEWS

Date	Institution	Address of Institution	Participants
3/13	Fondesurco	Av. República de Argentina 326 Urba. La Negrita, Arequipa, Peru	Héctor Madariaga Tapia, General Manager David Vela Quico, Research Manager
3/20	OikoCredit	Calle Porta 130, Oficina 809, Miraflores, Lima, Peru	Yolirruth Nuñez, Director for South America, Northern Region
3/20	Prisma	Av. Carlos González No. 251, Urb. Maranga, Lima, Peru	Diego Fernández Concha Norma Rosas Lizágarra, Manager of Social Performance Mariela Bustíos Díaz, Administration and Finance Director
3/20	Arariwa	Av. Garcilazo No. 516, Wanchaq, Cusco, Peru	Hugo Ramiro Yanque Martínez, Executive Director
3/21	Planet Rating	Francisco de Paula Ugarriza 813, Oficina 301, San Antonio, Miraflores, Lima, Peru	César Carcelén Romero, Director for Latin America and the Caribbean
3/23	Red Financiera Rural	Pasaje El Jardin E10-06 y Av. 6 de Diciembre, Edificio Century Plaza 1, 8vo Piso, Oficina 24, Quito, Ecuador	Javier Vaca, Executive Director
3/23	Micro Finanza Rating	Pasaje El Jardin 168 y Av. 6 de Diciembre, Edificio Century Plaza 1, Piso 6, Oficina No. 20 (frente a Megaxami), Quito, Ecuador	Mónica Eras, Senior Analyst Evrim Kirimkan, Senior Analyst Erlan Llanos, Bolivia Office Director
3/24	Fodemi	Ecuador	Rossy Roldan Robles
3/30	Espoir	Calle Iñaquito 1261 y NNUU, Edificio Comandato, Torre Iñaquito, Quito, Ecuador	Dr. Francisco Moreno, Executive Director

APPENDIX B
PPI SCORECARD AND LOOKUP TABLE FOR MEXICO

PROGRESS OUT OF POVERTY INDEX™ FOR MEXICO

Entity	Name	ID	Date (DD/MM/YY)
Member:	____________	____________	Joined:____________
Loan officer:	____________	____________	Today:____________
Branch:	____________	____________	Household size:____________

Indicator	Value	Points	Score
1. How many household members are ages 0 to 17?	A. Four or more	0	
	B. Three	7	
	C. Two	11	
	D. One	20	
	E. None	28	
2. What is the highest level that the female head/ spouse has passed in school?	A. None	0	
	B. Up to third grade	5	
	C. Fourth grade through high school	7	
	D. College preparatory 1–3	10	
	E. Normal/technical/commercial	14	
	F. Professional, master's or doctorate	20	
	G. No female head/spouse	14	
3. How many household members have a written employment contract for a salary or for an indefinite period?	A. None	0	
	B. One	6	
	C. Two or more	16	
4. What is the main material of the floor of this residence?	A. Dirt	0	
	B. Cement/concrete	2	
	C. Other	7	
5. How is water supplied to the residence's toilet for flushing?	A. No toilet, or no water supply	0	
	B. Carried by bucket	1	
	C. Piped	3	
6. Does the residence have a medium sink for washing dishes?	A. No	0	
	B. Yes	4	
7. What fuel do you usually use to cook or heat food?	A. Firewood	0	
	B. Other	2	
8. Does the household have a blender?	A. No	0	
	B. Yes	4	
9. Does the household have an electric iron?	A. No	0	
	B. Yes	4	
10. How many televisions does the household have?	A. None	0	
	B. One	0	
	B. Two	5	
	C. Three or more	12	

Microfinance Risk Management, L.L.C., ***http://www.microfinance.com*** **Total score**

This PPI was updated in November, 2009. For up-to-date PPIs and other information on the Progress out of Poverty Index™ for Mexico and other countries go to ***www.progressoutofpoverty.org***

CATEGORY LIKELIHOODS ACCORDING TO MEXICO PPI™ SCORE

	National Food Poverty Line		National Capacity Poverty Line		National Asset Poverty Line	
PPI SCORE	TOTAL BELOW THE NATIONAL FOOD POVERTY LINE	TOTAL ABOVE THE NATIONAL FOOD POVERTY LINE	TOTAL BELOW THE NATIONAL CAPACITY POVERTY LINE	TOTAL ABOVE THE NATIONAL CAPACITY POVERTY LINE	TOTAL BELOW THE NATIONAL ASSET POVERTY LINE	TOTAL ABOVE THE NATIONAL ASSET POVERTY LINE
0-4	83.9%	16.1%	89.6%	10.4%	98.8%	1.2%
5-9	80.7%	19.3%	88.9%	11.1%	97.1%	2.9%
10-14	68.0%	32.0%	76.4%	23.6%	94.2%	5.8%
15-19	51.4%	48.6%	67.8%	32.2%	92.2%	7.8%
20-24	46.9%	53.1%	61.4%	38.6%	86.8%	13.2%
25-29	35.7%	64.3%	49.4%	50.6%	81.1%	18.9%
30-34	27.8%	72.2%	40.6%	59.4%	71.6%	28.4%
35-39	15.7%	84.3%	25.2%	74.8%	60.2%	39.8%
40-44	9.9%	90.1%	15.0%	85.0%	50.6%	49.4%
45-49	7.5%	92.5%	13.9%	86.1%	41.6%	58.4%
50-54	4.6%	95.4%	8.1%	91.9%	26.4%	73.6%
55-59	2.2%	97.8%	4.9%	95.1%	17.8%	82.2%
60-64	1.1%	98.9%	2.4%	97.6%	10.7%	89.3%
65-69	0.9%	99.1%	1.4%	98.6%	6.5%	93.5%
70-74	0.2%	99.8%	0.4%	99.6%	2.9%	97.1%
75-79	0.0%	100.0%	0.0%	100.0%	0.1%	99.9%
80-84	0.0%	100.0%	0.5%	99.5%	2.0%	98.0%
85-89	0.0%	100.0%	0.0%	100.0%	0.0%	100.0%
90-94	0.0%	100.0%	0.0%	100.0%	0.0%	100.0%
95-100	0.0%	100.0%	0.0%	100.0%	0.00%	100.0%

Source: Microfinance Risk Management, L.L.C. based on the 2008 ENIGH.

This PPI was updated in November, 2009. For up-to-date PPIs and other information on the Progress out of Poverty Index™ for Mexico and other countries go to ***www.progressoutofpoverty.org***

APPENDIX C

END OF YEAR PPI REPORT FROM FONDESURCO

FONDESURCO'S CLIENTS' POVERTY LEVEL FROM DECEMBER 2010 TO 2011 (PPI METHODOLOGY)

Variable	Indicator	Participation/Nº of Credits	PPI - 100%	Poverty Level				
			(% of Poor)	High	Medium	Low	Nº Poor	Total
Gender		100.0%	20.8	14.1%	47.3%	36.6%	2.0%	100.0%
	Women	45.4%	21.3	12.3%	48.9%	37.0%	1.8%	100.0%
	Men	54.6%	20.5	15.6%	45.9%	36.3%	2.2%	100.0%
Age		100.0%	22.6	14.2%	47.3%	36.6%	2.0%	100.0%
	Children	19.8%	24.8	7.4%	46.1%	44.3%	2.2%	100.0%
	Adult	69.6%	16.2	16.1%	49.2%	32.9%	1.9%	100.0%
	Older Adult	10.6%	19.0	14.2%	36.8%	46.4%	2.6%	100.0%
Zone		100.0%	20.8	14.2%	47.3%	36.6%	2.0%	100.0%
	Rural	92.6%	21.3	14.8%	47.6%	35.7%	2.0%	100.0%
	Urban	7.4%	15.4	6.6%	43.0%	48.1%	2.2%	100.0%
Economic Sector		100.0%	20.8	14.2%	47.3%	36.6%	2.0%	100.0%
	Agriculture	34.3%	19.6	17.2%	42.0%	38.9%	1.9%	100.0%
	Ranching	19.6%	27.6	18.3%	55.9%	24.8%	1.1%	100.0%
	Commercial	21.2%	18.3	9.3%	47.4%	41.2%	2.1%	100.0%
	Services	11.4%	19.8	11.4%	47.2%	38.8%	2.6%	100.0%
	Public Admin.	0.5%	11.6	5.6%	30.6%	61.1%	2.8%	100.0%
	Banking and finances	0.1%	1.4	28.6%	0.0%	71.4%	0.0%	100.0%
	Construction	4.4%	26.5	11.7%	59.7%	27.4%	1.2%	100.0%
	Education	1.1%	11.2	6.0%	34.7%	56.0%	3.3%	100.0%
	Industry	1.2%	21.6	15.9%	48.8%	32.3%	3.0%	100.0%
	Mining	1.0%	23.0	15.0%	60.9%	21.1%	3.0%	100.0%
	Fishing	0.9%	17.1	13.3%	32.7%	49.6%	4.4%	100.0%
	Social and health	0.3%	5.7	8.9%	22.2%	60.0%	8.9%	100.0%
	Supply electricity gas water	0.0%	12.4	33.3%	33.3%	33.3%	0.0%	100.0%
	Transportation	2.9%	15.4	7.0%	44.7%	44.7%	3.6%	100.0%
	Tourism	0.9%	13.3	5.8%	38.0%	51.2%	5.0%	100.0%
Branch Office		100.0%	22.6	9.9%	52.6%	36.7%	0.8%	100.0%
	Tambo	21.0%	10.7	11.7%	31.2%	55.3%	1.8%	100.0%
	Colca	19.0%	27.9	18.2%	59.1%	20.2%	2.4%	100.0%
	Aplao	10.8%	18.8	9.0%	48.9%	40.6%	1.5%	100.0%
	Acari	8.1%	15.2	12.5%	41.9%	43.8%	1.8%	100.0%
	Moquegua	5.9%	13.4	6.6%	41.0%	50.6%	1.8%	100.0%
	Omate	6.2%	18.8	18.3%	44.2%	34.7%	2.8%	100.0%
	La Punta	6.4%	14.4	12.4%	36.6%	48.4%	2.6%	100.0%
	Puquina	4.9%	29.0	17.1%	59.9%	20.3%	2.6%	100.0%
	Pausa	3.9%	26.1	8.4%	58.3%	33.1%	0.2%	100.0%
	Cotahuasi	4.0%	41.9	25.2%	55.8%	17.7%	1.3%	100.0%
	Cabanaconde	2.6%	36.1	16.3%	69.5%	12.5%	1.7%	100.0%

Variable	Indicator	Participation/Nº of Credits	PPI - 100%	Poverty Level				
			(% of Poor)	High	Medium	Low	Nº Poor	Total
	Taya	3.1%	39.8	30.9%	60.3%	7.8%	1.0%	100.0%
	Pampacolca	0.9%	24.1	11.3%	64.3%	22.6%	1.7%	100.0%
	Arequipa	0.5%	8.3	18.6%	11.4%	55.7%	14.3%	100.0%
Purpose of Credit		100.0%	20.8	14.2%	47.3%	36.6%	2.0%	100.0%
	Fixed asset	19.5%	21.8	9.6%	52.0%	35.6%	2.9%	100.0%
	Working capital	63.5%	20.2	8.4%	49.2%	40.5%	1.9%	100.0%
	Cash	17.1%	22.9	40.8%	34.6%	23.2%	1.3%	100.0%
Type of Credit		100.0%	20.8	14.2%	47.3%	36.6%	2.0%	100.0%
	New	26.5%	21.3	7.8%	49.0%	40.7%	2.6%	100.0%
	Parallel (seasonal)	41.2%	20.5	19.2%	45.7%	33.3%	1.8%	100.0%
	Recurring	32.3%	20.8	12.9%	47.8%	37.5%	1.8%	100.0%
Interest Rates (monthly effective rate)		100.0%	20.8	14.2%	47.3%	36.6%	2.0%	100.0%
	i <=1%	0.1%	8.1	27.8%	16.7%	55.6%	0.0%	100.0%
	1%> i <=2%	0.5%	5.8	12.3%	21.9%	58.9%	6.8%	100.0%
	2%> i <=2.5%	2.8%	9.4	6.4%	29.7%	58.3%	5.6%	100.0%
	2.5%> i <=3.0%	23.9%	16.5	28.8%	36.0%	33.5%	1.7%	100.0%
	3.0%> i <=3.5%	62.8%	21.8	7.8%	51.7%	38.3%	2.2%	100.0%
	3.5%> i <=4.0%	8.2%	26.7	24.2%	50.6%	25.0%	0.3%	100.0%
	4.0%> i <=4.5	1.6%	28.4	8.5%	63.2%	27.8%	0.5%	100.0%
Classification of Superintendency of Banks, Insurance and Pension Fund Administrators		100.0%	20.8	14.2%	47.3%	36.6%	2.0%	100.0%
	Normal	95.4%	21.0	12.6%	48.5%	37.1%	1.8%	100.0%
	With Potential Problems	0.8%	19.8	8.7%	44.2%	41.3%	5.8%	100.0%
	Deficient	1.9%	18.0	71.5%	12.6%	13.8%	2.0%	100.0%
	Doubtful	0.6%	16.1	35.5%	22.4%	31.6%	10.5%	100.0%
	Lost	1.4%	13.7	37.1%	22.6%	29.6%	10.8%	100.0%
Credits in Arrears		100.0%	20.8	14.2%	47.3%	36.6%	2.0%	100.0%
	Yes	2.8%	16.0	25.7%	28.7%	36.9%	8.7%	100.0%
	No	97.2%	21.0	13.8%	47.8%	36.6%	1.8%	100.0%

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