The Impact of Credit Reporting and Credit Scoring on the Microfinance Sector

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The contents of this research—including but not limited to data, analysis, conclusions, interpretations, and inferences—are exclusively those of the authors, and do not necessarily reflect the positions and opinions of the supporters and reviewers.

Table of Contents

1 Abstract

This research analyzes a series of questions pertaining to the impacts on microfinance institutions (MFIs) when using credit bureau data (conventionally referred to as credit files) for purposes of underwriting credit; for the same purposes, it also analyzes credit scoring models and credit decisioning platforms that use credit bureau data. First, by comparing performance results from loans extended using manual underwriting to loans extended using credit file data or automated underwriting techniques (a credit score or a credit decisioning platform), it is possible to quantify impacts on acceptance rates and portfolio performance. Second, MFI cost impacts are examined in cases where the use of a credit file and/or automated underwriting is superior or equal to manual methods in terms of acceptance and default rates. Third, other potentially intervening variables are assessed for impact; these include the age of credit bureaus, and the capacity of MFIs to use credit bureau data and automated underwriting solutions including credit scores and other decision-making platforms. The research was designed to permit generalizability of findings. Analysis was conducted with multiple MFIs in two countries: India and Mexico. The MFIs varied in size and types of loans provided. The Indian MFIs provided group loans to women (though underwriting occurred at the individual level) and the Mexican MFIs provided individual loans. The results from the analysis support the use of credit bureau data and credit scoring models by MFIs. When compared with manual underwriting, MFIs were generally better able to differentiate low-risk from high-risk borrowers using credit scores based on credit bureau data. This finding holds across both countries (India and Mexico) and for poor and very poor borrowers. Results also provide evidence that MFIs can dramatically reduce their origination costs by using credit bureau scores for initial credit risk screening, as opposed to costlier manual underwriting for the lowest risk applicants. Data quality and coverage at both credit bureaus and data furnishers was seen to improve over time in India (which has a relatively young credit bureau environment); the result was better performing credit-scoring models for MFIs. Evidence from the analysis also strongly suggests that the capacity of any given MFI is constrained by its own abilities to utilize automated underwriting solutions such as credit scores. Tier 2 and tier 3 MFIs are often insufficiently staffed or have considerable staff turnover among both technical staff and senior management; therefore, sustaining a commitment to using credit files, credit score, and automated decisioning platforms is a challenge. Further challenges to MFI uptake of models using credit files and credit scoring comes from pervasive beliefs among some senior management at MFIs that their manual processes are unique, confer a competitive advantage, and are more reliable than credit scores and/or automated decisioning platforms. This deep-seated skepticism about the utility of credit scoring models and automated underwriting solutions among MFI executives may be the greatest obstacle.

2 Executive Summary and Key Findings

This analysis supports previous findings pertaining to the benefits to MFIs of using credit bureau data; furthermore, it extends earlier generation analysis by exploring impacts on portfolio performance and by examining MFI origination costs. The findings from this research add to established literature in empirical economics on this topic. Key findings from the results of our analysis include:

Credit Bureau Data and Credit Scoring Models Are Able to Differentiate Higher-Risk Borrowers ("bads") from Lower-Risk Borrowers ("goods"): In India, risk-rank ordering by credit scores (using both credit bureau and application data) of Grameen Koota's applicants found that those with the lowest credit scores had 30 times the non-performing loan (NPL) rate of those with the highest credit scores. 44 percent of NPLs were to borrowers in the bottom 10 percent of credit scores. In Mexico, the NPL rate of the bottom quintile of applicants (as ordered by a credit bureau data-only credit score) was 2.4 to 4.1 times the NPL rate of the top quintile of applicants. This means that credit scores can be used by themselves or in conjunction with more manual processes to substantially improve loan performance.

Credit Scores that Use Credit Bureau Data Are Effective across Different Populations and Types of MFI Lending: Credit scores using credit bureau data (and application data in some models) were able to separate higher-risk applicants from lower-risk applicants with an MFI in India (a lower income country) and in Mexico (a middle-income country). This was also true among group loans in India.

Use of Credit Scores Can Reduce MFI Origination Costs and Improves Margins: For consumers identified as lower risk by credit scores, MFIs can reduce origination costs by relying entirely upon credit scores and automated processes; this is because credit scores were shown to be able to differentiate higher-risk borrowers from lower-risk ones. The underwriting process can then be executed relying on a combination of credit scores and more manual processes for higher-risk applicants or applicants without a credit history. In Mexico, it was found in a study of one MFI that manual processes amounted to just under 20 percent of lending costs (55 pesos from a total cost of 306 pesos). For the other Mexican MFI, the cost to manually gather consumer information is 171 pesos per loan application, which would amount to just over 20 percent of the cost of loans for the smallest loans. A study of an Indian MFI found that to manually gather consumer information, (i.e. with heavy touch processes), cost a bit over 20 percent of the total loan. As such, switching from heavier-touch processes to more data-driven ones could result in meaningful cost savings to borrowers and/or MFIs (estimated 8 percent to 16 percent reduced origination costs for MFIs); this would hold true especially for the lowest-risk 40 percent of applicants by credit bureau or internal data scores. Crucially, these reduced "fixed" manual costs have the biggest impact on lower value loans that are most likely to be used by the lowest capacity/income borrowers. That is, movement to more efficient data-driven lending should give the most benefit to the poorest borrowers.

Other Benefits from Data-Driven Processes: In addition to lowering operational costs, the systematic assessment of borrower risks should also enable MFIs to seek lower cost capital and securitize their portfolios on better terms because investors often take greater investment risk when they have more information. It could also drive down the cost of acquiring new applicants and reaching new borrowers if lenders do not need to set up local staff (or as many local staff) in every area where they lend. Such data-driven and systematic assessment of borrowers could allow MFIs to broaden their traditional lending group (such as in India); this would allow them to offer higher-value loans to individuals in groups who are identified as lower risk and higher capacity. This could allow individual borrowers to efficiently access capital when they are in need of it for investments.

MFI Use of Credit Files and Credit Scores Are More Likely to Succeed with More Accurate, Higher-Coverage Credit Bureau and Internal MFI Data: In India, PERC built two scoring models for Grameen Koota, a large MFI. One model relied on data from 2012 and the other on data from 2013. The improvement in terms of the KS measure was an increase of about 25-30 percent between 2012 and 2013 (where a KS or "Kolmogorov-Smirnov" measure assesses the fit between the data and the model). In the past, this is where data quality, coverage, and depth have improved. In 2012, when there was a relatively young credit bureau, we discussed these issues and a number of MFIs agreed that credit bureau data during this period was improving in exactly these terms (data quality, coverage, and depth). In addition, Grameen Koota noted their belief that systematic data collection efforts had improved their own internal data. Given general IT advances, it makes sense that obstacles pertaining to data collection, storage, quality, and use should diminish for all organizations.

Technical Capacity Limitations at MFIs Constrain the Use of Credit Files and Automated Underwriting Solutions: Despite improved data-collection efforts, capacity and current data handling capabilities are clear obstacles with smaller MFIs. High turnover among technical staff and senior management impedes the adoption of automated underwriting solutions and makes it difficult to sustain efforts. MFIs also have various limitations that can result in poorer data quality; specifically, these include their insufficient technical capacity and insufficient organizational emphasis on accurate data collection.

MFI Executives Often Harbor Deep-Seated Skepticism About Automated Underwriting: Among the largest (tier 1) MFIs with sufficient capacity to employ them, the primary challenge to the uptake of automated underwriting solutions within the MFI community is one of belief. Sentiments about the business value of credit reports and credit scores are largely mixed, with many MFI executives believing they are better off relying on the art of manual underwriting and their established procedures versus the science of automated underwriting. Candidly, the reluctance to rely on technology is deeply rooted in a fear of sudden and dramatic change. However, this is not dissimilar to the resistance to scoring seen in the US and Europe among large mainstream lenders before such data-driven practices became the norm.

In addition to the above findings, challenges encountered in this research are discussed in the appendices of this report. These are valuable findings, particularly so for future researchers, given that methodological modifications were needed to accommodate the complexity of varying regulatory frameworks, recruiting and working with several MFIs over an extended period of time, and capacity constraints on participating MFIs.

3 Introduction

Since 1976, when Muhammad Yunus began experimenting with micro-lending in Bangladesh, micro-credit and microfinance has spread across the globe. Growth has been relatively steady but uneven among and within nations; MFIs range from large and sophisticated microfinance institutions such as Compartamos Banco (Gentera) in Mexico with over 2.5 million customers and a diverse array of offerings, to the model MFIs that exist in most countries and are defined as a small and low-capacity circle lender extending low-value credit-builder loans. Since the 2010 microfinance crisis that began in Andhra Pradesh, increased attention has been given to the potential value of MFI credit reporting and MFI use of value-added services (credit risk scores) offered by credit bureaus.

Credit reporting developed in order to overcome challenges of asymmetric information, moral hazards, and information monopolies in lending. Competition in lending, access to finance, and the health of the portfolio are all rightly thought to improve with credit reporting and credit reporting-enabled practices like scoring. Credit reporting and the ensuing valued-added services it has enabled have been quite successful in expanding lending, lowering origination costs, and improving risk assessment and thereby portfolio performance. These contributions are well known and largely uncontested.[1]

Unlike the case of bank lending, the value of credit reporting and credit report-enabled credit scoring is less established when it comes to microcredit. For some settings and some microfinance lenders, customers may have little or no relationship aside from one lender, reducing the value of sharing information. Moreover, many microfinance institutions are "high touch," meaning loan officers have to deal with numerous cases each day and have to be highly and frequently engaged with borrowers. So, in the view of some MFIs, credit reports may be of use (to see if there have been any past defaults or to see if the applicant has other loans); nonetheless, they believe that scoring is not useful. In the words of one MFI, "[We do] not use a credit score or plan to use one since the microfinance lending technology is not suited to implement a credit score, because one of the fundamental bases of the analysis in this technology are the qualitative aspects that are very complex to obtain a credit score."[2] In other words, some MFI executives believe that microlending entails measuring qualitative aspects that are at odds with the practice of scoring, and they either do not trust credit scores or see little value in them. Finally, for some settings, defaults are exceedingly low; as such, past behavior of the kind provided in credit reports are of little predictive value, because adverse selection is not a large source of risk. That said, the value of automated solutions in terms of cost reductions still holds.

While there is not a consensus among microlenders that credit reporting and credit scoring is suited for the sector, the high costs of origination and overall operating costs in microlending make the question of their impact on microlending a salient one, especially because this cost is passed on to borrowers. An analysis by the Microfinance Information Exchange, Inc. (MIX) showed that personnel and administrative operating expenses constituted 62 percent of the charges to borrowers. Automation or semi-automation of the underwriting process as promised by credit reporting and credit scoring approaches can render the process more efficient and, importantly, relatively more cost effective.[3]

There is also some uncertainty about the magnitude of any potential improvements in either operations or portfolio performance. While many MFIs can understand the logic of how credit reporting and credit scoring can improve their operational costs and portfolio performance, they are less clear about to what degree and in what timeframe these benefits could be realized. Most microlending has far lower default rates than are witnessed in mainstream lending; this difference is largely the result of the widespread use of joint-liability models. A shift to a model that uses credit reporting and credit scoring may not be possible without evidence of the benefits of the shift. This report provides that evidence.

Since the third quarter of 2011, we have been working in Mexico with two MFIs to test the impact of credit reports and credit scores in the states of Oaxaca and Jalisco, recruiting participants in a randomized control design framework. These MFIs allocated applicants to one of three lending channels: a manual process that assessed risk as if the applicant had no credit file data; a credit report channel that used application and credit report data; and a credit report and credit score channel. Manually approved applicants were reprocessed through the other two channels, and those approved in the credit report channel were also processed through the credit-scoring channel.

For Acreimex, the lending period began in the second quarter of 2014, in the region of Oaxaca City and surrounding areas in Oaxaca, Mexico. Loan officers recorded the loan data, including data on loan processing time, and the back office provided data on performance outcomes of the loans, as well as demographic information on the borrower. The data on loan outcomes came from Acreimex records. The repayment period for the loan ranged from 4.5 to 10 months.

For Tepeyac, the lending period began in the first quarter of 2014, in the regions around Guadalajara in Jalisco. As with Acreimex, loan officers recorded the loan data.

Beginning in mid-2013, we also worked with two Indian MFIs to measure the impact of credit reports and credit scores in group-based lending to individuals. The structure of the measurements here differed because India enacted new regulations while the study was underway; this, in conjunction with characteristics of group lending in India, meant that MFIs almost never rejected an applicant. In addition, the use of credit report checks was also required. Since the impacts measured are those on the MFI and not on the borrower, the absence of rejections did not fatally distort the study. The measure of whether credit scores that use credit bureau data are able to predict risk, for instance, does not require data on loan rejections.

Credit bureau data for MFI applicants was sparse in India when we began our study. In addition, application scores using credit bureau and application data did not exist. As such, we produced two custom scores, one for each of the participating MFIs (although there were several iterations of each); these were based on application data and credit report data because of our goal to measure the impact of credit bureau information. These were created to test whether credit scores using application and bureau data are effective in assessing risk among applicants for low-value group loans in low-income areas. This would complement findings from individual-level loans from middle-income Mexico.

We attempted to conduct a similar study in Bolivia that was more akin to what was done in Mexico. We began recruitment efforts in 2012, working with the microfinance regulator Autoridad de Supervisión del Sistema Financiero (ASFI). By mid-2013, it was clear that ASFI would not permit the experiment because of its parameters. Another obstacle was the strict oversight by ASFI regarding the use of credit reports in the microfinance sector and regarding underwriting in general. This was unfortunate because the co-evolution of microfinance and credit reporting and scoring among MFIs in Bolivia remains relatively unique and could possibly yield a range of useful insights if properly analyzed.

Having said that, data available from the microfinance trade associations in Bolivia, as well as the national MFI credit bureau InfoCred, can be used to benchmark findings from Mexico and India. Consistency among the three cases will strengthen the findings from Mexico and India, and make more defensible the generalizability of our findings.

In addition to the above, we have implemented a number of quantitative measures of the impact of credit reports and credit report-based credit scores on microlending. Further, we have attempted more qualitative measures of the difference made by the age of the credit bureau, the engagement of the credit bureau with the microfinance sector, and the capacity of the MFI to use credit reports and credit scores.

Notes for Introduction

[1] Joseph Stiglitz and Andrew Weiss, "Credit Rationing in Markets with Imperfect Information," 1981; George Akerlof, "The Market for Lemons," *Quarterly Journal of Economics* 1970. 84 (3): 488-500; Marco Pagano and Tullio Japelli, "Information Sharing in Credit Markets," *Journal of Finance* December, (1993): 1693-1718; Marco Pagano and Tullio Japelli, "Information Sharing in Credit Markets," and Margaret Miller, "Credit Reporting Systems around the Globe: The State of the Art in Public Credit Registries and Private Credit Reporting," in *Credit Reporting Systems and the International Economy,* ed. Margaret M. Miller, 273-310 (Cambridge, MA: MIT Press, 2003); John M. Barron and Michael Staten, "The Value of Comprehensive Credit Reports: Lessons from the U.S. Experience," in *Credit Reporting Systems and the International Economy,* ed. Margaret M. Miller, 273-310 (Cambridge, MA: MIT Press, 2003); Simeon Djankov, Caralee

McLiesh, Andrei Shleifer, "Private Credit in 129 Countries," NBER Working Paper No. 11078 (January 2005) http://papers.nber.org/papers/w11078; IADB, *IPES 2005: Unlocking Credit: The Quest for Deep and Stable Bank Lending* (Washington, DC: IADB, 2004): 178. http://www.iadb.org/res/ipes/2005/index.cfm; Giovanni Majnoni, Margaret Miller, Nataliya Mylenko and Andrew Powell, "Improving Credit Information, Bank Regulation and Supervision" (World Bank Policy Research Working Paper Series, no. 3443, November 2004). Available at http://www- wds.worldbank.org/servlet/WDSContentServer/WDSP/IB/2004/12/17/000. 160016_20041217171024/Rendered/PDF/WPS3443.pdf; Michael Turner and Robin Varghese, *The Economic Impacts of Payment Reporting in Latin America* (Chapel Hill, NC: Political and Economic Research Council, May 2007; Michael Turner, *The Fair Credit Reporting Act: Access, Efficiency, and Opportunity.* (Washington, DC: The National Chamber Foundation, June 2003); Michael Turner et al., *Give Credit Where Credit Is Due* (Washington, DC: Brookings Institution, December 2006); Michael Turner, Robin Varghese, and Patrick Walker, *On the Impact of Credit Payment Reporting on the Finance Sector and Overall Economic Performance in Japan* (Chapel Hill, NC: Information Policy Institute, March 2007); Walter Bagehot believed that England beat out its competitors not because it had more capital than its competitors but because it could mobilize it better. Also see R. G. King and Ross Levine, "Finance, Entrepreneurship, and Growth: Theory and Evidence," *Journal of Monetary Economics* vol. 32 (1993):513-542; R. Levine and S. Zervos, "Stock Markets, Banks, and Economic Growth," *American Economic Review* vol. 88 (1998): 537-558; Ross Levine, "Financial Development and Economic Growth: Views and Agenda," *Journal of Economic Literature* vol. 25 (June 1997): 688–726; Jose De Gregorio and Pablo Guidotti, "Financial Development and Economic Growth," *World Development* 23 no. 3 (March 1995):433-448; J. Greenwood and B. Jovanovic, "Financial Development, Growth, and the Distribution of Income," *Journal of Political Economy* vol. 98 (1990):1076-1107; J. H. Boyd and E. C. Prescott, "Financial Intermediary-Coalitions," *Journal of Economics Theory* vol. 38 (1986):211-232; F. Allen, "The Market for Information and the Origin of Financial Intermediaries," *Journal of Financial Intermediation* vol. 1 (1990):3-30; R. T. S. Ramakrishnan and A. Thakor, "Information Reliability and a Theory of Financial Intermediation," *Review of Economic Studies* vol. 51 (1985): 415-432; and, Thorsten Beck, Asli Demirgüç-Kunt, and Ross Levine, "Finance, Inequality and the Poor," NBER Working Paper No. 10979. National Bureau of Economic Research. December 2004, updated January 2007. Available at http://www.nber.org/papers/w10979.

[2] From a Bolivian MFI, "Nuestra entidad no utiliza credit score ni tiene pensado utilizarlo puesto que la tecnología crediticia de la Microfinanzas no se adapta a implementar un credit score, porque una de las bases fundamentales del análisis en esta tecnología son los aspectos cualitativos que es muy complejo obtenerlo de un credit score."

[3] Adrian Gonzalez, "Efficiency Drivers of Microfinance Institutions (MFIs): The Case of Operating Costs." *MicroBanking Bulletin*, Issue 15. Autumn 2007. Available at http://www.themix.org/sites/default/files/MBB%2015%20-%20Efficiency%20Drivers%20of%20MFIs.pdf, accessed on February 24, 2013.

4 Background

There is very little reputable research on the impacts that credit reporting that uses credit reports and scores has on microfinance. While there is a general consensus that credit reporting information can help, how much it can help is up for debate. This question should not be confused with the related question of whether credit scoring has positive impacts on lending[1]; here we refer to credit scoring that is based on the credit bureau and/or application data collected by an MFI.

Allain De Janvry and his collaborators found that credit reporting positively impacts access to finance both in terms of the size of the loans and their acceptance rates; they also found significant drops in arrears in an analysis of the introduction of credit reporting in Guatemala.[2] Luoto, McIntosh, and Wydick found that this dynamic of lower arrears also results in lower interest rates.[3] Research by Campion and Valenzuela, looking at MFIs that use Infocorp in Peru, shows a reduction in origination costs and waiting times, dropping from one week to one day.[4] The studies have limits in their rigor and their ability to show causality. Consequently, the objections to the value of credit reporting in microfinance persist. Perhaps the most prominent and persistent concern is the claim that the cause of default on a microloan in many markets are shocks, either personal or local, and as such, past behavior will not be an indicator of future ability and willingness to repay.

It may well be the case for certain types of loans to a specific class of borrowers that borrower profiles and behavior may appear more or less homogeneous; an example here is trade credit to small-holder farmers. But take the same population and change the credit instrument—having a tool to differentiate higher-credit risk applicants from lower- credit risk applicants becomes critical[5]; a good example is productive capital for buying additional acreage or an irrigation system. It is precisely in such cases where the use of credit reports and credit scores to supplement application data and traditional credit bureau data could yield considerable benefits to lenders in assessing the credit worthiness of a prospective borrower; this is especially true of those using alternative data (non-financial payment data, psychometrics, unstructured data, or Big Data). More predictive data and data with increased coverage of the applicant population have shown to result in sustained increases in lending to the private sector; this in turn has been linked to sustained economic growth.[6] [7] It is for these reasons that the exploration of impacts from MFI-credit reporting, and the use of credit reports and credit scores by MFIs, is warranted.

Notes for Background

[1] See Antonio Blancoa, et al., "Credit Scoring Models for the Microfinance Industry Using Neural Networks: Evidence from Peru," *Expert Systems with Applications* 40 no. 1 (January 2013): 356–364; Hans Dellien and Mark Schreiner, "Credit Scoring, Banks, and Microfinance: Balancing High-Tech with High-Touch," December 18, 2005. http://microfinance.com/English/Papers/Scoring_High_Tech_High_Touch.pdf; Dean Karlan and Jonathan Zinman, "Microcredit in Theory and Practice: Using Randomized Credit Scoring for Impact Evaluation," *Science* 332 no. 6035 (June 2011): 1278-1284; Mark Schreiner, "Credit Scoring for Microfinance: Can It Work?" *Journal of Microfinance* 2 no. 2 (2000): 106-118.

[2] "Credit Bureaus and the Rural Microfinance Sector: Peru, Guatemala, and Bolivia: A joint project between The University of California at Berkeley and The FAO Office for Latin America December 8, 2003. http://www.arabic.microfinancegateway.org/sites/default/files/mfg-en-case-study-credit-bureaus-and-the-rural-microfinance-sector-peru-guatemala-and-bolivia-2003.pdf

[3] Jill Luoto, Craig McIntosh, and Bruce Wydick. "Credit Information Systems in Less-Developed Countries: Recent History and a Test," *Journal of Economic Literature* (September 200): 313-333.

[4] Anita Campion and Liza Valenzuela, "Credit Bureaus: A Necessity for Microfinance?" US Agency of International Development Office of Microfinance Development. October 2001.

[5] In building a credit-risk model, the first step is always defining "goods" (those with desirable behavior given what is being modeled) and "bads" (those with undesirable behavior given what is being modeled). For example, in a standard generic credit-risk scoring model, a bad is defined as someone who is 90 days or more late on a payment, while a good is someone who has never been 90 days or more late on a payment.

[6] Simeon Djankov, Caralee McLiesh, and Andrei Shleifer, "Private Credit in 129 Countries," *Journal of Financial Economics* 12 no. 2 (2007): 77-99.

[7] Michael Turner, Robin Varghese, Patrick Walker, and Sukanya Chaudhuri. "The Impact of Information Sharing on Competition in Lending Markets." PERC. October 2014.

5 Objectives

There are a number of questions regarding credit reports and credit scoring in microfinance that this research project attempts to explore. These include:

- Can MFIs assess borrower risk with:
  - credit reports?
  - credit scores?
- Is this the case for MFIs in middle-income economies lending to individuals as well as MFIs in low-income economies lending to groups?
- If so, to what degree might credit reports and/or credit scores be useful in assessing borrower risk?
- Can credit report use and credit scores be cost-effectively deployed?

In order to explore these questions, we consider lending decisions and outcomes from manual processes that only use application data and previous performance data held by the lender (for returning clients); we then compare these to processes that use credit reports and processes that use credit scores.[1] Our study aims to address the generalizability and external validity issues. To do so, we ran experiments with four institutions in two different economies; due to data limitations, results were only produced from three of the four institutions. These comparisons are made with individual-level loans from MFIs in middle-income Mexico and group-based loans to individuals from MFIs in low-income India. The MFIs vary by size, and the economies vary by experience with credit reporting in microfinance. The variances provide some insight into the role played by several factors; these include MFI capacity regarding more sophisticated information and statistics-driven underwriting, as well as experience with credit reports.

For our study, the definition of a microlender is a lending institution that offers and services low-value loans for individuals or groups from disadvantaged social segments. This definition is broad; it does not differentiate between deposit-taking and non-deposit-taking institutions. For our study, none of the loans, lending partners, or case studies required collateral, though collateral freeness is a requisite to qualify as a microloan.

Notes for Objectives

[1] A number of past studies have focused on these issues with regard to traditional, non-MFI lending; for examples see the following: John M. Barron and Michael Staten, "The Value of Comprehensive Credit Reports: Lessons from the U.S. Experience," in Margaret M. Miller ed., *Credit Reporting Systems and the International Economy* (Cambridge, MA: MIT Press. 2003): 273-310. Michael Turner et al., *The Fair Credit Reporting Act: Access, Efficiency, and Opportunity* (Washington, DC: The National Chamber Foundation,

June 2003). Michael Turner and Robin Varghese, *The Economic Impacts of Payment Reporting in Latin America* (Chapel Hill, NC: Political and Economic Research Council, May 2007). Giovanni Majnoni, Margaret Miller, Nataliya Mylenko, and Andrew Powell, "Improving Credit Information, Bank Regulation and Supervision," World Bank Policy Research Working Paper Series, no. 3443 (Washington, DC: World Bank, November 2004).

6 Methodology

Our choice of the three economies (Mexico, India, and Bolivia) was based on how long microfinance institutions have been reporting to credit bureaus in these countries. MFIs have been reporting information to credit bureaus for a long time in Mexico compared to the other two countries. Credit reporting in Bolivia was almost 10 years old when we started the study. And credit reporting in India for MFIs is less than five years old.

We hypothesize that age is a good proxy for depth of data, coverage rates, and services offered; therefore, it likely affects the impact of credit reporting on the microfinance sector. With time, credit bureaus are able to offer more services. With time, data quality issues become resolved. With time, microfinance institutions are able to better understand how credit reports and scores can be used in lending.

The cases were chosen on the assumption that the older credit reporting systems are more likely to engage the microfinance sector. We have no reason to believe that the strength of the engagement is purely based on age. Mexico's credit bureau and Bolivia's credit bureau serve both the microfinance and non-microfinance sectors. Bolivia's, however, was created in 2003, with credit reports being sold in 2004, and is owned by the microfinance associations. Mexico's credit bureau was established in 1994 and is owned by large banks. India's Highmark is a bureau dedicated to the microfinance sector, is independently owned, and is only a few years old; although it was established in 2005, credit bureau activities did not begin until after 2008.

Our selection of MFIs was based on more complicated logic. Because we wanted to "replicate" the experiments and to generalize results all in the same study, we varied the MFIs. The intention has been to recruit two or more large MFIs, two or more medium-sized MFIs, and two or more small MFIs. These definitions are usually taken to refer primarily to whether the MFI has more than US$50 million in assets (large or tier 1 MFI), between US$50 million and US$5 million in assets (medium-sized or tier 2 MFI) or less than US$5 million in assets (tier 3 MFIs). Of the 4 MFIs participating in the study, there were no tier 3 MFIs. This is understandable given the potential costs for them in terms of additional losses and uncertainty about having the capacity to use scores.

SKS and Grameen Koota are large tier 1 MFIs, with US$414 million and US$100 million in assets respectively.[1] Acreimex's portfolio and Tepeyac are significantly smaller. Acreimex's portfolio stands at approximately US$65 million, while Tepeyac's is approximately US$14 million.

The first issue that needed to be resolved was the desired sample composition. For instance, suppose that 50 percent of the Mexican population is female, 40 percent of adult borrowers in Mexico are female, 75 percent of all Mexican MFI borrowers are female, and 85 percent of borrowers of a participating Mexican MFI are female. For which population should the results be relevant? For instance, sampling of the participating MFIs' applicants to mimic the national population could have been carried out. The downside to this is that the national population, for instance, may also vary in other ways not fully captured (or able to be accounted for) by the data. That population may not be relevant to the population of possible MFI applicants. And other populations, such as the overall MFI population, may change over time. It was therefore decided that the strongest results would generate if no such selective sampling took place, and that the participating MFI samples should reflect their actual pool of applicants. This pool is often referred to as the "through-the-door-population," or the TTD population. So, the results would be relevant for the participating MFIs, first and foremost. But, to the extent that the chosen MFIs chosen are typical of the other MFIs in the nation, the results obtained should also be relevant to the larger MFI sector.

There are limitations on the generalizability of our findings associated with the research design. Specifically, no single specific design for the lending experiments is possible across the economies and MFIs examined. This is due to variations in national laws (for instance requiring the review of credit reports in some cases) and individual MFI lending policies and procedures. The details of the actual lending experiments are tailored for each MFI. In addition, not all channels will be compared across each MFI. For example, in the more advanced market, Mexico, the use of a highly automated approach is available to be tested, but this underwriting software solution is not available in India.

In the most ideal case, the same borrower would be evaluated via all channels, and if he or she was accepted by *any* of the channels, then that borrower would receive a loan. So, the lending outcome of each channel would be known perfectly for each borrower. Those loans that would have been rejected by one channel but accepted by others would not be included in the loan performance of the rejected channels (i.e. only loans that were issued were counted—there were no negative cases). Therefore, in studying lending (from the lender's perspective), different treatments can be applied to the same cases (individuals). However, this becomes a little more complicated if different lending channels produce different types of approvals, in terms of amounts, interest rates, and fees. This possibility of examining different treatments for the same individual is not the case when examining borrowers, since a borrower cannot both receive a loan and not receive a loan.

To the extent possible, each applicant is evaluated by all lending channels. This serves as a semi-crossover study, because participants in the manual channel receive all treatments, and those in the credit-reporting channel also receive the score treatment. However, since there are significant costs (and time) associated with particular lending channels (such as an in-depth manual approach), it was not practical or possible for MFIs to put each applicant through every lending channel. Moreover, as we incurred regulatory burdens, such an approach was beyond this project's scope.

In other cases, such as the use of credit scores, the costs may be minimal and, so long as data exists, decisions with and without credit scores can be compared for all applicants. Since the perfect approach would involve accepting all applicants who would be approved by any channel, this could entail unacceptable lending risk for the MFIs, for instance, if one of the channels that an MFI did not typically use produced a much higher rate of accepts, and if these accepts then later defaulted. As such, the perfect approach described above was not feasible for MFIs in this study.

The approach we employed in Mexico was a combination of the *perfect* approach described above and a randomized controlled trial (RCT) approach in which applicants are randomly assigned to different treatments (lending channels). Importantly, the randomization must be among those applicants who can be assessed by every channel. An example of this is shown in the following table.

Table 1. RCT Structure

Does credit report exist?	**Credit score produced?**	**Random assignment of underwriting method**	**Loan status after credit file pulled and risk assessed**	**Tracking of loan performance**
Yes	For all	Application data alone	A. Accepted	--
			B. Rejected	N/A
		Application data and credit report	C. Accepted	--
			D. Rejected	N/A
		Application data, credit report, and credit score	E. Accepted	--
			F. Rejected	N/A
No (ineligible)	N/A	--	--	--
			--	--

In the first step for the Mexico MFIs, we determined whether an applicant can be processed by all of the lending channels, i.e., do they possess credit reports? If so, we can proceed to randomly assign them to particular lending channels. If not, they are not allocated to the study. As there may be biases in the population who have credit histories and those who do not, we limit the pool of eligible borrowers to those with credit histories. As shown in the figure, because credit scores are of little cost to produce, all who can be scored will have scores produced. In the third step, applicants who can be processed across multiple channels would be randomly assigned to a channel (because it was not feasible to process all via all channels). Then, lending decisions were made. Finally, loan performance outcomes are tracked.

In addition to loan performances, loan details, and borrower details, accept rates and reject rates by lending channel were also recorded.

On the other hand, for the India MFIs that have very few rejected applications and have requirements to use credit reports for all applicants, we designed credit scores for each MFI and then produced credit scores for each borrower.

Furthermore, for those India MFI cases for which we are developing scores, the score development process also provides a measure of the differences in performance. Because the lending data on which scores are built will provide hold-out samples, the process of score construction also allows us to evaluate the scoring with the test of the score on the hold-out sample (a set of loans that are not used for score construction).

In the second quarter of 2014, PERC conducted a pilot study of the RCT with Acreimex in Mexico in order to identify any potential incentive conflicts or biases in the design of the RCT. We identified none. On that basis, PERC proceeded with both Acreimex and Caja Tepeyac as planned.

Notes for Methodology

[1] See 2012 Mixmarket reports for SKS http://www.mixmarket.org/mfi/sks and http://www.mixmarket.org/mfi/gfspl.

7 The MFIs and Results

We targeted two MFIs in each economy. Running more than one RCT/experiment in each country, and running the RCTs/experiments in multiple countries, was an attempt to "replicate" results and determine robustness of results.

We have worked with microfinance associations and, to a lesser extent, regulators to recruit the participating MFIs.

In order to incentivize the MFIs, we offered to develop a custom credit-scoring model for participants. The scoring models are developed on a combination of application variables and credit report data. Given that the cost of developing a scoring model would far exceed any additional losses MFIs would likely incur in the manual-only channel, participation is a net benefit for any participant interested in exploring scoring. In Mexico, we offered MFIs an opportunity to use for a fixed time period an automated but customizable decisioning system developed by Buró de Crédito with a generic score that has been revalidated for microfinance.

7.1 Indian MFI Participants

We engaged the Indian MFI sector in November of 2011. The initial two quarters witnessed slow responses, as the sector was struggling to deal with the microfinance crisis. Furthermore, HighMark had regulatory concerns about being able to provide information to PERC, as we were not clients. Management changes in HighMark also slowed the process. Eventually, a workaround was found in late 2012; PERC formally became "consultants" for the participating MFIs. HighMark agreed to directly sell sector tracking data to PERC as consultants of SKS in early 2013.

Of the many MFIs we reached out to in India, we had face-to-face and extensive discussions with Aarohan, Bandhan, Chaitanya, Grameen Koota, Janalakshmi, SKS, Trident, Ujjivan and Utkarsh. All but Grameen Koota and SKS were skeptical of the value of scoring and did not wish to participate. In the explanation provided by Trident, other than measuring total outstanding credit and seeing if there are any past defaults, credit scoring offers little to the microfinance sector.[1]

Grameen Koota and SKS had (1) a large portfolio with modest but sufficient variation in performance, (2) sufficient data in an accessible format, and (3) an interest in using scoring solutions to improve portfolio performance and/or lower origination costs. In addition, Grameen Koota stated that regardless of the results, they did not plan to deviate from their established lending practices. By contrast, SKS expressed an interest in expanding into individual loans and views credit reporting, and the use of credit reports and scores, as tools to enable them to diversify their loan types.

Just before the experiment was implemented, the Reserve Bank of India (RBI) enacted a new set of regulations stating that the total number of loans for a MFI borrower cannot exceed two, and the total outstanding balance cannot exceed Rs. 50,000. To a large degree, these new rules and the already-low rejection and default rates helped shape how our experiments in India were designed.

Each of the two participating India MFIs is described and discussed in detail in following sections. Results from their experiment are also shared.

7.1.1 SKS Microfinance

SKS was founded in 1997 as a non-governmental organization (NGO) in the state of Andhra Pradesh. In 2005, it was incorporated as a Non-Bank Financial Company (NBFC), a for-profit institution. By 2009 SKS was the largest MFI in India. Headquartered in Hyderabad, Andhra Pradesh SKS took severe losses during the MFI crisis in Andhra Pradesh. SKS was able to raise significant funds through their IPO and thereby ride out their financial losses localized in Andhra Pradesh. Despite those losses, SKS continued to actively lend in other states and remains a major MFI in India. SKS operates in over 100,000 villages in 19 states.

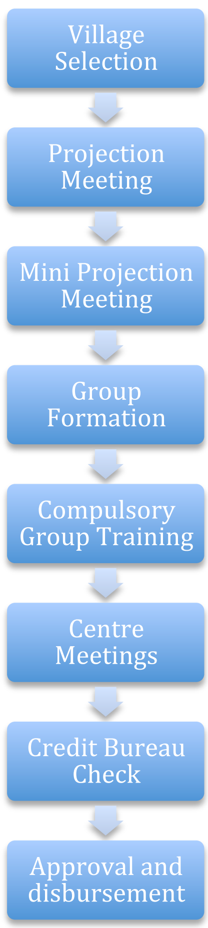
The following table provides an overview of their activities and operations prior to the full fallout from the crisis and during the period when our research began.

Table 2. SKS Finances and Operations

Operational information	FY 2012***	FY 2011**	FY 2010**
Total # branches	1,461	2,379	2,029
Total # districts	--	378	341
Total # staff	16,194	22,733	21,154
Total # members (‘000)	4,256	7,307	6,780
Amount distributed for the period (INR million)	--	78,310	76,180
Portfolio outstanding (INR million) *	18,007	41,110	43,210
Number of loans outstanding (‘000)***	3,976	4,269	6,242

*Includes assigned loan portfolio **Data from SKS ***Data from Mixmarket

The impacts from the crisis of fall 2010-2011 have been quite substantial, as indicated in table 2.



SKS's Origination and Underwriting Practices

SKS utilizes a joint liability group (JLG) model of lending in which *individual* loans are given to women who in turn are members of a five-member group. The women act as each other's guarantor and are usually from the same locality, where they have known each other for some time. In the application phase, the women effectively screen for high-risk borrowers, given that the rest of the members of the group are guarantors for each member. The idea is to create social collateral that replaces financial collateral. Like all MFI loans, SKS loans are also non-collateralized.

Details of Operational Methodology

First, SKS identifies villages into which it expands lending operations. Village selection involves a survey by the staff of SKS to evaluate local conditions. Specifically, SKS measures poverty (need) level, means of livelihood, political stability, accessibility, and the size of the population.

This assessment and preliminary selection is followed by a projection meeting with villagers. The main purpose of the meeting is to introduce the villagers to the SKS products, its methodology for recruitment, and qualifications for borrowers. A second projection meeting is then conducted with the interested borrowers. This meeting will include some who may have missed the first meeting.

The next step is group formation in which the women form self-selected five-member groups. The Compulsory Group Training (CGT) is a four-day training (an hour-long each day) where members are taught the importance of collective responsibility, how to elect group leaders, affix signatures, make timely payments, and manage activities. The group training is concluded with a group recognition test in which staff members of SKS ensure that the borrowers fully understand their responsibilities and relationship with SKS. Ultimately, only qualified women are accepted as SKS members.

Elegible

- No. of other MFIs ≤1
- Current Balance ≤ Rs. 50,000
- Overdue Amount = 0
- No. of Default Accounts = 0

Ineligible

- No. of other MFIs > 1
- Current Balance > Rs. 50,000
- Overdue Amount > 0
- No. of Default Accounts > 0

Center meetings provide the platform for conducting financial transactions between the borrowers and SKS. Collections are made and new loans are disbursed. Selected leaders and deputy leaders ensure that all SKS rules are followed. In addition to financial transactions, new loan options are discussed, along with community issues. The center meetings are held in the early hours of the day so as to ensure that the daily activities of the borrowers are not affected. About 3-10 groups assemble at a center meeting.

At the end of CGT, a credit bureau check is performed for the qualified borrowers. The credit report is used to check to see if applicants meet RBI lending guidelines, specifically whether (1) applicants have no more than one loan from another MFI, and (2) if the total balance outstanding does not exceed INR 50,000. If the new loan would place the total debt burden of the applicant above INR 50,000, they are ineligible. SKS further requires that the applicant have no late payment and that the applicant not be in default on any account during their borrowing history. If the applicant meets the credit check criteria listed above, the loan is extended and disbursed.

<u>Credit Score Development</u>

Given that credit reporting and the internal collection of borrower data is still developing among MFIs in India, credit scoring is not a common practice for Indian MFIs. Neither SKS nor Grameen Financial Services utilized automated scoring before or during our research period for this study. As such, it was necessary to construct credit scores using borrower data collected from the MFIs (application data and questionnaire data) and borrower data from the credit bureau used by the MFIs.

For the purposes of this study, a number of challenges arise. First, in order to construct a credit score, the data needs to contain a sufficient number of "bads." Other variables can be used to predict these "bads." The structure of the lending with SKS is such that there are very few defaults. The observed "bad" rate is around 0.6 percent. Expanding the so-called "bad" rate to encompass any late payments produces a rate of around 1 percent. While this is relatively low, it nonetheless produced a sufficient number of "bads."

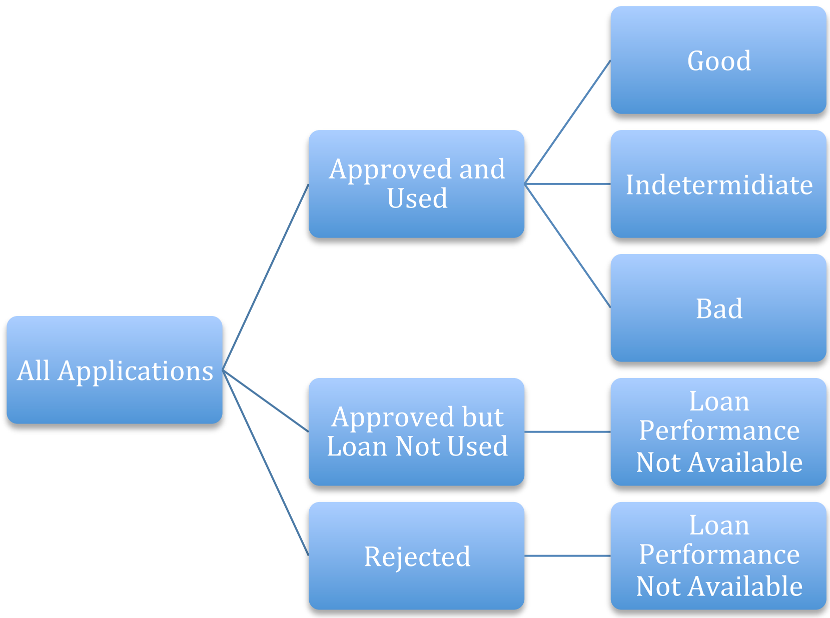
Also, generally, there is very limited underwriting. The major reasons for excluding borrowers include if they do not meet RBI criteria, if they are not chosen by a group, or if they would not get along with other group members. But these exclusion criteria would need to be part of any underwriting approach, including one using credit scores.

Finally, an automated solution would likely reject borrowers with recent defaults. However, to model and estimate the credit risk of those with past defaults (how old, amounts, etc.), it would be necessary to extend a large number of loans to those with past defaults, something which was not available.

As such, given the approach of group lending (of only excluding those who could not receive loans due to regulations, practical considerations, or the most severe past delinquencies), it appeared that an automated approach would not be able to approve more borrowers than the status quo in the research setting. That is, both would reject these groups, and automated underwriting would help identify additional high-risk applicants. Given this, there would not be distinct groups in which one group would be accepted with the status quo and one accepted with automated underwriting. Instead, the group accepted with automated underwriting would be a subset of the status quo-accepted group. This means a lending experiment can be based on the status quo, and then one can monitor how well the use of data via automated underwriting can identify high-risk applicants.

Credit Score Development (In General)

The purpose of building credit scores is to use data on past and present applicant behavior and characteristics to predict future outcomes (credit repayment). The typical goal is to build statistical models that identify the people who are likely to default on loans in general or certain types of loans. Data on past loan performance is typically used to build such a model. The following flow chart describes the entire "through-the-door" (TTD) population.



We used the available data on the known goods (loans that have performed) and bads (loans that have clearly not performed) to build our initial models. The known goods and bads are labeled "Good" and "Bad" in the above diagram.

In order to build our model, we need a good/bad indicator. Our definition of a bad account involves an account with any recorded amount in arrears or which is otherwise outstanding after the full term of the loan. In the context of SKS, the number of final defaults was extremely low.

We first built our model on the known goods and bads. That is, the dependent variable is zero if Good and one if Bad (any arrears or delinquency). We use basic summary statistics (such as correlations or the information value of the variable in relation to the dependent variable) to identify the most predictive independent variables. There can be a huge list of potential independent variables. For the Indian MFIs (as explained in the next few paragraphs), the list of independent variables includes application variables and credit bureau variables. We exclude the variables that are least predictive of the dependent variable in a basic bivariate approach.

From here, decision trees or stepwise regressions are used to further reduce the set of independent variables. These approaches are important (as opposed to a bivariate approach), because what we are interested in is the most predictive group of variables. For example, variables A, B, and C may be the most predictive of the dependent variables, and D is less predictive, but it could be that A, B, and C all contain the same useful information, so only B, and not all three, are necessary. And so, the combination of B and D would outperform the combination of A, B, and C. One needs to examine the variables in combination. Usually a handful of variables (around 15) may be the most predictive group of variables.

Next, the variables are binned, usually based on what is referred to as optimal or weight-of-evidence binning. In this way, the values of the independent variables are put in bins or categories, so the number of months since first establishing credit variables might be put in greater-than-24-months, between-12-and-24-months, and less-than-12-months categories. Models (typically logistic regression models) are then built on these binned variables and more refinements may reduce the number of independent variables further, perhaps to between 10 and 12. These contain the key variables for predictions of loan performance. The models built with these key variables perform virtually as well as models with all (perhaps hundreds of) independent variables included. This narrowing down of independent variables to a handful of key variables produces parsimonious, robust models.

During the above process, it is also determined whether multiple scorecards should be developed. It is determined whether, for instance, borrowers with little credit information (such as two or fewer past accounts) should have a different score card than those with more information. This would allow for different points to be allotted for these two groups. Thus, for a borrower with few accounts, the fact that the age of the credit is over 36 months may add more to their score than for someone who had many accounts. On the other hand, one minor derogatory may be more harmful to some with fewer accounts than someone with many accounts. A note of caution, especially in the Indian context, is that for most borrowers, the credit history is very shallow (this is typical in many countries, such as Australia which is transitioning to full-file credit sharing). Since the credit bureaus only recently took off, many borrowers will have only recorded a short payment history. However, most MFIs have maintained their own database for a long time, and if the borrower is a returning borrower, then richer historic data may be obtained directly from the MFI.

SKS Credit Scorecard

The results (coefficients) of the logistic regression are typically translated in terms of simple scorecards. An example of a scorecard (in terms of KS value for the model) created with the SKS data is presented below. Points are added up for each value of the independent variable to produce a score. The score then has a corresponding probability of being a bad. A higher score here means lower risk. In the case of the SKS scorecard, the probability of default/delinquency is the “bad” that is being predicted.

The SKS Scorecard [cont. on next page]

Variable	Value	Score points
Member literate	FALSE	52
	TRUE	58
Husband age	<37	66
	[37.00,39.00]	60
	[40.00,44.00]	57
	[45.00,48.00]	52
	>48	49
Borrower age	<30	64
	[30.00,37.00]	59
	[38.00,41.00]	56
	[42.00,44.00]	53
	>44	52
Household income	[0.00,30,000.00)	52
	null or [30,000.00,60,000.00)	58
	>60,000.00	55
Number of children	[0.00,4.00]	57
	>4.00	56
Number of children below 5	0	56
	>0	63
Number of children between 5-15	0	56
	[1.00,3.00]	58
	>3	55
Amount of agro land owned	<1	56
	[1.00,2.00]	66
	>2	56
Current balance	<850.00	57
	[850.00,1,900.00]	68
	>1,900.00	55
Number of closed accounts	[0.00,1.00]	58
	[2.00,10.00]	57
	>10.00	46
Number of active accounts	0	59
	>0	56

The SKS Scorecard Scale

Base points	600
Points to double the odds	20
Base odds	50

Note that higher points denote lower risk (lower probability of bad or delinquency/default). As described above, the points are created directly from the results (coefficients) of a logistic regression.

The following summarizes the main steps:

1. Define a dependent variable to predict, where 0 = good, 1 = bad. In the present case, an account is bad if arrears or write-offs are noted at end of loan term.
2. Determine which independent variables from the application data, credit report data, and other data are most correlated with the created good/bad dependent variable.
3. From the above set, use decision trees and stepwise logistic regressions to narrow down the set of independent variables.
4. In the narrower set of independent variables, bin the variables so that each variable only has a few values (such as age being transformed to 18-29, 30-37, 38-41, 42-44, and 45+). This binning is optimal for predicting the dependent variable, a way called WOE binning.
5. A logistic regression on the narrow set of binned variable is then performed. The results from this (the coefficients) are used to produce a scorecard with points.

Model Performance

The performance of the score developed for SKS was less than expected, with K-S values in the range of 0.15 to 0.20 for various scorecards developed. Typically, credit scores developed using application data only would show a KS of 0.3, and a hybrid model containing very little credit bureau data should perform in the 0.3-0.4 range. To help close this gap with the SKS model, PERC brought in outside consultants with extensive score-building experience from a major analytics firm to analyze the data. The outside consultants concluded the same thing, namely that the underlying data was not very predictive of the loan outcomes. One possible explanation for this is low data quality.

Discussions with SKS revealed that the staff had low confidence in the quality of the data used for this study. When this study began, SKS was not processing their internal data for credit scoring or automated underwriting, and so the data assembled for this research may not have been of sufficient quality. That said, the staff was very progressive and believed that use of data for underwriting, product marketing, and perhaps pre-qualification purposes would continue to grow in their operations, and so had begun upgrading IT/data processing/systems to improve data quality and processing. Unfortunately, this was too late for the current research. Nonetheless, SKS's participation in this effort speaks to the forward-looking attitude of management and staff. Its participation in the work, including score development, no doubt further emphasized the benefits of IT upgrades. In addition to its internal data assets, the staff also suspected issues could exist with credit bureau data quality/matching (whether this was suspected as an issue at the SKS end, credit bureau end, or a combination is not known). The identification of this issue comes across in the use of credit reports to meet RBI lending guidelines.

Discussions with SKS made it clear that they are interested in pursuing data-driven solutions to reduce costs and open up new lending opportunities. They recognize that improving data handling and quality is a key way forward to developing solutions. Importantly, staff at SKS appear open to altering the lending model if new, better approaches are identified. This could include pursuing higher-value, individual loans (to the extent permitted) by using individual credit scores of current group lending members as a way to ID good borrowers for higher-value loans. And it could also include substituting data for some high-cost/high-touch efforts. For instance, it may be possible to identify lower-risk clients who need less high-touch effort, and thus reduce those costlier efforts for them.

7.1.2 Grameen Koota

Grameen Financial Services Pvt. Ltd. (GFSPL), popularly known as Grameen Koota, is a registered Non-Bank Financial Company (NBFC) founded in 1999. Grameen Koota focuses on rural, poor, low-income women. Grameen Koota offers loans for a variety of reasons, including loans for starting a business, agriculture investment, education investment, as well as household needs and even personal consumption. Its operations are considerably smaller than those of SKS.

Table 3: Grameen Koota Finances and Operations

Operational information	FY 2012	FY 2011	FY 2010
Total # branches	160	168	215
Total # districts*	41	42	--
Total # staff	1,199	1,267	1,748
Total # members (‘000)	289	313	321
Portfolio outstanding (INR million)	3,458	4,112	3,704
Number of loans outstanding (‘000)	477	462	461

Source: Mix Market
*Data from Grameen Koota

As comparing figures in table 3 to table 2 suggests, Grameen Koota is almost one-tenth the size of SKS. While large by global standards, it more closely represents a medium-sized Indian MFI. Its focus on rural lenders also will help to assess the scalability of any set of results from the experiment.

Table 4 lists the loan products offered by Grameen Koota. For the purposes of the experiment, no loan with a repayment period of more than 52 weeks was considered. Only applicants applying for loan products with a repayment period of a year or less were considered. By this criterion, those who are applying for sanitation loans and income generation loans will not be considered. While we would like to consider the impact of credit reporting and credit scoring on these loans, the repayment periods are too extensive for the practical aspects of this study.

Table 4. Grameen Koota Loan Products

Features	Loan amount	Interest rate	Processing fee	Repayment period
Education loan	Up to Rs. 5,000	22% (on reducing balance)	1.1236% of loan amount	52 weeks
Festival loan	Up to Rs. 2,000	22% (on reducing balance)	1.1236% of loan amount	24 weeks
Medical loan	Rs. 200 to Rs. 2,000	22% (on reducing balance)	1.1236% of loan amount	24 weeks
Arogya loan	Rs 500 to Rs. 1,000	22% (on reducing balance)	1.1236% of loan amount	10 weeks
CGI cook stove loan	Rs. 700 to Rs. 1,600	24% (on reducing balance)	1.1236% of loan amount	24 weeks
Water loan	Up to Rs. 5,000	22% (on reducing balance)	1.1236% of loan amount	52 weeks
Sanitation loan	Up to Rs. 10,000	22% (on reducing balance)	1.1236% of loan amount	104 weeks
Emergency loan	Up to Rs. 1,000	24% (on reducing balance)	1.1236% of loan amount	10 weeks
Income generation loan	Rs. 15,000 to Rs. 25,000	26% (on reducing balance)	1.1236% of loan amount	104 weeks
Income generation loan	Rs. 5,000 to Rs. 15,000	26% (on reducing balance)	1.1236% of loan amount	52 weeks
GRAVITY loan (vocational training)	Up to Rs. 10,000.	22% (on reducing balance)	1.1236% of loan amount	21 months

Note: Rs. = Indian Rupees

Grameen Koota's Origination and Underwriting Practices

The underwriting process followed by Grameen Koota involves two steps. The first step involves an individual becoming a member of Grameen Koota as part of a group. This is where the basic data collection and the group training occur. After a group is formed, basic data is collected on members. Using a standard form, loan officers collect basic data on the members and their homes. This data (Member's Basic Data Form, or MBDF) will also be used in the development of the score.

It is ensured that all group members are present when one individual's information is being collected. Also, all family members are part of the information gathering process. They are made aware of the five-day compulsory group training for the member and all other Grameen Koota rules and regulations.

Along with the collection of basic data, a progress-out-of poverty (PPI) survey is also completed. The PPI index is a good measure of the poverty and is used by Grameen Koota for a better understanding of the client profile and what kind of products may improve their situation.

In the next step, the group submits a proposal and Grameen Koota checks the credit bureau to see if RBI and their own internal eligibility criteria are met. Those who pass the credit bureau check are then given a five-day mandatory training course.

This Compulsory Group Training (CGT) lasts approximately 35-45 minutes each day. The purpose of the training is to educate members about:

- Savings habits and insurance
- Loans offered and repayment practices
- Kendra activities that mainly deal with the weekly meetings to discuss new loans, community issues, etc.
- Group selection and group activity criteria
- Group administration
- Responsibilities of the group
- Election of group leader/secretary
- Leadership roles and responsibilities of group/Kendra leader and secretary

- Maintaining the attendance register
- Relationship between attendance and loan

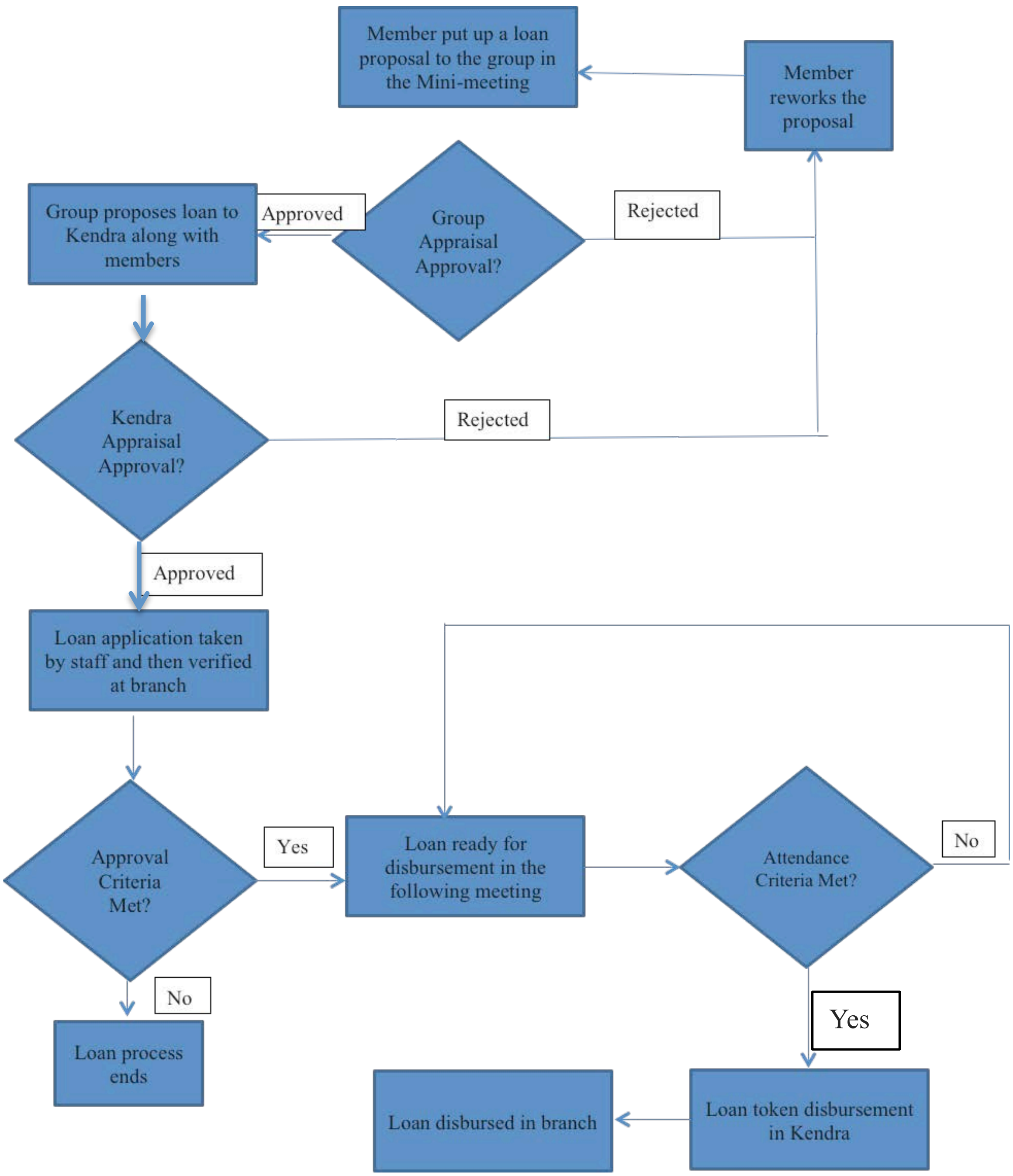
After the CGT, the branch manager conducts the re-interviews to assess the level of understanding among the group members. The branch manager visits the borrower's residences in order to understand the socio-economic background of the borrower. In addition, the branch manager inquiries about their knowledge of Grameen Koota, borrower responsibility, the role of leader/secretary, etc. Once the branch manager is satisfied with the knowledge level of the borrower, she is recommended for the next level of training.

Following the CGT, a Group Recognition Test (GRT) is conducted by high-level officials of Grameen Koota to gauge the overall quality of the group. It also confirms that the borrowers meet the Grameen Koota criteria of borrowing. It is mainly a question-and-answer session in which all group members participate. A group that fails to meet the required criteria is given another chance to go through an extended training followed by another GRT.

After the GRT is successfully completed, there is one more Kendra meeting before loans are approved and disbursed. The following figure illustrates the process. The Kendra meeting (or the center meeting) is meant to facilitate the meeting of the borrowers and the officials of Grameen Koota. This ensures that all borrowers are aware of their responsibilities and repayment structure.

See figure 1 on following page.

Figure 1. Grameen Koota's Loan Approval and Disbursement Process



The loan approval criteria followed by Grameen Koota consists of:

- Previous LUC (loan utilization check) and repayment record: i.e. for any defaults
- Attendance record: how frequently the borrowers attended the Kendra meetings
- Cash flow and repayment capacity: proof of income and expenses
- Other borrowings: this includes a credit report and also information gathered from friends and neighbors
- Group approval: everybody in the group is aware of the group liability
- Family consent: all family members are aware of the new loan and are supportive
- Credit Bureau check: this is to check total outstanding liability and number of loans (to ensure RBI regulations are satisfied)
- Approval by senior field staff (Area Manager, Regional Manager): this is an internal criteria to ensure credibility to the underwriting system
- Issuance of Sanction Letter: the final letter is issued by Grameen Koota to declare that the borrower satisfies all criteria and is approved for the loan

The loan underwriting process consists of two steps. The first involves an individual becoming a member of Grameen Koota (as described in figure 1), and the next step involves the actual underwriting of the loan (as shown in figure 1). The loan underwriting process ensures that the RBI regulations are met and that additional internal checks are performed. The initial data collection happens when an individual becomes a member of Grameen Koota. She has to undergo the group training, qualify in the group recognition test, and attend the Kendra meetings. Once she is a member, the actual underwriting takes place, which includes a credit bureau check and also income verification, family approval, etc. For returning borrowers, the initial data is updated if there is any change and then the underwriting of the loan takes place.

Grameen Koota: Scorecard Development

As we note above, Grameen Koota's loan origination process, as with those of other MFIs, involves the collection of a considerable amount of data. Both the PPI index and the MBDF involve the collection of many fields. Combined with application data and credit report data, the data gathering process involves a rich set of variables that can be very useful in a score. The following lists the variables we will be able to access for scorecard construction.

PPI Variables

- Household's ownership of a television
- Household's ownership of bicycle, scooter, motorcycle
- Household's ownership of a dressing table

- Household’s ownership of pressure cookers or pressure pans
- Household’s ownership of a sewing machine
- Household’s primary source of energy for cooking
- Number of electric fans owned by household
- Number of people in the household
- Principal occupation of the head of the household
- Status of residential structure

Variables Collected in the MBDF

- Address
- Amount of agricultural land owned
- Availability of electricity connection
- Caste status
- Education level of borrower:
- Food situation
- Number of children of primary school age but not attending school
- Number of years in current location
- Number of years in the present village
- Ownership of house plot
- Ownership status
- Religion
- Roof materials
- Size of building
- Total family income
- Value of livestock owned
- Value of other assets owned
- Wall features

Application Data Would also Provide

- Amount requested
- Interest rate
- Loan cycle
- Loan type
- Purpose of loan

Information from Credit Bureau

- Actual borrowings with other MFIs

- Current outstanding balance (This cannot exceed Rs. 50,000 as per RBI regulations)
- Membership with other MFIs
- Number of active accounts (this cannot exceed 2 as per RBI regulations)
- Number of default accounts
- Recent delinquencies

These are mainly the socio-demographic variables, and some of them will prove to be very predictive. However, past experience tells us that economic variables, especially the account payment information, are highly predictive of loan performance. This information is mostly available from the credit bureau.

The purpose of building credit scores is to use data from the past and present to predict what is likely to happen in the future, with the aim being to develop models that identify the people who are likely to default on loans.

We use the available data on the known goods (loans that have performed) and bads (loans that have not performed) to build our initial models.

In order to build our model we created a good/bad indicator. As mentioned previously, our definition for a bad account is if there is any missed or late payment on that account. In the context of GFSPL, the number of final defaults was extremely low.

(A fuller discussion of credit score development can be found in the previous section covering SKS.)

In the case of GFSPL, we created separate scorecards based on the duration of the loans. Three separate scorecards were developed for loans less than one year, for loans of one year, and for loans of more than one year in duration. Though, in this experiment, only the first two cards are used, since we are focusing on loans with terms of one year or less.

What follows is referred to as reject inference. Essentially, it is a way to incorporate the records that did not have a known good or bad. This is done since the credit model is to be used on all the potential borrowers who come through the door, so it should be built using all available information. One way to incorporate this information is to assign a good or bad outcome to those with an unknown or indeterminate outcome. This can be done by using the credit model built with the known goods and bads and using it to predict outcomes for the records without known goods or bads. These *predicted* good and bad outcomes are then used. At this point, then, all records have either a known or predicted good or bad. Then, the model development goes back to the beginning stages and ultimately produces models based on all the records, using either the actual or predicted outcome. The main possible challenge in this context is that there was no or incomplete information collected for the rejected applicants.

We worked with the MFIs to see if it was possible to collect the information for the entire "through-the-door population." However, the data provided by GFSPL to build the score did not have a sufficient number of rejects for reject inference to be meaningful, so this step was not used. More recent data in which the proportion of rejects had risen to 6-7 percent, however, would allow for the use of reject inference. Also, along these lines, in future experiments on this topic, the data collection procedure should be improved in order to capture the rejections made by field officers (such as rejections based on disapproval of other members) in order to further enable and refine the development of a reject inference for risk model development.

The results (coefficients) of the logistic regression are then translated in terms of simple scorecards. Examples of scorecards follow. They are generic scorecards predicting the probability of a 30+ days past due (DPD) on any account or other severe derogatory over the following 12 months. Points are added up for each value of the independent variable to produce a score. The score then has an associated probability of being a bad. A higher score here means lower risk. In the case of GFSPL scorecards, the probability of missing a payment is predicted.

An example scorecard follows:

Table 5. Grameen Koota Scorecard [cont. on next page]

Number of past GFSPL loans	0	66
	[1,10]	61
	[11,22]	60
	> 22	64
Years at GFSPL	< = 1	66
	[2,6]	61
	> 6	65
Current balance (CB variable)	No hit with CB	65
	< 1965	60
	[1965, 50,000)	57
Loan cycle	< = 1	46
	> 1	100
Product category	Home improvement, income generation	74
	Livelihood improvement	58

	Social welfare product	45
Activity category	Agriculture, assets	54
	Animal husbandry, production, trading, transportation	75
	Service sector, unassigned	61
Education	Both illiterate, not marked	77
	Both literate, only client/spouse	58
Member age	< = 24	97
	[25, 44]	62
	> = 45	59
Loan amount	< 6000	84
	> = 6000	37

Note that higher points denote lower risk. As described above, the points are created directly from the results (coefficients) of a logistic regression that was designed to predict the likelihood of an account going bad.

The model created for GFSPL has a reasonable ability to predict credit risk.

In the figure below, the hatched black line shows the random or no-information case. In that case, 10 percent of chosen accounts would have 10 percent of all bads. In the red line, the perfect information case is shown, where the bottom 0.5 percent of records contain all the bads and the remaining records are all good. The blue line shows the performance of the developed credit score. In this case, you see that the riskiest 10 percent account for over 40 percent of all the bads, while the least risky 30 percent account for under 10 percent of all the bads. Such a model is strong when identifying those who are very high and very low risk. The more challenging task comes with correctly identifying goods and bads among those who have a moderate risk profile.

[cont.]

Figure 2. Grameen Koota's ROC Curve

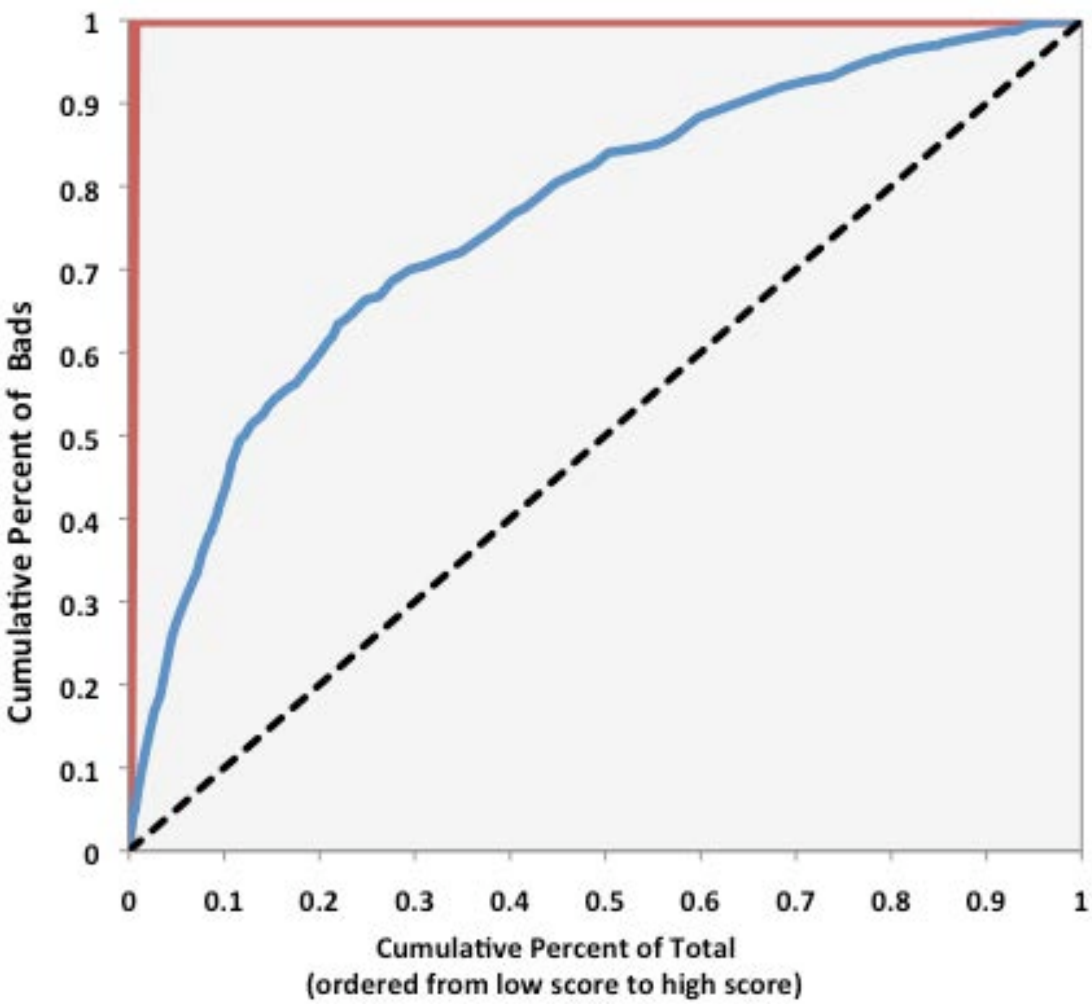


Figure 2 indicates that over 40 percent of all bads are amongst the 10 percent lowest-scoring accounts.

The credit score was developed on 60 percent of the sample; the KS (measure of goodness of fit) is 0.44 for this development sample. The KS on the holdout validation sample is 0.39.

The credit score was built using data from 2013. The 2013 data showed improved model performance relative to the 2012 data. The improvement in terms of the KS measure was an increase of about 25-30 percent between 2012 and 2013. This has been seen in the past when data quality improves. *This is a key finding*. GFSPL confirmed that by their own judgment and experience, internal data quality had noticeably increased over this period.

And PERC's analysis of the summary credit bureau data over this period also shows an expanding credit bureau database. Given this quantitative and qualitative increase in data between 2012 and 2013, it is not surprising that credit model performance built on data over these years would also improve.

As mentioned above, model performance could be further improved by adding additional data elements, by adding records/data from rejected applicants, and by continued data quality improvements.

Among the tested loans, credit scoring appears to be very promising.

The table below is similar to the figure above but it breaks down the rate of bads by particular score ranges, where lower scores indicate higher risk.

Table 6. GK Bad Rate by Credit Score

Score	% of accts	% of all bads	Bad rate (%)
681-751	10	1.9	0.1
673-680	10	2.1	0.1
667-672	10	3.8	0.2
662-666	10	3.9	0.2
657-661	10	4.3	0.2
652-656	10	7.4	0.4
647-651	10	6.7	0.3
634-646	10	9.8	0.6
609-633	10	16.5	0.9
597-608	5	15.9	1.7
508-596	5	27.8	3.0

In table 6, those with the highest credit score are 30 times less likely to have had a late payment than those with the lowest credit scores.

The following are basic summary statistics of the loans originated in February 2014.

In all, there were 164,527 loans disbursed in February 2014. The performances of these loans were monitored for up to a year. The final data request for performance needed to wait until April 2015 to capture any late payments. We began to receive final performance data in late May of 2015, and findings showed modest degradation in score performance over time with a fall in KS from 0.39 to 0.34, but this still remains moderately predictive.

The following are loan descriptive statistics for the 2014 loans.

Table 7. GK 2014 Loan Descriptive Statistics

Loan amount	Share (%)
<2000	47.93
2000-4999	3.16
5000-9999	4.96
10000-19999	28.36
20000-30000	15.59

Term	Share (%)
10 weeks	46.72
11-23 weeks	2.48
24-51 weeks	4.28
1 year	28.6
> 1 year	17.91

Loan purpose	Share (%)
Agriculture	2.0
Animal husbandry	12.9
Assets	6.7
Consumptions	51.0
Education	0.0
Production	5.7
Service sector	3.1
Trading	15.6
Transportation	3.0

Loan location	Share (%)
Rural	63.4
Urban	36.6

Loan location	Share (%)
Karnataka	75.9
Maharashtra	21.8
Tamil Nadu	2.3

Loan location	Share (%)
Married	90.01
Not marked	8.39
Unmarried	0.26
Widowed	1.34

Number of children	Share (%)
0	14
1	15.87
2	44.01
3	18.36
4	5.73
5+	2.01

Years at GK	Share (%)
0	31.64
1	21.29
2	10.03
3	2.05
4	14.65
5+	20.32

Age	Share (%)
19-25	7.89
26-35	35.03
36-45	35.54
46-55	19.94
55+	2.6

Poverty status	Share (%)
Non-poor	0.1
Poor	84.6
Very poor	15.29
Not marked	0.01

7.1.2.1 Cost Reductions

As described in the beginning of this section, the underwriting process for Grameen Koota can be very labor intensive and high touch: for instance, the Compulsory Group Training (CGT) that lasts approximately 35-45 minutes each day for five days, the branch manager conducting the re-interviews to assess the level of understanding of the group members, the branch manager visits to the borrower's residences, and the weekly meetings. Each new borrower could represent 3-4 or more hours a year of direct Grameen Koota personnel time during the first year. This excludes needed support staff and other costs (such as travel and supplies). If we assume Rs. 20 per hour, this could translate to about Rs. 80. As table 7 showed, loans under Rs. 2000 were the most common loan amounts. Costs of Rs. 80 (or more) on loans of Rs. 2000 or less represents 4 percent or more of the dispersed loans. With an interest rate of 22 percent (see table 3), 4 percent could represent a large cost savings for the borrower or a large margin increase for Grameen Koota. If the lowest-risk borrowers (say the lowest-risk 40 percent of borrowers) as assessed by collected internal data and credit bureau data required a less high-touch approach, meaningful savings could be had. This also includes borrower/applicant time. Importantly, the "fixed" fee has the greatest impact on the lowest-value loans. So, it may be that the lowest-income borrowers would benefit the most from a switch to a more data-driven, efficient process.

Furthermore, a more data-driven process could also drive down the cost of acquiring new applicants and reaching new borrowers if lenders do not need to set up local staff (or as many local staff) in every area where they lend.

The systematic assessment of borrower risks should also enable MFIs to seek lower cost capital and to securitize their portfolios on better terms, as investors tend to reward greater information on investment risk.

In addition, systematic assessment of borrowers could also open up the traditional group-lending MFIs to offer higher-value loans to individuals who are identified as lower risk and higher capacity.

7.1.3 Challenges in Score Development

The challenges for the MFIs in India have stemmed from issues of data quality, data collection, IT systems, and so forth. There is evidence that data quality may prove a hurdle to score development. The initial score developed for Grameen Koota had a low K-S score. We worked with them to obtain newer data that was captured following data quality/quantity improvements (both internally and with the credit bureau) to develop a model with improved performance.

Initial score development activities with SKS identified what appeared to be significant data quality challenges. K-S scores for models developed for SKS were low, lower than those initially developed for Grameen Koota. PERC requested additional data elements from SKS, hoping to improve model performance. These additional fields yielded little benefit. PERC retained the services of two veteran credit score modelers—one of whom was an early FICO employee and has built hundreds of models around the world, the other of whom is a top-tier risk modeler with a large software firm—and the enhanced team was still stymied by the SKS data. Ultimately, it was concluded that any model built on data would likely be weak at best.

SKS, in response to their desire to move to more data-driven processes, is working on upgrading their IT systems to improve their data quality moving forward. They are doing this with an express interest in using credit report data, in-house data, and credit scores for extending loans to individuals and/or to reduce group lending costs. The lessons they learned through their participation in our research and their own internal data analysis no doubt is resulting in changes to business practices and a long-term commitment to credit reporting, credit reports, credit scores, and more data-driven solutions.

SKS also reported data matching issues they have encountered with credit bureau data. Data quality issues at the bureaus, of course, can be driven by data furnishers (MFI data) or internal processes. In addition, many bureau records lacked sufficient data and historic depth to produce robustly predictive variables. This, however, will decline as an issue over time as the credit bureaus continue to collect data.

None of this may be problematic for MFIs that do not intend to extend credit to individuals in a data-driven manner. However, it presents a challenge to other MFIs that are intending to make loans in such a manner. That said, it seems like a normal development path that data collection and quality efforts would improve at the same time that lenders move to more data-driven processes. Each drives and enables the other.

7.2 Mexican MFI Participants

We engaged Mexico immediately upon the launch of this research in July/August 2011. We signed agreements with Buró de Crédito in late 2011 to assist in sector tracking, providing a microfinance scoring solution and a customizable, automated decisioning system to MFI participants. Since the engagement was pro bono, timeframes would be subject to adjustment and research requests would be subordinate to any income-generating activities. Subsequent three-party contracts (comprising the MFI, Buró de Crédito, and PERC) would take longer, given MFI concerns and CNBV review.

We identified potential MFI participants working with microfinance associations, Buró de Crédito, regulators, and local experts. We had identified and recruited four MFIs initially: Caja De Ahorros Tepeyac, Cooperativa ACREIMEX, Cooperativa Yolomecatl SC de RL de AP de CV, and Crediconfia. (Crediconfia withdrew mid-point, in the fall of 2012.) Late in the fall of 2012, we held our first training session with the remaining three MFIs.

In early 2013, and in response to discussions held with them about our experiment, PERC was notified by CNBV that their guidelines require a 100 percent reserve for all loans made without a credit report check and/or for loans that are required to be rejected by CNBV knockout rules. While the methodology for the RCT insures that all loans have been checked against credit bureau information before dissemination, some loans made through the manual channel may violate CNBV "knockout" rules. PERC estimated that the cost is approximately $20,000-$30,000 per MFI. Participating MFIs requested much more—in some cases reserve amounts in excess of $450,000.

PERC offered to provide the funds to serve as reserve until the loans reached maturity. As noted in the interim report, the size of the commitment necessitated a reduction of the participating MFIs from three to two: Caja De Ahorros Tepeyac and Cooperativa ACREIMEX. Further, loan value had to be dramatically reduced to accommodate budgetary constraints. Unfortunately, by restricting the loan value to lower levels, and reducing the number of participating MFIs, new challenges emerged that dramatically delayed completion of the RCT in Mexico.

Specifically, generating a robust sample of lower-value loans required substantially more time given the few participants and the modest level of qualifying loans underwritten by the two remaining participants. Owing to the significant extension of the timeframe necessary to obtain the loan sample, other issues arose that further challenged the study. Turnover among the technical staff—both IT and on the risk team—as well as changes among the senior management resulted in further delays. Buró de Crédito needed to be retained to train new technical staff at both MFIs on multiple occasions during the life cycle of this project, and PERC staff had to reintroduce and promote the project to new senior management at both MFIs as well. This "start-and-stop" process, with some lengthy interruptions, massively impeded progress.

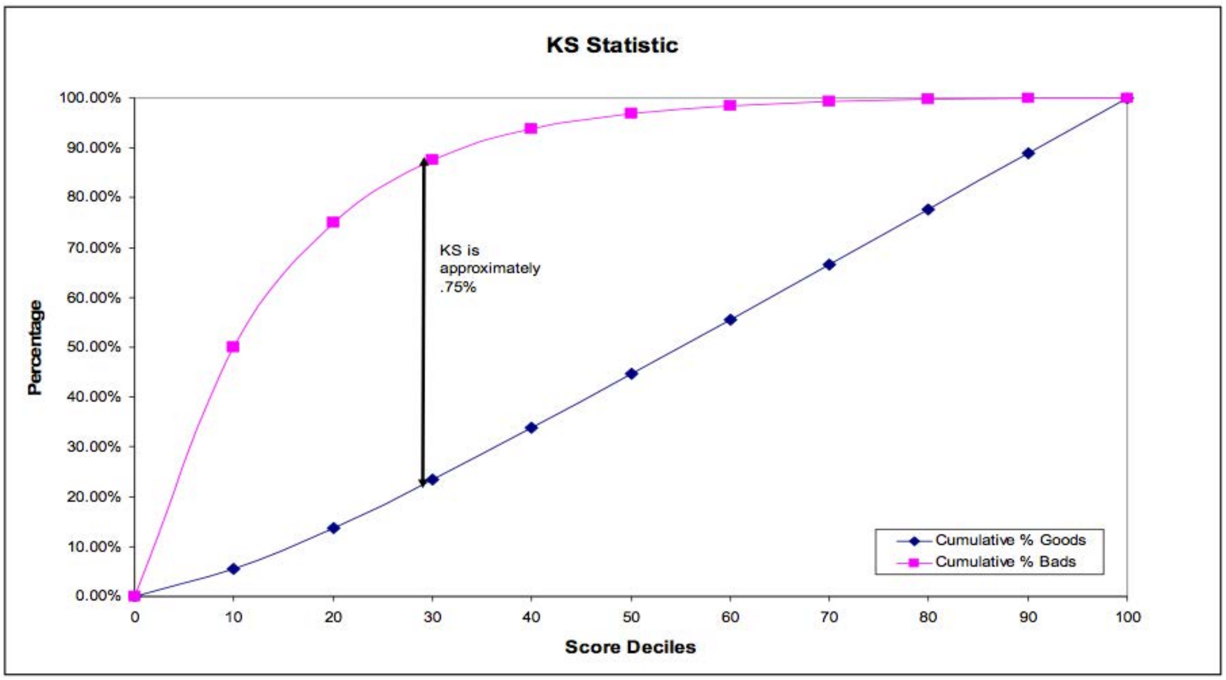
For the research in Mexico, we used for the scoring channel a generic credit score developed by Buró de Crédito. The credit score has been validated for microfinance, as well as for bank lending. The score was developed on data from the files of 17 million consumers with 75 million accounts. The performance period of the score was from 2000 to 2006 with an observation period of one year (12 months), 2006 to 2007. As with other generic scores and in keeping with CNBV definitions for both bank loans and microfinance loans, the score uses a 90+ day past due as the definition of "bad." "Bads," accounts with 90+ days past due, account for 21.3 percent of all accounts in the sample.

The score has the following performance metrics:

- Kolmogorov-Smirnoff statistic: 0.75

- Gini coefficient: 0.83
- Information value: 4.88

Figure 3. KS Score for Buró de Crédito's Buro Credit Score



This credit score was validated for microfinance accounts, defined as accounts from MFIs, Sofomes, Cooperatives, Sofoles, and Cajas de Ahorro, accounts of institutions that fall under CNBV microfinance regulations.

In addition to scores, we used a decisioning engine that uses credit bureau services—identity verification, fraud detection, and compliance procedures (CNBV "knockout" rules)—called eValua. eValua also encodes lender policies for assessing repayment capacity and other credit risk procedures.

7.2.1 Caja Tepeyac

Caja Tepeyac is a Cooperative Savings and Loan institution founded in 1960 based in the city of Guadalajara. The hallmark of the institution has been transparency, robustness, and security. All savings of members are fully secured.

Caja Tepeyac mainly operates in the two states of Jalisco and Zacatecas in central Mexico. It specializes in individual loans and largely services cities and towns. The average loan size is $220, and the loan duration varies from twelve to eighteen months. Apart from entrepreneurial loans for micro business, there are also personal loans offered by Caja Tepayac.

Caja Tepeyac plays an important part in social banking. They provide effective instruments for the development of individuals, families, and the community. They encourage a cooperative attitude through a system of credit unions. Apart from providing micro loans, Caja Tepeyac engages in a lot of social activities to provide the borrowers with a better life. They provide scholarships for young borrowers and life insurance for other borrowers.

In cases of the death of a borrower, funds are provided for covering funeral expenses. Also, the capacity for sending money both within Mexico and outside is an important service. Members of Caja Tepeyac are also eligible to receive discounts at certain hospitals.

Apart from microcredit to its borrowers, automatic credit is offered to members who have savings with Caja Tepeyac. Automatic credit is given to its members equivalent to 90 percent of total savings at 12 percent fixed annual interest rate and 1 percent monthly fixed rate. The loan tenure can be up to 48 months for such borrowers. For members who seek loan amounts equivalent to double their savings, they are charged a 1.5 percent fixed interest rate monthly and 18 percent fixed annual interest rate. The term of loan is usually 24 months in this case.

For borrowers seeking four times the value of their savings with Caja Tepeyac, the loan tenure is 36 months and with a 2 percent fixed interest rate monthly and 24 percent fixed rate annually. However, failure to pay will generate additional fees and default interest payments. In addition, it will affect the member's credit history.

Risk assessment costs for loans with and without credit reports are largely similar (minus the cost of the report itself), in part because other information costs, such as a collections check, are also conducted. However, as the reserve cost of applicants without a credit report is high, Caja Tepeyac provides very few loans for those without a credit report. In addition to pulling credit reports, a socio-demographic assessment is conducted on all applicants. A number of social and demographic indicators are considered, including:

- Family size
- Household's cooking fuel
- Household's ownership of a television
- Household's ownership of transport (e.g. bicycle, car, motorcycle)
- No. of people in the household

- Principal occupation of the head of the household
- Roof material
- Status of residential structure (e.g. number of rooms)

The risk assessment costs breakdown is shown in the following table. Given today's exchange rate, in US dollars the average cost of underwriting a loan for Caja Tepeyac is just over $16. Total cost for credit reports from each of the two main credit bureaus are about $1.66, or approximately 10 percent of the total loan underwriting cost. The manual component in Caja Tepeyac's loan underwriting process costs around $3 (55 pesos).

Table 8. Caja Tepeyac Underwriting Costs (in Mexican Pesos)

Cost per loan, CAJA TEPEYAC	**Pesos**
Public record investigation	95.00
Legal collection	20.65
Collection messaging	6.00
Messaging, home visit, interview neighbors, application data verification	55.00
Judicial bulletin	0.65
Credit report Buró de Crédito	19.50
Credit report Círculo de Crédito	12.00
Printer rent	30.00
Credit committee	59.31
Other	7.75
TOTAL	305.85

Presently, Caja Tepeyac and Acreimex (and all lenders) are required to review credit reports, but not use them in any scoring model. Neither do. During the course of our discussions with both risk managers and senior executives, we discovered that there is a very low level of trust in both credit bureau data and automated underwriting platforms. The prevailing belief among MFI executives and risk managers is that the two major credit bureaus underserve the MFI market, and the data in credit reports for most MFI loan applicants is thin and inaccurate and therefore of limited value.[2] Consequently, MFIs remain biased toward manual underwriting processes as opposed to using automated processes such as eValua.

7.2.1.1 Caja Tepeyac Lending Outcomes

Two groups of lending experiments were carried out with Caja Tepeyac. The first sample captured lending decisions from manual-only approaches (that did not take into account credit bureau data), while the second sample did not use a manual-only approach. Both samples included decisions produced by the current/actual approach and the automated processes of Buró de Crédito's eValua. In addition, a bureau credit score (Buró de Crédito's credit score) was produced for both samples. For illustrative purposes we assumed a credit score decision based on a credit score cutoff of 620, which produces an acceptance rate of between one-half to two-thirds for Caja Tepeyac and Cooperativa Acreimex. An important note regarding the loan outcomes shown for Caja Tepeyac in the following tables is that loans were extended only to borrowers who would have been approved by the actual/current channel. The definition of a non-performing loan for the Caja Tepeyac's loans is "loan default" as defined by Caja Tepeyac.

Table 9. Lending Outcomes (Sample 1)

		Manual	**Actual**	**eValua**	**Credit score (≥620)**
(0)	Total	121	121	121	121
(1)	-Accept	113	99	1	59
(2)	--Disbursed	94	99	1	56
(3)	---Perform	56	57	1	40
(4)	---Not perform	38	42	0	16
(5)	--Not disbursed	19	0	0	3
(6)	-Reject	8	22	120	62
(7)	--Disbursed	5	0	98	43
(8)	---Perform	1	0	56	17
(9)	---Not perform	4	0	42	26
(10)	--Not disbursed	3	22	22	19
(11)	NPL rate, (4)/(2)	40%	42%	0%	29%
(12)	Acceptance rate, (1)/(0)	93%	82%	1%	49%

One thing that stands out in table 9 is the very high default rate. The differences between the Manual and Actual channels are of little practical importance; both have high acceptance and default rates. On the other hand, results from the eValua are radically different. This could be interpreted as eValua having cutoffs far too conservative for a lender looking to lend to higher-risk consumers, or it could be seen as an application set to accept moderate- and low-risk consumers. Here, only a single application is accepted, and it performs. On the other hand, setting a 620 credit score cutoff on the Buró de Crédito credit score produces a moderate acceptance rate of around half of applicants and a default rate noticeably lower than the Manual or Actual/Current channel.

Table 10. Lending Outcomes (Sample 2)

		Manual	**Actual**	**eValua**	**Credit score (≥620)**
(0)	Total	NA	200	200	200
(1)	-Accept	NA	152	6	108
(2)	--Disbursed	NA	152	6	95
(3)	---Perform	NA	92	6	66
(4)	---Not perform	NA	60	0	29
(5)	--Not disbursed	NA	0	0	13
(6)	-Reject	NA	48	194	92
(7)	--Disbursed	NA	0	146	57
(8)	---Perform	NA	0	86	26
(9)	---Not perform	NA	0	60	31
(10)	--Not disbursed	NA	0	48	35
(11)	NPL rate, (4)/(2)	NA	39%	0%	31%
(12)	Acceptance rate, (1)/(0)	NA	76%	3%	54%

Table 10 includes loan outcome data on an additional 200 applications. Again, the Actual channel has the highest acceptance rate and default rate. eValua accepts 3 percent of applications, but they all perform. And the credit score cutoff of 620 accepts fewer borrowers than the Actual channel and has a lower non-performing loan (NPL) rate.

Table 11. Lending Outcomes (Samples 1 and 2)

		Manual	**Actual**	**eValua**	**Credit score (≥620)**
(0)	Total	121	321	321	321
(1)	-Accept	113	251	7	167
(2)	--Disbursed	94	251	7	151
(3)	---Perform	56	149	7	106
(4)	---Not perform	38	102	0	45
(5)	--Not disbursed	19	0	0	16
(6)	-Reject	8	70	314	154
(7)	--Disbursed	5	0	244	100
(8)	---Perform	1	0	142	43
(9)	---Not perform	4	0	102	57
(10)	--Not disbursed	3	22	70	54
(11)	NPL rate, (4)/(2)	40%	41%	0%	30%
(12)	Acceptance rate, (1)/(0)	93%	78%	2%	52%

Table 11 combines the samples, again showing that the Manual channel that uses no credit bureau data accepts the most applicants but has the highest NPL rate. Then the Actual/Current channel (which includes both internal lender data and some credit bureau data) accepts fewer applicants but has a relatively high NPL rate. Then using only credit bureau data and setting a credit score at 620 produces a lower acceptance rate of 52 percent with a lower NPL rate. Finally, the eValua automated solution (using both credit bureau data and internal guideline), accepted only 2 percent of applicants (seven applicants) with no non-performing loans.

Table 12. NPL Rate by BC Credit Score Quintile

Top 20%	26%
Second 20%	23%
Middle 20%	38%
Fourth 20%	60%
Bottom 20%	61%

To delve deeper into the ability of credit bureau data to distinguish between applicants that will or will not produce performing loans, we look at the NPL rate by credit score quintile. These results are shown above in table 12. Clearly the top 20 or 40 percent of applicants as ranked by credit score have a much lower default rate than the 20 or 40 percent applicants with the lowest credit scores.

To better illustrate this point, table 13 shows the tradeoff between the acceptance rate and the total portfolio NPL rate. For instance, if the top 40 percent of applicants (as ranked by credit score) were accepted, the total portfolio acceptance rate would have been 24 percent. Or if 100 percent of applicants were accepted, the total portfolio acceptance rate would be 42 percent.

Table 13. Tradeoff between Accept Rate and Total Portfolio NPL Rate (using BC Credit Score)

Accept	NPL
20%	26%
40%	24%
60%	29%
80%	37%
100%	42%

Tables 9 through 13 demonstrate that credit bureau data is predictive of MFI loan risk. Tables 12 and 13 demonstrate that credit scores based on credit bureau data could be used in risk-based pricing, which could expand lending and make it fairer to lower-risk borrowers. The results for eValua provide a possible indication that credit bureau data could be used to identify low-risk applicants among an otherwise high-risk pool.

7.2.1.2 Cost Reductions

Beyond the use of credit reporting data to enable risk-based pricing and reduce the number of lending mistakes (delinquencies/defaults), the use of credit bureau data, credit scoring, and automated underwriting can be used to reduce lending/origination costs. As we shall discuss in more detail below, this is a mistake that could be costing MFIs revenue, earnings, and growth. By simply implementing a step-wise underwriting process that first assesses the depth of credit report data and whether a good score is generated, better and less expensive lending decisions can be made. Only if an applicant is a thin-file or no-file (meaning that the credit reports from the two bureaus have insufficient information to generate a score) should the MFI invest in the manual component of their underwriting process.

By saving US$3 per loan on even just 20 percent of all loans granted, not to mention the accrued from a reduced default rate and a larger portfolio from extending more loans, a typical Mexican MFI's margins could improve dramatically. This reduction in fixed costs would have the greatest impacts in the smallest loans, those potentially going to the lowest-income borrowers.

7.2.2 Cooperativa Acreimex

Cooperative Acreimex is a credit union headquartered in the city of Oaxaca, operating largely in the state of Oaxaca. It was established in 2001. Membership is open to all. Cooperative Acreimex was founded by three former employees of Caisses Populaires Credit Union. It provides a number of different credit products including mortgages, microcredit, commercial loan, auto loans, and general consumer loans. Its mission is to provide needed financial services efficiently and with a human touch. They also strive to promote a culture of savings and responsible use of credit among their members, with a focus on social and economic development.[3]

Cooperative Acreimex's underwriting process is a combination of manual and automated with the use of credit reports. The process consists of five major stages:

1. Promotion/acquisition/application
2. File/data integration
3. Evaluation/decisions
4. Granting
5. Monitoring

In the evaluation stage, credit reports (from Buró de Crédito or Círculo de Crédito) are used to help assess risk. Additionally, a credit-scoring tool is utilized, as well as home visits and socio-economic data. The scoring tool is not statistically validated but it is a judgmental scorecard, based on Acreimex's experience.

Credit reports are used in the screening process to assess risk. The credit reports are reviewed at the beginning of the evaluation stage to determine borrower credit standing. Although returning borrowers undergo the same underwriting procedures (as mandated by the CNBV if the same reserve requirements are to hold), those with a very good history are offered preferential interest rates. The applicants' age and gender also enter into the decision process in so far as they are in the credit-scoring model. The overall annual loan acceptance rate is 24 percent. Cooperative Acreimex currently has about 64,000 borrowers, and acquires about 1,000 new borrowers a month. Its default rate on its total portfolio of loans is about 7 percent.

The average loan amount is 20,000 Mexican Pesos ($1,060 USD), with the average loan term being about two years. Loan payments are typically made every two weeks. The terms of loan (pricing) are fixed, that is, risk-based pricing is not utilized (other than the preferential interest rate); the guarantees required (collateral), however, are dependent on the amount requested and the specific type of credit.

Risk-assessment costs for applicants with credit reports are considerably different than for applicants without credit reports. A socio-demographic assessment is conducted on applicants without credit reports, whereas for those with credit reports, risk assessment consists largely of a credit bureau check and credit report review. The cost of assessing risk on those who are not in the credit bureau is 171.87 pesos on average.

Tables 14 and 15. Acreimex Risk Assessment Costs (Integration and Evaluation)

Integration

Components	Units	Average	Cost in Pesos
Time	Minutes	55.00	11.00
Daily Transport	Pesos	83.33	83.33
Communication	Calls	3.67	3.96
Personnel	Individuals	2.00	48.00
			TOTAL: 146.29

Evaluation

Components	Units	Average	Cost in Pesos
Time	Minutes	241.33	48.27
Daily Transport	Pesos	0.00	0.00
Communication	Calls	3.33	3.60
Personnel	Individuals	5.00	120.00
			TOTAL: 171.87

The source of the costs stem from the need to conduct an on-site assessment that gathers socio-economic indicators such as:

- Family size
- Household's ownership of a television, refrigerator, and other appliances
- Household's ownership of transport (e.g. bicycle, car, motorcycle)
- Number of people in the household
- Principal occupation of the head of the household
- Roofing material
- Status of residential structure (e.g. number of rooms)

7.2.3 Challenges in Implementation of RCT at MFI Level

The implementation of the RCT, given that we would test not only a score but also a credit bureau data-based decisioning system, took the form of the following modification.

Step 1: When an applicant comes to apply for a loan, check to see if they have a credit report.

- If yes, proceed to step 2. (Do not examine report.)
- If no, process outside of study.

Step 2: Record date and time. Pull card (or randomization program) to see which channel to allocate borrower.

(If there are no more cards, no options presented on computer, or if loan quota has been completed, end the trial.)

Step 3: Begin underwriting process depending on method.

If manual, once a decision has been made:

1. Record time
2. Reprocess through BC Score
   - Do NOT alter decision
   - Record BC Score results
3. Reprocess through eValua
   - Do NOT alter decision
   - Record eValua results

If manual plus credit report, once a decision has been made:

1. Record time
2. Reprocess through BC Score (for benchmarking)
   - Do NOT alter decision
   - Record BC Score results
3. Reprocess through eValua
   - Do NOT alter decision
   - Record eValua results

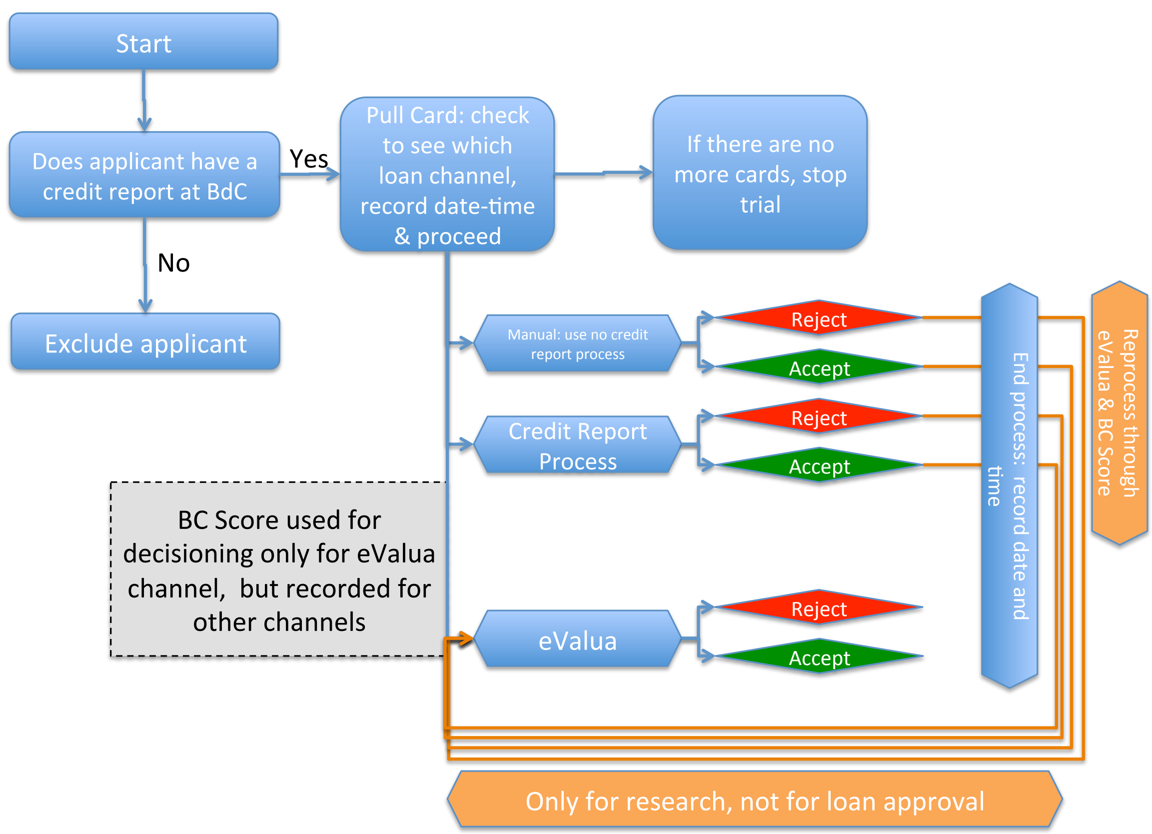
If through eValua, once a decision has been made:

1. Record time

2. Reprocess through Manual
   - Do NOT alter decision
   - Record results

The following graphic illustrates the process:

Figure 4: Modified Randomization of Two Treatments and Control for Mexico



In implementing an RCT, in addition to regulatory challenges, there were operational challenges stemming from the MFIs and to some extent credit bureaus. In Mexico, the challenges stemmed from MFI capacity with respect to understanding and using credit reports. One of the objectives of this research was to run the experiment on different-sized MFIs with different levels of experience and/or literacy with credit reports. As noted above, MFIs in Mexico are the smaller (tier 2 MFIs) ones engaged. The point of varying MFIs by size and capacity was to offer an assessment of the ability of different MFIs to engage in credit reporting and the use of credit reports and value-added services.

We engaged both Mexican MFIs in a number of training sessions. We approached these sessions with an initial understanding that the MFIs would be trained on RCT procedures and on the use of eValua. In the course of engaging both MFIs, we found an additional need to train the MFIs on the use of credit scores and even credit reports.

We held several full-day sessions on the training of the MFIs, focusing on credit scores, eValua and, for Tepeyac, the use of credit reports beyond CNBV requirements and internal bank knockout rules. The training sessions for Tepeyac in Guadalajara consisted of between 8 and 13 loan officers and the CEO. The training sessions for Acreimex included 4-5 risk managers. These training sessions were repeated three times for both participating MFIs owing to the need to extend the life cycle of this project.

Training sessions were held for both MFIs during the following periods:

- November 2012
- July 2013
- February-March 2014
- December 2014
- June 2015
- September 2016
- November 2016

Retraining was necessary due to staff and management turnover and delays in implementation. For a variety of reasons, this was a frequent occurrence at the two MFIs we worked with in Mexico. While the churn was relatively higher among technical staff, several CEOs came and went during the course of our analysis. This required that PERC introduce the study to a number of different senior management teams at the same MFI. With technical staff, the issue was further complicated by the necessity of securing cooperation from Buró de Crédito to train and retrain MFI staff on eValua—their MFI scoring solution that we used for our RCT. Getting the MFIs comfortable with the details of the lending experiments has also been a challenge.

7.2.3.1 Acreimex Lending Outcomes

Three groups of lending experiments were carried out with Acreimex. One sample (sample 3) captured lending decisions from a manual-only approach (that did not take into account credit bureau data), while the other two did not. All samples included decisions produced by the current/actual approach and the automated processes of Buró de Crédito's eValua. In addition, a bureau credit score (Buró de Crédito's credit score) was produced for all samples. For illustrative purposes, we assumed a credit score decision based on a credit score cutoff of 620, which produces an acceptance rate of between one-half to two-thirds for Caja Tepeyac and Cooperativa Acreimex. Unlike the case with Caja Tepeyac, loans were extended to applicants in a number of cases whether or not the applicant would have been approved by the current underwriting approach in place at Acreimex. The definition of a non-performing loan for the Acreimex's loans is whether the borrower was late in a payment (delinquent). This was used due to the small number of actual defaults.

Table 16: Lending Outcomes (Sample 1)

		Actual	**eValua**	**Credit score (≥620)**
(0)	Total	36	36	36
(1)	-Accept	35	13	24
(2)	--Disbursed	35	13	24
(3)	---Perform	28	10	20
(4)	---Not perform	7	3	4
(5)	--Not disbursed	0	0	0
(6)	-Reject	1	23	12
(7)	--Disbursed	1	23	12
(8)	---Perform	1	19	9
(9)	---Not perform	0	4	3
(10)	--Not disbursed	0	0	0
(11)	NPL rate, (4)/(2)	20.0%	23.1%	16.7%
(12)	Acceptance rate, (1)/(0)	97%	36%	67%

Table 17: Lending Outcomes (Sample 2)

		eValua	Actual	Credit score (≥620)
(0)	Total	32	32	32
(1)	-Accept	27	30	32
(2)	--Disbursed	27	26	27
(3)	---Perform	26	25	26
(4)	---Not perform	1	1	1
(5)	--Not disbursed	0	4	5
(6)	-Reject	5	2	0
(7)	--Disbursed	0	1	0
(8)	---Perform	0	1	0
(9)	---Not perform	0	0	0
(10)	--Not disbursed	5	1	0
(11)	NPL rate, (4)/(2)	3.7%	3.8%	3.7%
(12)	Acceptance rate, (1)/(0)	84%	94%	100%

Tables 16 and 17 show little difference between the NPL rate among loan decisions by eValua and those made by the current Acreimex method (Actual). This said, eValua has a lower acceptance rate.

Table 18: Lending Outcomes (Sample 3)

		Manual	Actual	eValua	Credit score (≥620)
(0)	Total	131	131	131	131
(1)	-Accept	130	35	12	74
(2)	--Disbursed	130	35	12	74
(3)	---Perform	114	33	12	74
(4)	---Not perform	16	2	0	0
(5)	--Not disbursed	0	0	0	0
(6)	-Reject	1	96	119	57
(7)	--Disbursed	1	96	119	57
(8)	---Perform	1	82	103	41
(9)	---Not perform	0	14	16	16
(10)	--Not disbursed	0	0	0	0
(11)	NPL rate, (4)/(2)	12%	6%	0%	0%
(12)	Acceptance rate, (1)/(0)	99%	27%	9%	56%

Table 18 shows results from the sample that includes the manual channel. This is probably the most important set of results from the Mexico loans, since it represents a relatively large sample with manual approach (no credit bureau data) and includes loan outcomes from loans that were not approved via the actual Arceimex process. This represents a clean comparison across multiple channels.

In this sample we see that manual underwriting (with no credit bureau data) accepts the most applicants (99 percent) but has the highest delinquency rate (12 percent). Next, the actual process (using some credit bureau data) accepts significantly fewer applicants (27 percent) but has a much lower delinquency rate (6 percent). The third approach, eValua (using credit bureau data), produces a portfolio with a very low delinquency rate (0 percent) and the lowest acceptance rate (9 percent). Interestingly, the bureau credit score cutoff produces a relatively large acceptance rate (56 percent) along with a very low delinquency rate (0 percent).

As with Caja Tepeyac, it may be the case that eValua was set to be conservative. This is not surprising since this tool was not native to either MFI, was implemented for the experiment, and as such did not go through the usual process adjustments that lending tools go through in actual implementation. On the other hand, the cutoff of 620 was chosen by taking into account the data from the two MFIs. Since eValua uses more data than the credit score and can take into account lending guidelines, a properly adjusted process using eValua (or a similar underwriting system) should be able to outperform decisions based only on a credit score cutoff.

Table 19: Combined Lending Outcomes (Samples 1, 2, and 3)

		Manual	Actual	EV	Credit score (≥620)
(0)	Total	131	199	199	199
(1)	-Accept	130	100	52	130
(2)	--Disbursed	130	96	52	125
(3)	---Perform	114	86	48	120
(4)	---Not perform	16	10	4	5
(5)	--Not disbursed	0	4	0	5
(6)	-Reject	1	99	147	69
(7)	--Disbursed	1	98	142	69
(8)	---Perform	1	84	122	50
(9)	---Not perform	0	14	20	19
(10)	--Not disbursed	0	1	5	0
(11)	NPL rate, (4)/(2)	12%	10%	8%	4%
(12)	Acceptance rate, (1)/(0)	99%	50%	26%	65%

Table 19 adds the samples together. This again shows that the NPL and acceptance rates are highest for manual approaches, followed by the actual approach, and followed by eValua. But, as before, the credit score cutoff has a relatively high acceptance rate (65 percent) and the lowest NPL rate (4 percent). As such, the credit decisions using the credit score cutoff outperforms the *actual* underwriting process in the sample examined. The score cutoff of 620 produces a greater acceptance rate and a lower NPL rate compared to the actual underwriting method.

To drill down on the credit score cutoff, the last column in table 19 is supplemented with two additional columns, one using a lower credit score cutoff point and one using a higher cutoff point.

Table 20: Use of Various Credit Score Cutoffs

		Credit score (≥600)	**Credit score (≥620)**	**Credit score (≥640)**
(0)	Total	199	199	199
(1)	-Accept	153	130	121
(2)	--Disbursed	148	125	116
(3)	---Perform	138	120	111
(4)	---Not perform	10	5	5
(5)	--Not disbursed	5	5	5
(6)	-Reject	46	69	78
(7)	--Disbursed	46	69	78
(8)	---Perform	32	50	59
(9)	---Not perform	14	19	19
(10)	--Not disbursed	0	0	0
(11)	NPL rate, (4)/(2)	7%	4%	4%
(12)	Acceptance rate, (1)/(0)	77%	65%	61%

Table 20 clearly shows the tradeoff between acceptance and NPL that can be possible with different cutoff points. All of these cutoffs outperform the actual underwriting method seen in the previous table (table 19).

The next table shows that the NPL rate among the first three quintiles are in the single digits, while the fourth quintile has a 15 percent rate and the lowest quintile has a 33 percent NPL rate.

Table 21. NPL Rate by BC Credit Score Quintile

Top 20%	8%
Second 20%	5%
Middle 20%	0%
Fourth 20%	15%
Bottom 20%	33%

Finally, table 22 shows that, for instance, accepting applicants with the top 60 percent of bureau credit scores would result in a total portfolio NPL rate of 4 percent, while accepting 80 percent of applicants would produce a 7 percent NPL rate.

Table 22. Tradeoff between Accept Rate and Total Portfolio NPL Rate (BC Credit Score)

Accept	NPL
20%	8%
40%	7%
60%	4%
80%	7%
100%	13%

7.2.3.2 Cost Reductions

As was shown in tables 14 and 15, not using data and relying on manual, high-touch, on-site assessments can be costly. For Acreimex, collecting data on applicants costs 171.87 Mexican Pesos, or about US$9. For smaller loans, of say 3,000 or 5,000 pesos, this could represent a relatively large cost. For a 3,000-pesos loan, for instance, a cost of 171.87 represents over 5 percent of the loan. Given the typical interest rate of 21 percent, this could translate to a large shift in margins or costs for borrowers of these loans. This demonstrates the magnitude of costs/margin shifts from moving from a manual high-touch lending approach to a data-driven one.

7.3 Efforts to Engage Bolivian MFIs

We engaged Bolivia in March of 2012. Identification of a third case was difficult. We needed to identify an economy in which credit reporting in the microfinance sector was established less than eight years ago but more than three years ago. (This definition of a “medium run” may seem arbitrary, but a survey of credit reporting in microfinance in a few economies seems to suggest that three years may be needed to develop stable institutional practices of use, reporting, and the introduction of some value-added services.)

Initially, we were slated to work in Egypt and use that experience as our third case. Our efforts were overwhelmed by global politics, as in December of 2010 the Arab Spring began in Tunisia and thereafter spread into other countries, including Egypt. As a fallback plan, we identified Pakistan and secured approval to use it as our middle case country. We lined up interviews and scheduled meetings with the varying stakeholders in order to secure participation, but here too, it was not meant to be. On May 2, 2011, the US Navy conducted a raid on Osama Bin Laden’s compound. This exercise made things suddenly unsafe for Americans on the ground in Pakistan, which was already on the U.S. State Department’s list warning against all non-essential travel to the country.

At that point, we vetted several potential options with our funders and determined that the best among the remaining strong middle cases was Bolivia. In just a decade, microfinance had gone from a peripheral activity to a robust and thriving industry in Bolivia. Many attributed the growth and success of MFIs in Bolivia to the emergence of an organically grown and developed MFI credit bureau. This seemed an excellent case to highlight the potential relationship between credit reporting, the use of credit reports and scores, and MFI performance, as well as the capacity of MFIs to undertake these activities.

After securing agreements to participate from the MFI credit bureau (Infocred) and two MFI trade associations, we reached out to the national regulator to explain our intentions and describe the project in detail. We were initially informed by the regulator Autoridad de Supervisión del Sistema Financiero (ASFI) that we would only be able to work with the unregulated microfinance sector. Regulated MFIs were required to conduct a credit bureau check. Five months into our engagement, ASFI indicated that it would move to regulate all microfinance institutions, though the pace would be staggered. MFIs that became interested in participating in the study in exchange for a custom score were the larger ones, which in turn were on the fast track for regulation.

By the third quarter of 2013, we approached Peruvian MFIs and came to an agreement with the credit bureau Equifax in Peru. We also consulted legal experts in Bolivia to assess the legality of a workaround provision of 100 percent of any loan that did not conform to the knockout rules. (The provisioning would allow the study to conform to the law.) We worked for six months recruiting MFIs in Peru, but despite our best efforts, all interested MFIs declined, citing regulatory complications and compliance issues given the proposed RCT methodology.

7.4 Summary of Results of MFI Underwriting Research

The results from our analysis strongly suggest that:

- MFIs can reduce origination costs by relying exclusively on credit scores for lower-risk borrowers and a combination of credit scores and manual for middle-tier and higher-risk borrowers;
- Credit bureau data and credit scoring models are able to differentiate higher-risk (“bads”) from lower-risk (“goods”) borrowers even among the poor and very poor, both individually and among group-guaranteed loans;
- By using credit scores for underwriting, MFIs can improve loan portfolio performance—and thereby margins—for any given target default rate;
- In general, older credit bureaus tend to have deeper (older) and richer (more diverse) data. MFIs are likely to have more success using credit bureau data and scoring models as credit bureaus mature and credit bureau and MFI data become richer and higher

quality;

- Capacity is a clear issue with tier 2 (and highly probable tier 3) MFIs. High turnover among technical staff and senior management impedes the adoption of automated underwriting solutions and makes sustaining the commitment difficult; and
- The primary challenge to the uptake of automated underwriting solutions within the MFI community, even among tier 1 MFIs with sufficient capacity to employ them, is one of belief. Sentiments about the business value of credit reports and credit scores are largely mixed, with many MFI executives believing they are better off relying on the art of manual underwriting versus the science of automated underwriting.

Notes for MFIs and Results

[1] We came to learn from outreach with MFIs in Mexico that skepticism about the value of using credit reports and credit scores is pervasive among the MFI community. Based upon our experience in India and Mexico, only a few tier 1 and tier 2 MFIs credit report and use credit reports and scores, or are willing to consider doing so. Bolivia stands in stark contrast, and represents a case in which a broad and reflective swath of MFIs saw great value in credit information sharing and invested to build a credit bureau and erect a national credit information sharing architecture. Unfortunately, we were unable to include the Bolivian case in our analysis largely, if not exclusively, owing to obstructionism on the part of the Bolivian government.

[2] While these beliefs are held by risk managers and senior executives at the two MFIs that participated in our study, it is by no means limited to these two. In fact, PERC staff had occasion to meet with dozens of risk managers and executives from a wide range of MFIs and MFI trade associations, and skepticism about the value of automated underwriting was nearly universal, as was the general low regard with which they held both major national credit bureaus. When asked by PERC staff, very few MFI executives expressed a desire to transition to automated underwriting in the near- to medium-term. PERC interviews and discussions with various MFI employees. April 2012 – November 2016. Conducted by Robin Varghese, Patrick Walker, Michael Turner, and Hayde Navarro.

[3] From the stated mission and vision on http://www.acreimex.com.mx.

8 Conclusions

This extensive, multi-year, multi-country research project has generated net benefits for participants and supporters alike. First, the research yielded valuable insights into MFI impacts from credit reporting, credit report use, and credit scores. These insights pertain both to firm-level operations and loan portfolios (accept/reject rates, risk management, and overall performance). Second, we learned lessons about designing experiments in this space that should improve their quality in the future (see Appendix A). And third, business practices of several participating MFIs (SKS, Acreimex, and Caja Tepeyac) were either modified as a direct result of participation in this project, or said MFIs provided corroborating evidence for plans to modify business practices.

The value of this project extends beyond these direct effects. Findings from this report can be used as compelling evidence to exhort MFIs around the world to begin systematically collecting internal data and integrating credit reports and credit scores into their origination processes. While participating in this project, one of the world's largest MFIs (SKS in India) had committed to upgrading their IT systems in order to improve data integrity and to better utilize such data and automated underwriting solutions. Should other tier 1 MFIs respond similarly, this could have a dramatic impact on financial inclusion, as growth in lending to the private sector will result from a broader uptake of these risk analyses.

The key findings from this analysis corroborate earlier research on the relationship between credit reporting, the use of credit bureau data and credit scores in underwriting, and MFI performance. As with previous studies, we found that by using credit bureau data and credit bureau credit scores, MFIs can safely extend credit to individuals. Credit scorecards developed for MFIs participating in this study demonstrated an ability to differentiate between high-risk and low-risk individuals. In so doing, the use of credit bureau data and credit bureau credit scores by MFIs could significantly decrease origination costs. In the cases examined, participating MFIs could reduce costs by as much as 20 percent on many of their loans by greater reliance on credit scores and data-driven processes. These reduced costs in the "fixed" manual costs would impact lower-value lending the most, meaning it should be the poorest borrowers who would most benefit from movement to more efficient data-driven processes. In addition, the lender could save from a lower default rate and would increase margins through increased lending. Greater use of data-driven processes may also reduce capital cost/securitization terms as investors reward objective data on investment risks. And finally, a move to data-driven processes would drive down the cost of acquiring new applicants and reaching new borrowers if lenders do not need to set up local staff (or as many local staff) in every area where they lend. And systematic assessment of borrowers via data could also open up the traditional group lending MFIs (such as in India) to offer higher-value loans to individuals in groups who are identified as lower risk and higher capacity.

This could allow individual borrowers in need of greater capital for productive investment to efficiently access it.

Results from India highlighted the predictive value of credit bureau data even when applied to populations of prospective borrowers who are poor or very poor. It was also demonstrated that MFIs could meaningfully rely upon credit bureau data and credit scores to extend credit to individuals, offering an alternative to traditional circle lending. The data quality, depth, and coverage of the credit bureau (perhaps proxied by the age of a credit bureau) was also found to be a critical factor in the ability of MFIs to successfully use credit bureau data and credit scores. Very new credit bureaus may lack sufficient breadth and depth of data to provide significant lift over manual underwriting, and may need some years to build a database that would be useful for MFIs. This is more reason to invest in credit bureau development. In fact, in just the span of one year, the KS measure for one credit scorecard developed for a large Indian MFI improved by 25 percent to 30 percent, seemingly on the basis of improved data quality at the credit bureaus and within the MFI.

In Mexico, where there are two mature nationwide credit bureaus, not only are credit scores predictive (Actuel had a KS of 0.77), but there also exists an automated decisioning platform specifically designed for MFIs. Our trials in Mexico demonstrated that automated underwriting solutions are effective in rank-ordering prospective borrowers, and can be relied upon by MFIs for risk assessment. MFIs that use credit scores for extending credit to lower-risk borrowers can significantly reduce origination costs by obviating the need for manual verification processes. The Mexican example provided strong evidence that technical capacity limitations at tier 2 and tier 3 MFIs represent a real constraint on the ability of such MFIs to use credit bureau data and credit scores for underwriting purposes. Also, further evidence was found in Mexico that the age of a credit bureau matters. Specifically, an older, more established credit bureau worked to gather considerable quantities of data from a large swath of MFIs and developed a decisioning tool for MFIs.

While Bolivian regulators prohibited MFIs from participating in this project, it is well documented that MFI activity went from an afterthought to a major source of financial services activity in less than a decade after an MFI credit bureau organically evolved. This provides an interesting case, as the credit bureau co-evolved with the MFI sector, and was owned by MFI trade associations. In this instance, the age of a credit bureau is less relevant because the credit bureau was specific to MFIs as opposed to a general-purpose credit bureau for all types of lenders (banks, non-bank financial institutions, savings and credit organizations or SACCOs, or credit cooperatives).

Because the key findings relating to impacts on portfolio performance from this research project are consistent with earlier generation studies, there is a high degree of confidence in them. Further, findings in this study regarding impacts on MFI origination cost, the age of a credit bureau, and capacity constraints of tier 2 and tier 3 MFIs are supported both by earlier generation research and the consistency across countries within this analysis. Consequently, the authors of this study are highly confident in the full spectrum of findings presented herein.

While the results collectively provide strong evidence of the potentially transformative value to MFIs from credit reporting, using credit bureau data, using internal data, and using credit bureau credit scores and application scores for underwriting, they also point to several considerable challenges that may limit the pace and scope of the adoption of these tools by MFIs. High attrition rates within IT departments and senior management evidenced at tier 2 MFIs strongly reduce the probability that underwriting processes will be changed, and create further problems in sustaining a commitment to move from manual to automated underwriting. In addition, senior executives and risk managers at MFIs of all sizes possess a strong amount of distrust for automated underwriting solutions, and believe that their manual underwriting processes are proven and reliable. That said, the fact that SKS was very interested in pursuing data-driven underwriting solutions is prima facie evidence that some MFIs are currently ready to explore the use of credit bureau data and credit bureau credit scores. The rise of smart phone usage rates, IT advances, growing data sets (including big data), biometrics, and the continued development of credit bureaus should, no doubt, eventually make the use of data-driven solutions an obvious decision for most tier 1 and 2 MFIs. Those that do not use such approaches will suffer from adverse selection, as others that do adopt these strategies are able to identify and lend to the lowest-risk individuals across wide areas.

Appendix A: Future Research Considerations

Like most social scientific researchers, when we embarked upon this empirical project we had no guidebook or roadmap. While there is abundant material available on structuring various types of randomized control trials, far less was available on the subjects in our research—MFI impacts (operational, loan performance) and credit information sharing (using credit reports and value added services/scores based upon credit bureau data).

Feeling that it would have been helpful to consult insights by earlier scholars for structuring the design and implementation of our project, we determined that this study should include advice to future researchers who wish to explore this and related topics through an RCT or a similar experiment. Our hope is that in so doing, should the advice be followed, future researchers can conduct their projects more efficiently and effectively.

We begin by addressing some of the most significant challenges confronted while completing this study. Thereafter, we offer advice on methods to either avoid these pitfalls or mitigate their consequences.

We have encountered the following challenges in conducting the research.

A.1 Regulations

A principal challenge we have faced in each market stems from adapting the research methodology to regulations.

A.1.1 India

In response to the Andhra Pradesh microfinance crisis, the Indian government passed a series of regulations. In 2012, the Reserve Bank of India set new regulations stating that the total number of loans for a MFI borrower cannot exceed two, and that the total outstanding balance cannot exceed INR 50,000. These were in addition to other regulations for the sector.[1] The crisis had resulted in default rates in excess of 60 percent in the state. (Part of the defaults can be attributed to the withdrawal of SKS from Andhra Pradesh, leaving no system of repayment collection.)

The central bank, in response, required that a qualifying asset must fulfill the following criteria (in addition to others) that bear on credit reporting:

- The loan amount cannot exceed INR 35,000 in the first cycle, and for subsequent cycles the limit is INR 50,000.
- The maximum indebtedness any household can have at any given time is INR 50,000.

- There can be no more than two micro lenders providing loans at any time to a borrower.

The implementation of RBI rules that limit total indebtedness to INR 50,000 had a considerable impact on the size of the average loan. In January 2012, the (weighted) average loan ticket size was INR 27,594. One year later, that figure remained approximately the same, INR 26,780. By June 2013, the (weighted) average ticket size was less than 50 percent of the year preceding, INR 13,631.

For our RCT, the drafting of the regulations and their content had a few consequences. The only means of complying with the regulations is to use credit reports, either by themselves or in conjunction with interviews. Given the applicant's incentives to not disclose additional loans that may disqualify the application, the credit report plays a more important role. MFIs therefore had to screen a borrower's legal eligibility using credit scores.

Credit reports were not used beyond verifying these minimum requirements in the MFIs with which we worked. As such, this was taken as the base, status quo case.

This requirement, however, also had implications for the pool of borrowers who could be lent to legally. The new legal constraints on who could apply/qualify for a loan meant that legally qualified applicants were now much more likely to be low risk, and therefore likely to be approved. This is also in the context of group lending, which has low reject and default rates (among the Indian MFIs examined). Grameen Koota, for example, does not reject significant numbers of qualified applicants.

For the case of India, rejections ranged from rare to non-existent for legally qualified applicants. (With the recent 2015 shift in the indebtedness ceiling, rejections may become more prominent.)

As such, a strict RCT approach in India was not possible and would not be efficient. Furthermore, the initial concept for this research was to include an assessment of the impacts on consumers from MFI lending. For this, an RCT approach is completely appropriate. This is the case since the same individual cannot have both taken a loan and not taken a loan, just as with medicine, the same individual cannot have taken a pill and not taken a pill. In such cases, RCTs are useful. In assessing lending approaches for lenders, RCTs are less useful. This is because the same individual can be underwritten in two or more ways. Along with the fact that RCTs can be cumbersome and inefficient compared to other research designs, non-RCT or non-strict RCT approaches should be explored when examining lender impacts from different underwriting approaches (as we did in this research).

A.1.2 Mexico

The regulatory challenges in Mexico have also had an impact on the experiment design. Mexican regulations insist on a reserve requirement of 100 percent for loans made without a credit bureau check. Credit report checks are understood to be the only means of inspecting whether CNBV (Comisión Nacional Bancaria y de Valores) "knockout" rules are being met. The requirement accepts a check that results in a "no-hit," that is, a response of no credit report on file, as sufficient.

As all loan applicants in the RCT would have a credit bureau check, as well as a credit score check, we believed we were in compliance with the requirement. However, the CNBV insisted that the MFI provide 100 percent reserve for loans that are accepted under a manual credit report-less process but that would have been rejected on the reassessment with credit reports and scores. (They did not ask for 100 percent reserve for loans that were accepted in the manual treatment, and that were accepted in the credit report retreatment.) That is, even though the results would be adhering to regulations, PERC and our Mexican MFI partners would have to comply as if no credit report check had been made, since regulators do not prescribe any specific risk levels for acceptance.

The MFIs understandably did not wish to challenge their regulators and requested that we provide sufficient reserve funds for the duration of the loan life to assist them. The need to provide funds to cover reserves had one significant impact. Lacking the funds to cover reserves for a sufficient number of loans from a pool of all their loan products, we have been forced to restrict the RCT to applicants for lower-value loans.

The practical effect has been to slow the rate of loans in the RCT. Given that the number of applications has dropped, the timeframe needed to administer treatments for a sufficient sample has widened. This has been true for both Acreimex and Caja Tepeyac.

The expansion of the required timeframe had several additional consequences, cascading across every aspect of our project in Mexico. First, while we persuaded management at both Acreimex and Caja Tepeyac to participate, both had at least one senior management reshuffling, requiring us to revisit participation with the new management. In both cases, new management put the project on hold until PERC staff could visit with them in person to discuss the benefits of continued participation. In the case of Caja Tepeyac, there were three distinct senior management changes requiring this type of attention.

Second, while PERC and Buró de Crédito trained MFI staff on how to use credit reports and credit scores for underwriting loans, and trained MFI staff on the RCT methodology, the turnover rate for IT and risk staff at both MFIs proved to be high, and required additional training sessions. While this was difficult in and of itself, it was further complicated by the fact that PERC had to involve Buró de Crédito in the training process, as the scorecard being used was their IP (eValua). Senior management at BdC frequently wavered in their support for this project, and in 2014, Buró de Crédito discontinued their direct involvement in the project, leaving PERC shorthanded in subsequent training exercises. This also ended PERC's ability to secure quarterly (or any) credit file data for sectorial benchmarking.

In both cases—in terms of providing reserves for the full class of loans accepted without credit reports, and for obtaining credit file data for benchmarking—an additional budget would have either fully mitigated these constraints or at the very least greatly reduced them. The lack of available budget to cover even medium-sized loans resulted in a substantial extension of the project life cycle in Mexico. The extension subjected us to the "churn effects" from staffing turnovers at MFIs, creating a need for additional rounds of training and further direct and indirect costs. And the lack of budget to pay Buró de Crédito for participation in the project—for use of eValua, for assistance in training the MFIs, and for the quarterly benchmarking data—meant that their involvement was constantly deprioritized. This created a need for PERC to expend additional resources—both through our adjunct fellow based in Mexico City and directly by sending PERC staff to Mexico for many additional trips that were not originally envisioned—in order to secure continued engagement by Buró de Crédito. Had we the resources to pay them, the life cycle of the project would have been greatly reduced, as would have the unexpected additional costs that pushed the project into negative returns.

This is an important finding for future efforts to undertake similar research in the future. Reliance on goodwill and "the greater good" to enlist and engage different stakeholders—especially MFIs and credit bureaus—is a poor approach, and will dramatically increase the likelihood that the project will be subjected to the same undue delays that this project experienced owing primarily to budget constraints. In our estimation, an additional $500,000 would have reduced the project's lifespan in half, and would have substantially increased the quality of the results with more data from more MFIs and deeper and richer benchmarking data from the credit bureaus. Regulators would also have been satisfied with additional reserves and would have been less likely to delay the project, or kill it outright as was the case in Bolivia.

A.1.3 Bolivia

The most impactful regulatory intervention in our multi-year, multi-country RCT occurred in Bolivia. After resounding initial successes on the ground in Bolivia—PERC retained the former chairman of Infocred as their Bolivian adjunct fellow to manage the project, PERC secured agreements from the two major MFI trade associations to recruit their members for participation in the RCT, and PERC received positive feedback from the Bolivian microfinance regulator, Autoridad de Supervisión del Sistema Financiero (ASFI)—the project experienced a series of setbacks that ultimately resulted in abandoning efforts in Bolivia.

First, ASFI was supportive of the project and even seemed enthusiastic about the possibility that Bolivian microfinance could be featured in an important global study. The allure of our project must have either quickly dissipated or was not evenly distributed across senior executives at ASFI. When the first MFIs to express interest proved to be the largest MFIs, ASFI informed PERC that such MFIs were regulated and required to conduct credit bureau checks for all new loan applications. Given this, ASFI encouraged PERC to reach out to the unregulated MFI sector, which, while containing very small MFIs, did have several that processed a reasonable number of loans and met our criteria for small MFIs.

Several months after we began recruiting efforts in the unregulated sector, ASFI moved to regulate all remaining unregulated MFIs. They instructed us to cease and desist our engagement with the MFIs we had just recruited. At this point, PERC and the IFC requested and were granted an audience with top regulators at ASFI. Our attempts at a workaround—offering reserve requirement penalties for not checking credit reports—were not accepted by ASFI. They pointed to a handful of very low-capacity MFIs in remote locations as the possible remaining universe of unregulated MFIs, but could not guarantee that even those wouldn't soon be regulated as well. Our efforts in Bolivia crashed and burned, understandably, as the MFI lenders did not wish to challenge the regulator for a study and a custom scoring model.

This issue is raised for several reasons. First, we feel compelled to explain to the study supporters that despite considerable efforts to secure the desired outcome, there are limits to what can be done when dealing with a capricious government. In retrospect, given what was publicly known about the Morales administration, we should have given far more weight to the political risk in Bolivia.[2] For example, at the time that our MFI recruitment efforts were beginning, Evo Morales was passing laws that applied retroactively to political opponents. In fact, a former finance minister was jailed for retroactive non-compliance for a trivial amount of travel funds he even offered to pay out of his own pocket. Second, it highlights the complexity associated with designing a multi-country, multi-year RCT. PERC's unswerving commitment to the research design—varying case countries by geography, the age of credit reporting networks, and MFI size/capacity—while understandable from a scientific viewpoint, resulted in rejecting cases in more stable countries, such as Peru, in favor of riskier countries that better fit the case definition (Egypt, Pakistan, Bolivia). Ultimately, the best case studies are the countries where data is easily available and governments are stable and are expected to be supportive of research efforts. This should be the primary criteria for defining the universe of potential case countries, and then whatever variation can be managed from within that group must suffice.

A.2 Credit Bureau Engagement

In all three case countries, credit bureaus were initially excited about the proposed research. Given the anticipated results, they immediately considered it as potential tool that they could use to recruit additional MFIs and to sell reports and/or scores to MFIs. With that said, we encountered more than a few challenges with participating credit bureaus over the course of the project.

The first is simply that credit bureaus have assigned low priority to the engagement. In every case, priority is given to revenue-generating activities. Buró de Crédito was explicit about this constraint early on. HighMark, in addition to the regulatory challenge, noted that their capacity was stretched and that they would not really be able to participate. They ultimately engaged as a result of purchasing the market tracking data through SKS. That is, PERC paid for the benchmarking data, albeit for a reduced rate, for purposes of this research. Infocred made similar statements: that resources were strained and that priority would be given to revenue-generating activities. We never tested this with Infocred, as the project never went live in Bolivia. Clearly, however, credit bureaus would have been more engaged in this project if PERC had been able to compensate them for their time and costs. This would also have given PERC greater leverage, as there would have been a contractual relationship between PERC and the participating credit bureaus.

A second challenge in the case of HighMark and Infocred has been the multiple changes in management. During the first year after we began engaging these two bureaus, each had two changes in their senior management team. With each change, we were required to practically start anew. While Infocred later settled its management shake-up as we shuttered our operation in Bolivia, the problem continued in India.

Additionally, there was evidence that HighMark data was in need of improvement in terms of data quality, coverage, and depth during the period of our research in India. This is not surprising given the age of the bureau. We encountered suspected data quality problems with both Grameen Koota and SKS. Furthermore, the participating MFIs reported "frequent" disputes of credit report data by borrowers. The test of the effectiveness of shared data on origination costs and portfolio performance depends, in large measure, on the relative accuracy of the data in the credit bureau. There are indications that this data is improving, as we experienced efforts to improve data quality with Grameen Koota and with SKS.

A.3 Lessons for Future Research

For any party interested in undertaking similar research in hypotheses regarding the relationship between MFI operational performance/loan portfolio performance and credit reporting/use of credit reports and scores, the principal lesson would be to commercially engage a national credit bureau either directly or through an MFI. As the sector and the data providers are heavily regulated, working through permitted institutional channels proves smoother for the research. In addition, neither PERC nor the IFC possessed any particular leverage with the participating credit bureaus. As a consequence, the requests made of the credit bureaus for data, analytics, MFI training (on credit report literacy and on how to use credit scoring solutions), and discussions with regulators were routinely delayed owing to being continuously pre-empted by revenue-generating tasks. Had the requests been levied by an actual paying client rather than a non-profit or multi-lateral NGO, the project delays attributable to the participating credit bureaus—and the cascading consequences—likely could have been greatly diminished.

A second lesson related to the first lesson would be to pay MFIs for participation in the research, though this may introduce some biases, not into the research design, but in MFI selection. Specifically, volunteers are much more likely to be less profitable MFIs, and thereby less efficient MFIs. Of course this can be controlled to some extent when researchers are identifying and recruiting potential MFI participants. Given the undue delays experienced by researchers for this project as a result of MFI de-prioritization and staff changes, the moderate risk of a potential selection bias would be more than offset by the efficiency gains from having the participating MFIs reasonably engaged throughout the life cycle of the project.

A third lesson involves engagement with national regulators. Specifically, researchers must fully engage relevant regulators through the life of the project—especially at the beginning. In so doing, researchers should expect that such engagement will lead to initial delays (potentially lengthy ones) and additional costs including but not limited to provisioning assistance for participating MFIs or other lender participants. However, this will also reduce the probability of subsequent and multiple delays resulting from regulators being vested in the process from the onset. Further, investing in a front-loaded outreach strategy to regulators will provide usable intelligence about whether or not regulators are likely to be capricious—as in Bolivia—and will enable timely adjustments.

Relatedly, a fourth lesson is that regulatory engagement could result in a restructuring of the project design, and possibly even the cancellation of the project. Credit bureaus and MFIs are cautious of regulatory constraints, and some are excessively cautious. Despite the fact that we engaged regulators at the very beginning in Mexico and Bolivia, and despite how enthusiastic regulators were about the project in Mexico, they have little ability to bend regulations. In Bolivia, MFIs were so concerned by the response from regulators—even when a workaround was identified that would have permitted MFIs to participate—they universally declined to proceed with the project. The same workaround in Mexico permitted the project to proceed, but not without substantial delays and budget overages.

In Mexico, regulatory requirements to reserve 100 percent of loans that have been approved without a credit report check was only noted at a late stage by a loan officer employed at one of the participating MFIs. This requirement had been overlooked by regulators at CNBV and senior executives at both participating MFIs during previous discussion and despite explicit requests from researchers for descriptions of the MFIs' loan process when credit reports are not available.

While each type of project stakeholder—credit bureaus, MFIs, and regulators—presents different types of challenges, many of the challenges could have been resolved (or at least mitigated) had additional funds been available. By compensating credit bureaus and MFIs for participation, many of the delays could have been reduced or avoided. The same goes for challenges posed by the regulators. With sufficient funds to provide assistance for provisioning requirements for loans underwritten without a credit report for purposes of this project, the variety of loans and the volume of loans would have been enhanced, thereby improving the quality of the findings and reducing or eliminating delays.

Despite positive outcomes with several MFIs and at least one credit bureau (Buró de Crédito in Mexico has new clients for their eValua solution), as well as the insights gained for future research and the compelling evidence on the value of credit reporting, credit report and score usage by MFIs, the project was fraught with challenges from launch to conclusion. Most of these challenges were simply unforeseeable owing to the pioneering nature of this project—especially given the ambitious scale and scope. Others, however, can be avoided simply by allocating sufficient budget to compensate participating MFIs and credit bureaus, and by investing in a front-loaded and heavier outreach strategy with regulators to vest them in the project at an early stage. We would also counsel against using case studies with executive administrations that have exhibited capricious behavior, as the risk of government interference becomes non-negligible and could threaten the project.

The principal challenge in this project was one of incentives. MFI participants were all motivated by the prospect of receiving a customized scoring model and/or testing credit decisioning systems. However, once they received these benefits, their motivation to prioritize this project, or stay engaged at all, immediately and dramatically dissipated. Credit bureaus were motivated to access MFI data and/or test MFI scoring solutions. Here too, once this was accomplished, their incentive to remain responsive to PERC and the IFC also diminished. Any leverage either could exert was based purely on good will and past relationships—and this too had limits.

Regulators also had very little incentive to support the project. In their eyes, the value of MFI credit reporting, and the use of credit reports and credit scores, was already established and in most cases required. They saw little upside in permitting MFIs exemption from existing rules, and were generally unwilling to bend them. In at least one case, erratic behavior and mixed messages from national regulators effectively killed the program despite a legal workaround. This is a bit of a dilemma, as such research can only be conducted in countries possessing established credit information sharing networks.

Future researchers must recognize that paying stakeholders for participation introduces some selection bias into the study, as modernizing and inefficient MFIs are the ones most likely to participate. This bias can be controlled for by selecting at least one MFI participant per country that has above-average IT capacity and no near-term needs for an IT upgrade. The benefits from changing stakeholder incentives by introducing a financial incentive, in the opinion of the researchers involved in this project, greatly outweighs any bias in the subsequent results especially given options for reducing and controlling for the bias.

Ultimately, if properly structured, the lessons from these experiments will be of great value to policymakers and MFIs alike. We urge our supporters to consider the valuable lessons learned and extend this research to gain further value that would result from increased credit reporting by MFIs, and the increased use of credit reports and scores in MFI loan underwriting in developing markets worldwide.

Appendix B: India, Microfinance Sector

B.1 Sector Tracking

As part of the study, PERC also tracked the microfinance sector using significant numbers of credit files. Using credit files allows us to track a large, representative, and statistically significant sample of MFI loans. Originally, our research plan included tracking credit file data on MFIs periodically over the project term, ideally quarterly, and to use this data to understand the contours of the microcredit market and identify MFIs for recruitment, if needed.

While we were able to secure data regularly in one case (India), regular and ongoing access to the same in our other case (Mexico) was more problematic. In both cases, considerable effort was expended in securing this data. In India, PERC had to be classified as a consultant to the participating MFIs in order to access the data. Even then, without the IFC's active lobbying of High Mark (now CRIF High Mark) on our behalf, we would have been unlikely to receive any data. Beyond that, in many cases the data transfer was de-prioritized and took months of haranguing by PERC staff of High Mark to "nudge" along the data transfer. In Mexico, PERC and the IFC had far less leverage with the dominant credit bureau.

The rationale behind tracking the sector is to also understand the context of the RCTs, especially near the time of the implementation of the RCT.

B.2 India

Although prior to January 2012 a majority of microloans were already being reported to High Mark, reporting by MFIs to High Mark and Equifax increased over 2012 and the ensuing few years. As such, data from High Mark in January 2012 should cautiously be considered reflective of the characteristics of the MFI sector engaged in credit reporting. As was also implied in the experience of score development, there may be significant data quality issues in the microfinance sector that, in turn, are creating data quality problems for the microfinance credit bureaus.

High Mark reports 41.7 million non-distinct clients in January 2012, 49 million non-distinct clients in January 2013, and 53.9 million non-distinct clients in June 2013. Given the depressed state of lending in 2011 and early 2012 in the wake of the microfinance crisis, the increases may be less a product of the entrance of more MFIs into the credit reporting sector than of the recovery of the microfinance sector in India.

It does seem to be the case that by mid-2013, most MFIs were reporting full-file information to High Mark, and the ones that remained outside credit reporting were primarily if not exclusively small MFIs. This qualification is the reason we cannot infer that microlending increased by 123 percent between January 2012 and January 2013.

From January 2012 to January 2013, the number of MFIs active in Indian states (or more properly, MFIs that are active in a state and reporting to High Mark) increased by more than 25 percent. For reasons that remain unclear, between January 2013 and June 2013, the number of active MFIs decreased in nearly all Indian states, though they did remain above January 2012 levels.

The total amounts disbursed have steadily increased from January 2012 to January 2013 and have continued to increase through June 2013. January 2013 figures from High Mark indicate INR 373,316,642,969 in outstanding microloans. By June 2013, that figure had risen by 15.4 percent to INR 430,967,731,005. By contrast, the total amount disbursed as reported to High Mark in January 2012 was INR 167,506,642,580.

Changes in the average size of loans disbursed are less likely to be influenced by changes in the rate of reporting to a credit bureau than changes in other indicators. They are, however, very likely to be altered by changes in regulations as noted above. The implementation of RBI rules that limit total indebtedness to INR 50,000 appear to have had a considerable impact on the size of the average loan. In January 2012, the (weighted) average loan ticket size was INR 27,594. One year later, that figure remained approximately the same, INR 26,780. By June 2013, the (weighted) average ticket size was INR 13,631.

The overwhelming majority of microloans in India remain group loans. With the exception of northeastern states such as Assam, Aranchal Pradesh, and Sikkim (see Appendix), individual loans never account for more than 9 percent of loans made by Indian MFIs within the Indian states.

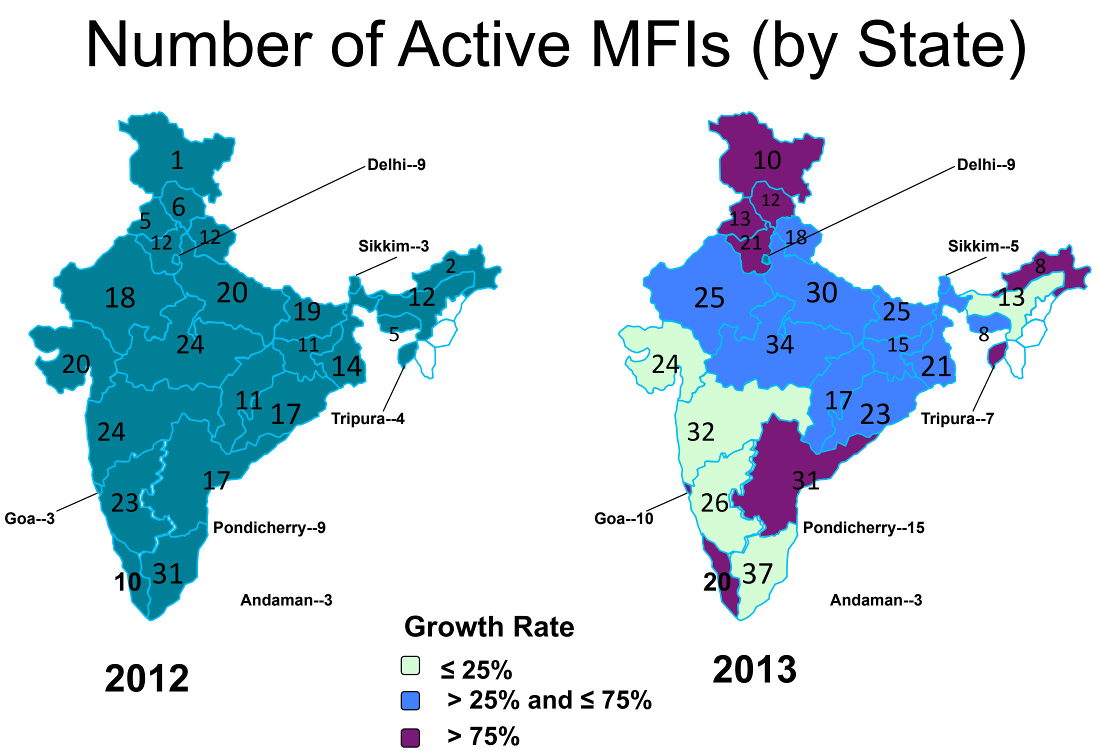
Delinquency rates remain very high in Andhra Pradesh since the crisis. MFIs have largely withdrawn from Andhra Pradesh, and the infrastructure for collection of repayment installments is largely absent. Delinquency rates are also high in states neighboring Andhra Pradesh, Orissa, and Maharasthra. They are also high in Himachal Pradesh.

Grameen Koota operates in the states of Maharashtra, Karnataka, and Tamil Nadu. Delinquency rates in all three states are within normal ranges for India. As of June 2013, in Karnataka, 3 percent of clients are overdue on loan payments, compared to 6.4 percent in Maharashtra and 7.4 percent in Tamil Nadu.

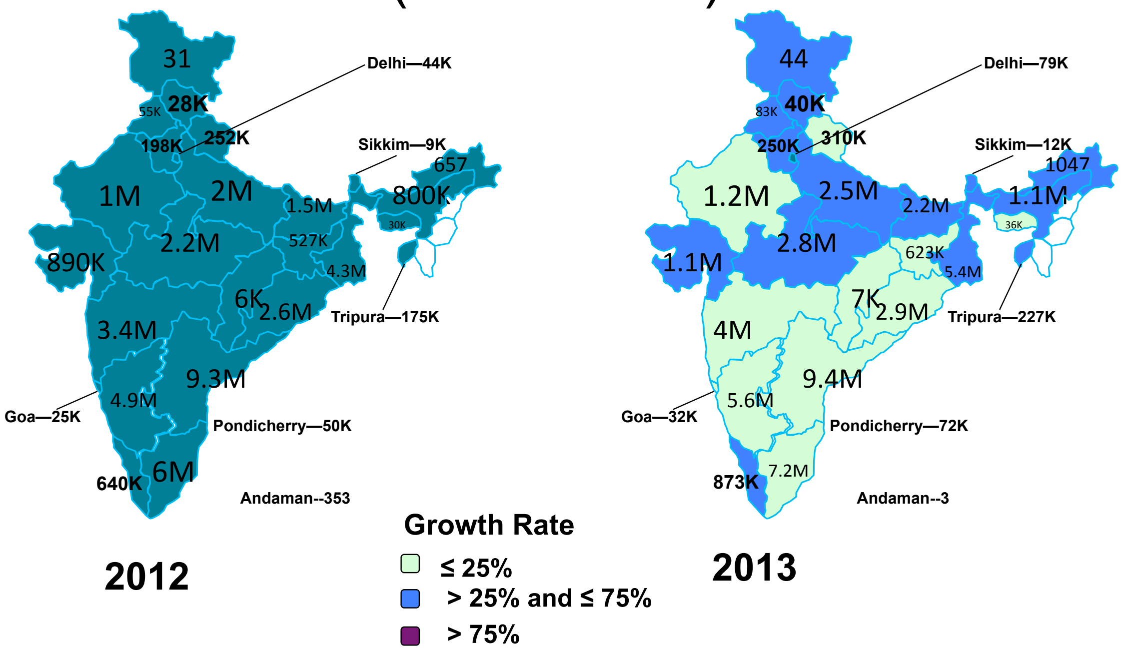
SKS by contrast operates in 19 Indian states. Having been at the center of the microfinance lending crisis in Andhra Pradesh, SKS has halted all lending in that state.

B.3 India MFI Data

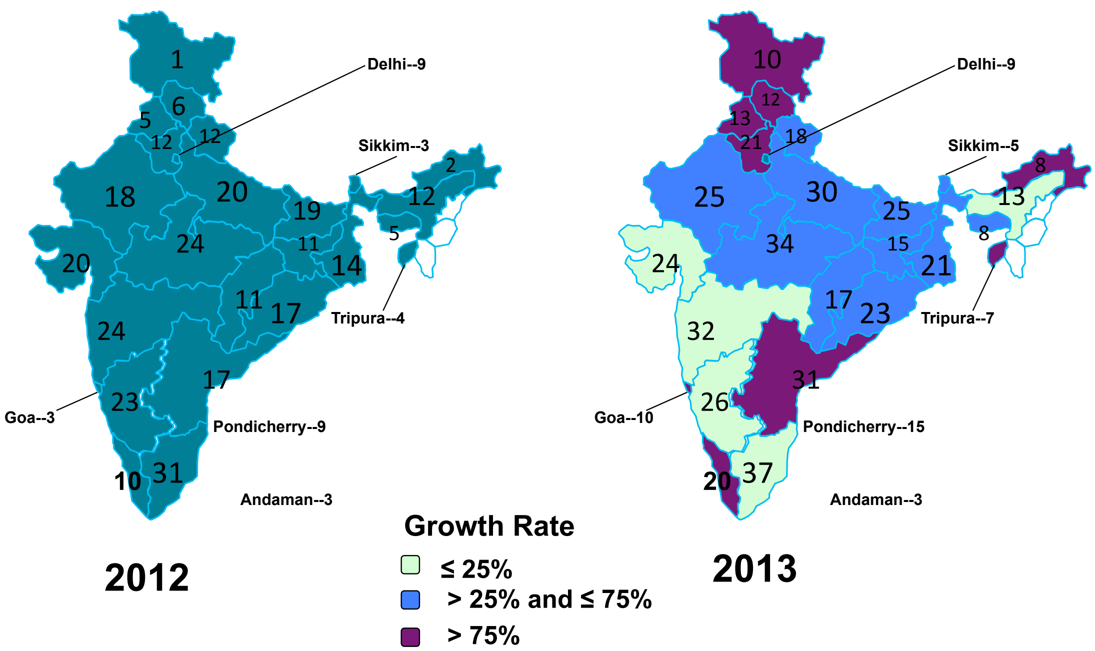
The data presented in this Appendix for India are figures produced by High Mark (now CRIF High Mark). The figures are based on data as of January 2012 and January 2013. The requests for the data were made in 2012 and 2013.



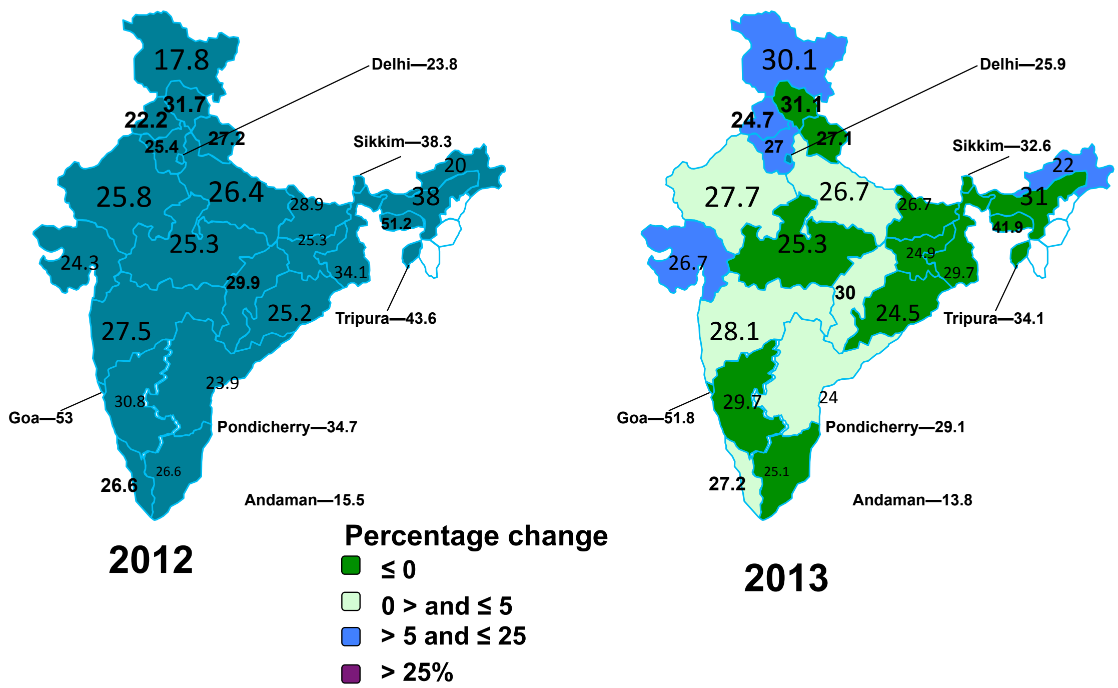
Number of MFIs Clients (non-distinct)



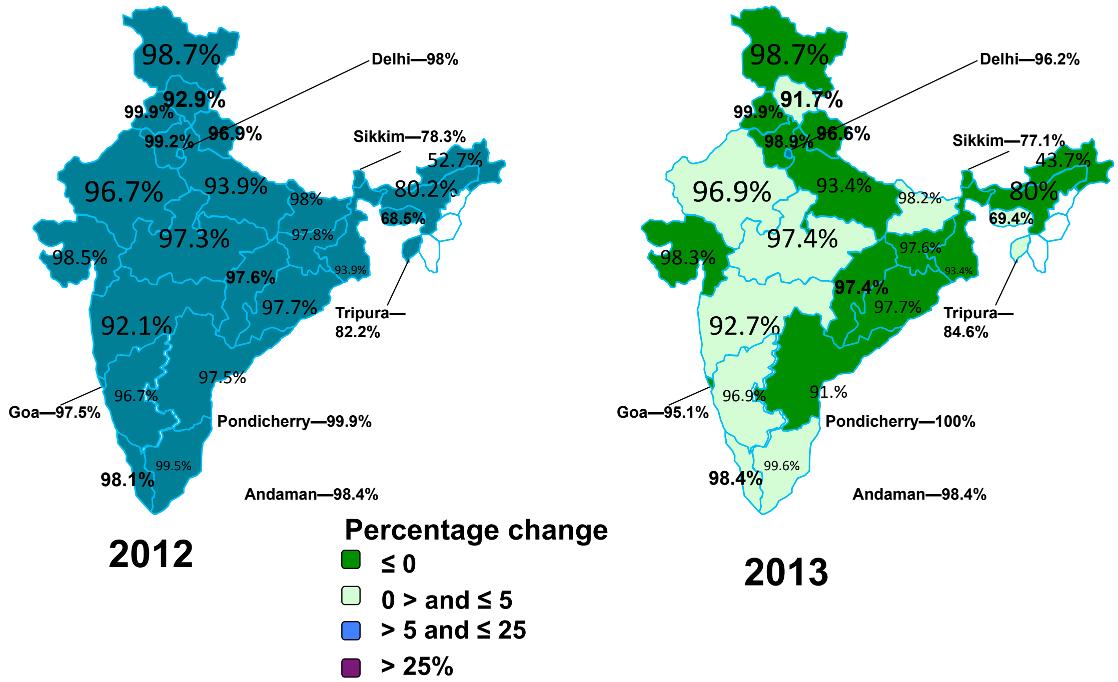
Number of Active MFIs (by State)



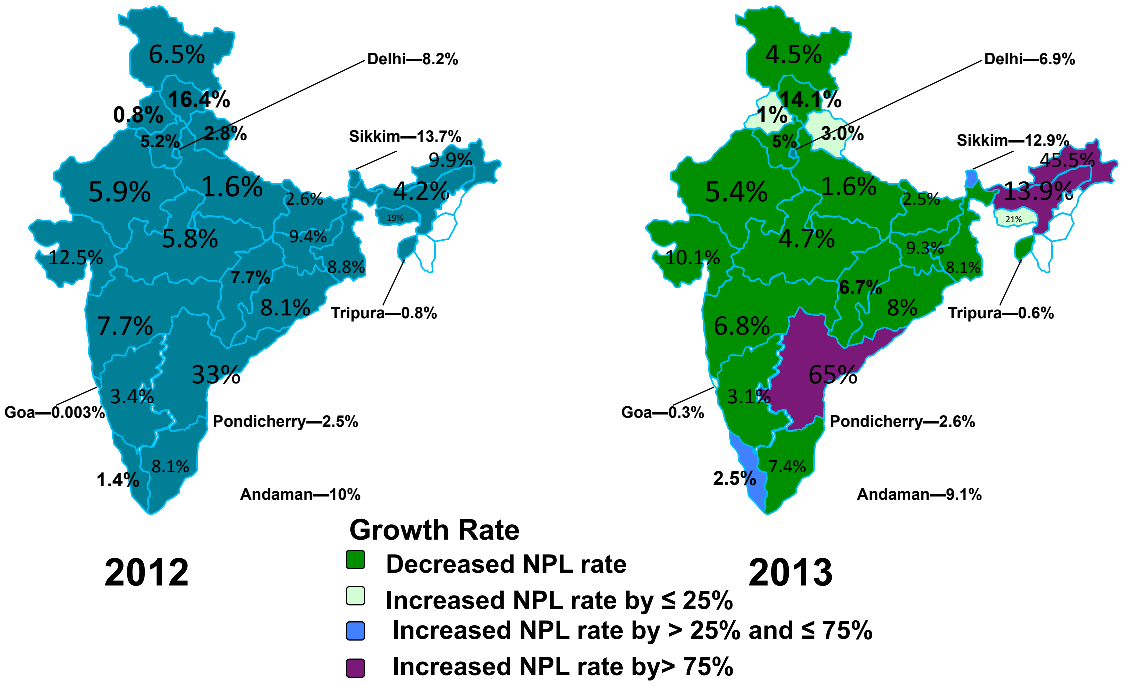
Average Loan Size (in '000 INR)



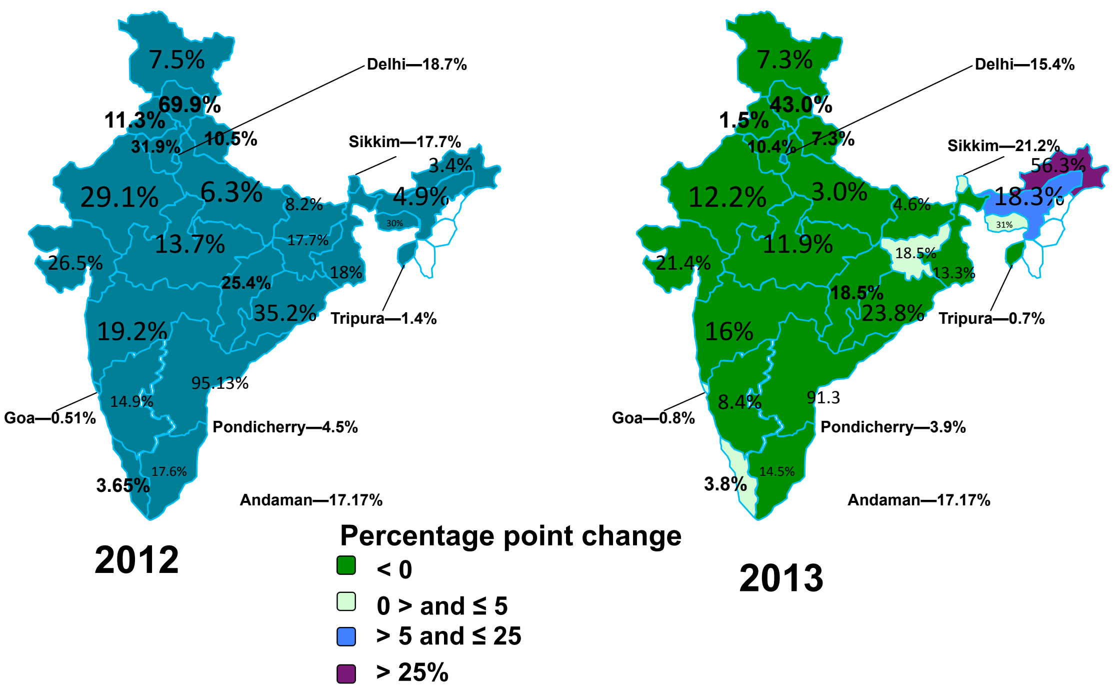
Percentage of Loans as Group Loans



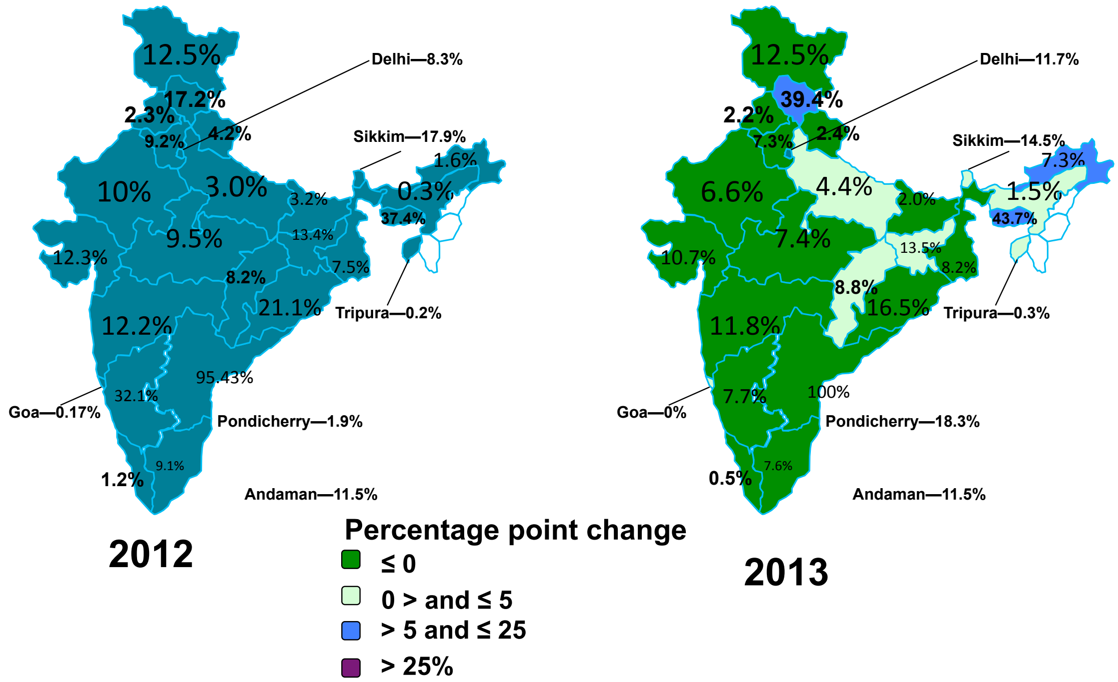
Percentage of MFIs Clients Overdue



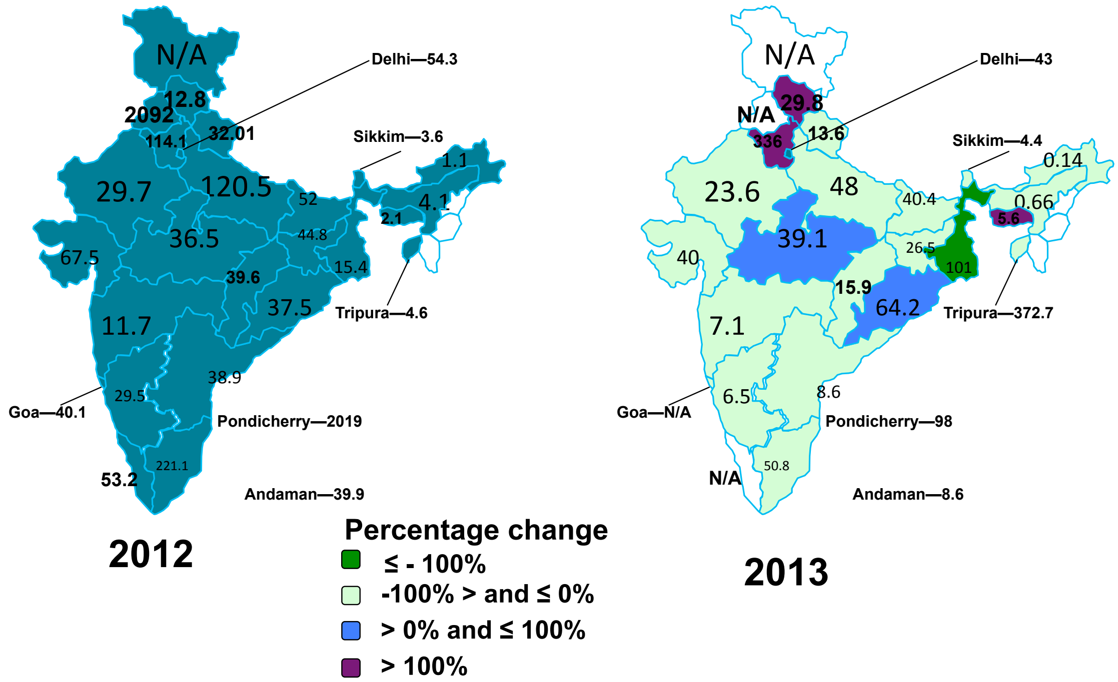
Percentage of MFIs Loans Overdue



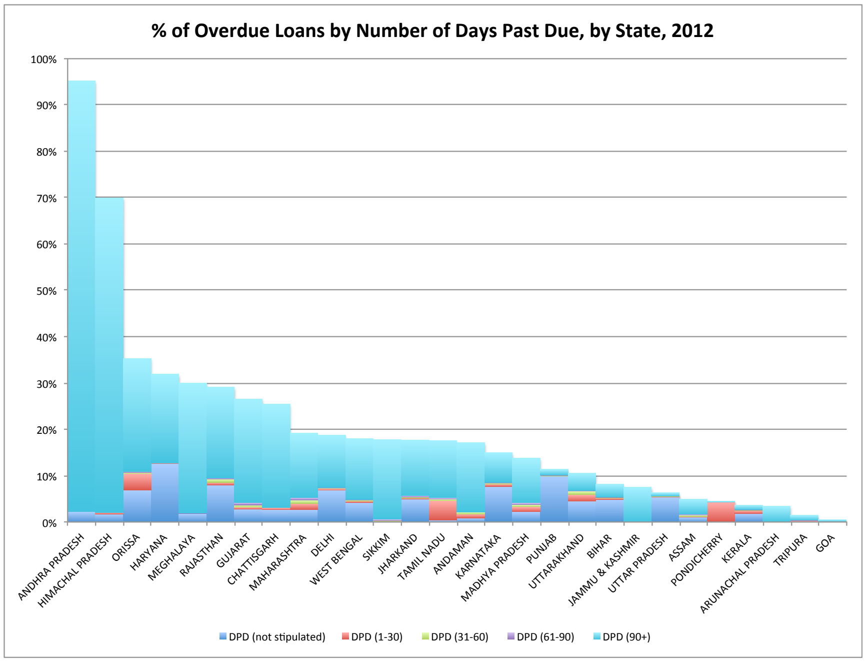
Percentage of MFIs Portfolio Overdue



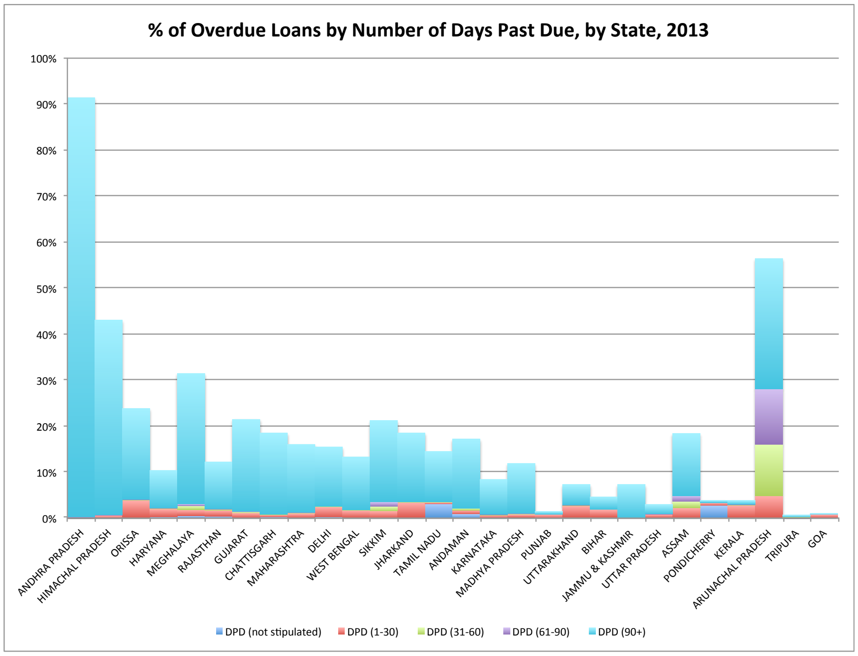
Ratio of Group Loans Overdue to Individual Loans Overdue



India


% of Overdue Loans by Number of Days Past Due, by State, 2012
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
ANDHRA PRADESH
HIMACHAL PRADESH
ORISSA
HARYANA
MEGHALAYA
RAJASTHAN
GUJARAT
CHATTISGARH
MAHARASHTRA
DELHI
WEST BENGAL
SIKKIM
JHARKAND
TAMIL NADU
ANDAMAN
KARNATAKA
MADHYA PRADESH
PUNJAB
UTTARAKHAND
BIHAR
JAMMU & KASHMIR
UTTAR PRADESH
ASSAM
PONDICHERRY
KERALA
ARUNACHAL PRADESH
TRIPURA
GOA
DPD (not stipulated)
DPD (1-30)
DPD (31-60)
DPD (61-90)
DPD (90+)

India


% of Overdue Loans by Number of Days Past Due, by State, 2013
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
ANDHRA PRADESH
HIMACHAL PRADESH
ORISSA
HARYANA
MEGHALAYA
RAJASTHAN
GUJARAT
CHATTISGARH
MAHARASHTRA
DELHI
WEST BENGAL
SIKKIM
JHARKAND
TAMIL NADU
ANDAMAN
KARNATAKA
MADHYA PRADESH
PUNJAB
UTTARAKHAND
BIHAR
JAMMU & KASHMIR
UTTAR PRADESH
ASSAM
PONDICHERRY
KERALA
ARUNACHAL PRADESH
TRIPURA
GOA
DPD (not stipulated)
DPD (1-30)
DPD (31-60)
DPD (61-90)
DPD (90+)

Appendix C: Mexico, Microfinance Sector

All figures, save the "Structure of the Buró de Crédito Database," refer to microfinance accounts, defined according to CNBV designations, unless specified. The data in this Appendix were requested by PERC and produced by Buro de Credito. These data are "snapshots" as of December 2013.

Buró de Crédito has records on 87.3 million people and 271.8 million accounts. Many of these records contain only personal identifying information. Approximately 26 percent of these accounts came from savings and credit unions, cooperatives, Sofomes (multipurpose financial society) in 2013, a figure which rises to 31 percent by 2014. Buró de Crédito estimates that more than 70 percent of MFIs report to them. MFIs in Mexico report full-file information to one or both of the credit bureaus, and the vast majority do so to Buró de Crédito.

From December 2008 to December 2013, the number of active microfinance accounts in the database increased from 3.7 million to 9 million. The number of closed accounts increased more dramatically, from 12.5 million to 59.1 million. The increases result from an expansion of participation by MFIs in credit reporting and specifically in the increase in the number of MFIs reporting to Buró de Crédito.

The total amounts disbursed and the average amount borrowed both steadily increased from December 2008 to December 2013. The former increased from 38 billion to 129 billion Mexican Pesos. Part of this increase may stem from the rise in the number of MFIs reporting to Buró de Crédito. Average loan size has steadily increased as well, from 9,047 to 14,333 Mexican Pesos. While the possibility that this increase is accounted for by the inclusion of MFIs that provided larger loans cannot be ruled out, this possibility is less likely considering that the larger MFIs have been reporting to Buró de Crédito for a long time.

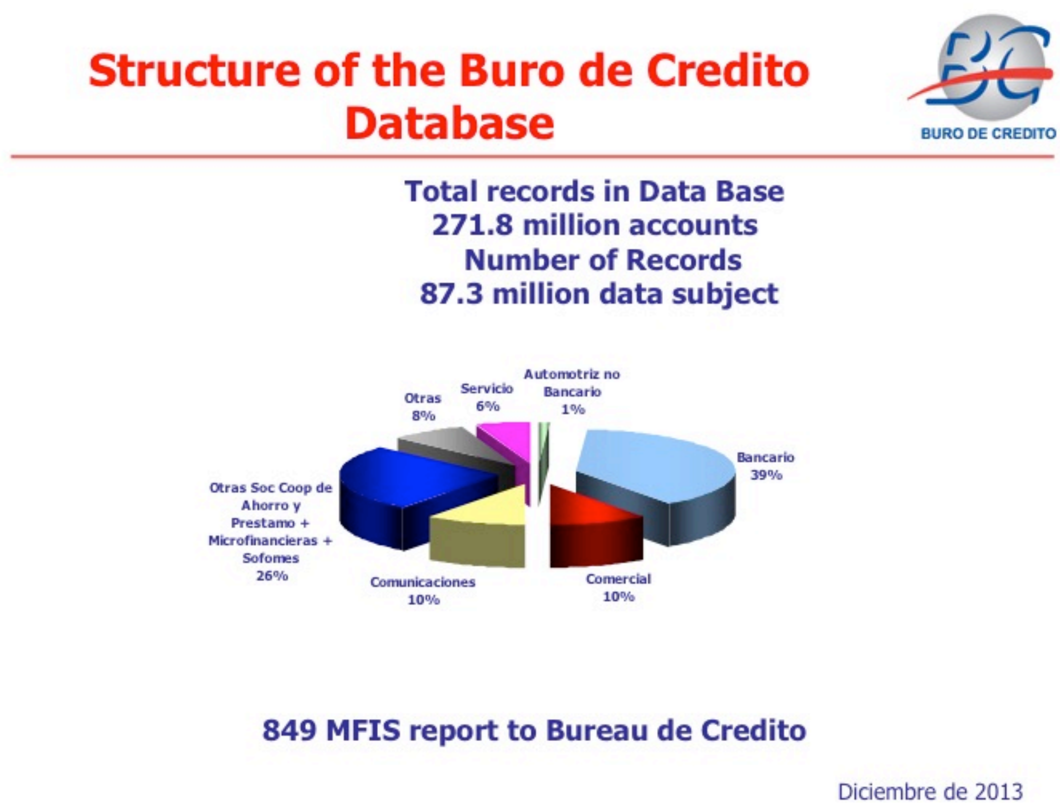
As of December 2013, nearly half of all microloans (44 percent) are smaller than 5,000 Mexican Pesos, and 17 percent were larger than 20,000 Mexican Pesos. There has been a clear trend toward larger loans. In December 2008, 56 percent of all microloans were smaller than 5,000 Mexican Pesos, and only 7 percent were larger than 20,000 Mexican Pesos. The trend toward shifting to loan products of larger value has been steady. While statistically this may be a product of the new MFI entrants into credit reporting, it is unlikely, as the larger MFIs (which offer more diversified products) have been largely reporting since before 2008. The more likely cause is organic growth in average loan amounts and an increasing diversity in MFI loan types as a result of increased credit information sharing.

Delinquency rates increased in Mexico over the period. Buró de Crédito files indicate that accounts in default increased from 12 percent in December 2008 to 22 percent in December 2013. It seems to be the case that the rising default rates are partly the result of newly reporting MFIs adding their accounts in default to the database.

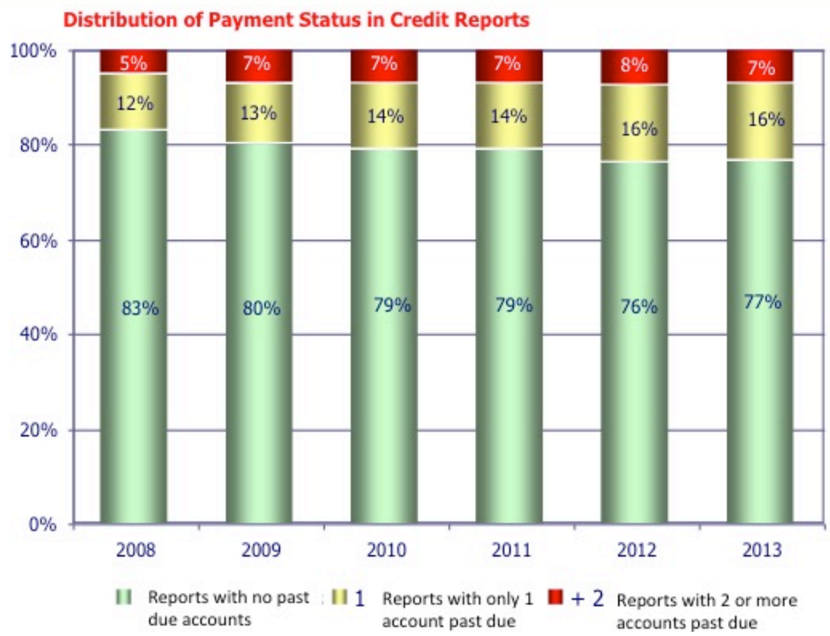
The state of Oaxaca, where Acreimex operates, accounts for 4.6 percent of all microloans (or 412,000 active loans as of December 2013) in Mexico. The total microloan portfolio for the state is 6 billion Mexican Pesos, and the average loan size, 14,700 Mexican Pesos, is approximately that of the national average.

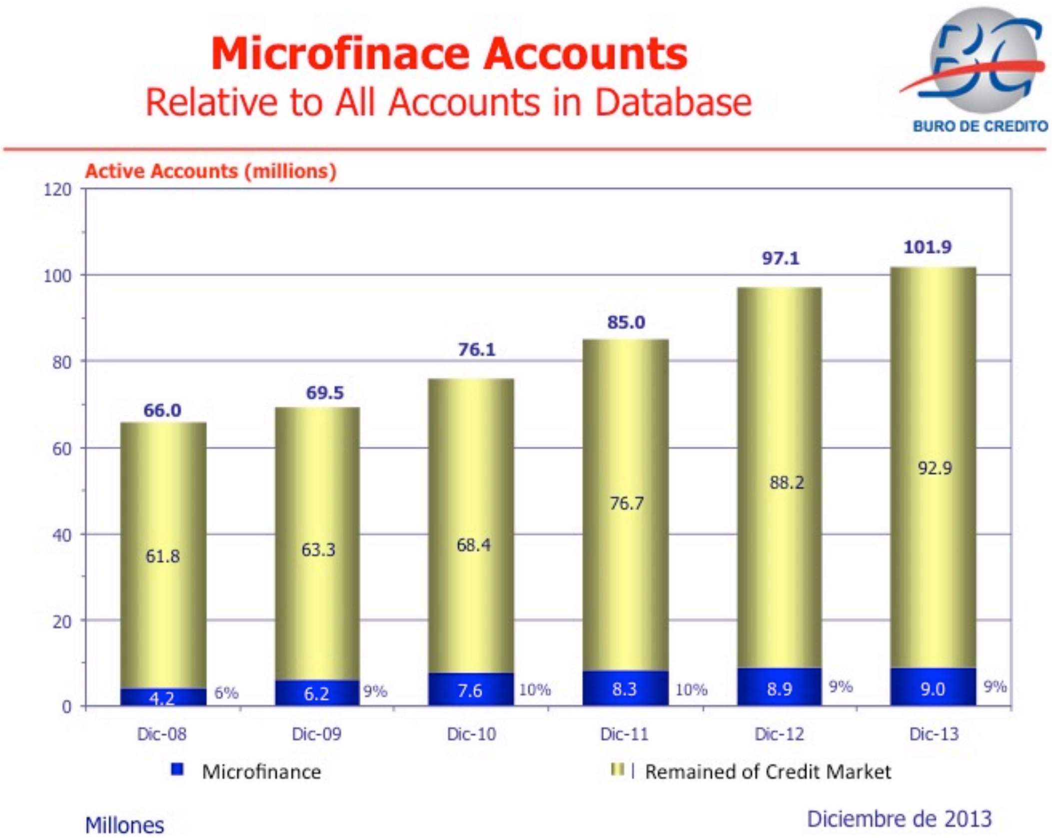
The state of Jalisco, where Caja Tepeyac largely operates, accounts for 7.1 percent of microloans made in Mexico (approximately 635,000 as of December 2013), possessing a total loan portfolio of 12 billion Mexican Pesos and an average loan size of 18,900 Mexican Pesos.

The following data for Mexico MFI sector were requested by PERC and produced by Buro de Credito. These data are “snapshots” as of December 2013.



Evolution of Overdue Accounts
All Accounts





Microfinace Accounts
Relative to All Accounts in Database
BURO DE CREDITO
Active Accounts (millions)
120
100
80
60
40
20
0
66.0
69.5
76.1
85.0
97.1
101.9
61.8
63.3
68.4
76.7
88.2
92.9
4.2
6%
6.2
9%
7.6
10%
8.3
10%
8.9
9%
9.0
9%
Dic-08
Dic-09
Dic-10
Dic-11
Dic-12
Dic-13
Microfinance
Remained of Credit Market
Millones
Diciembre de 2013

Microfinance accounts
Relative to the market for credit

Diciembre de 2013

Evolution of Defaults
Microfinance

BURO DE CREDITO

Account Activity

Millones

Percentage

Defaults are defined in accordance with CNBV criteria, 90+ days past due

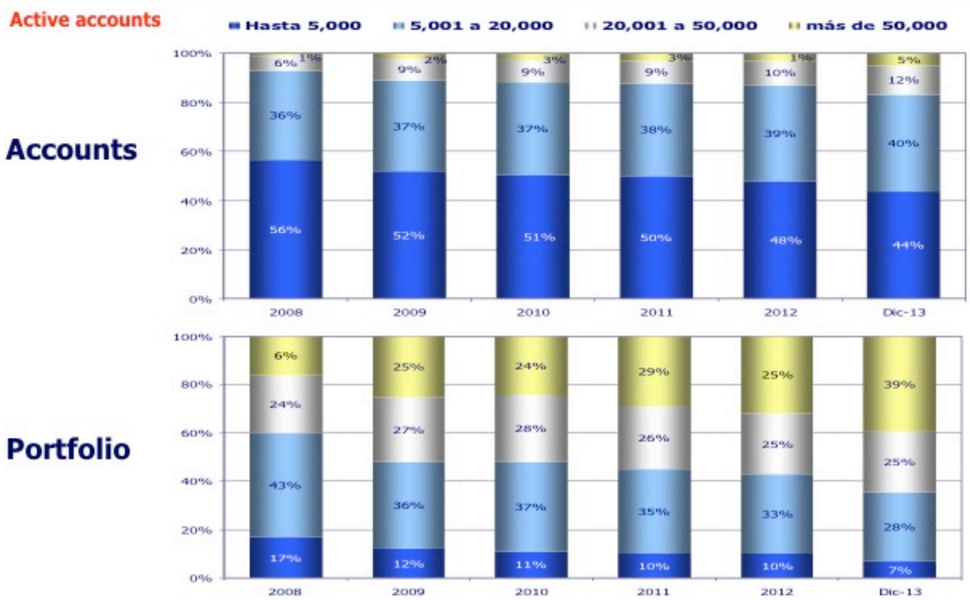
Diciembre de 2013

Microloans
Average Loan Account

Miles de Pesos

Microloans

Distribution by Size of Loan



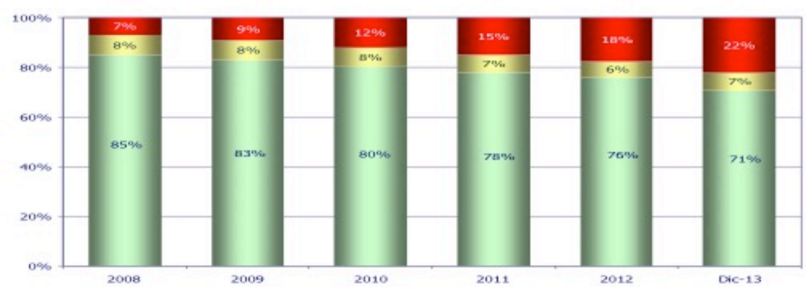
Diciembre de 2013

Microloans
by Timeliness of Payment

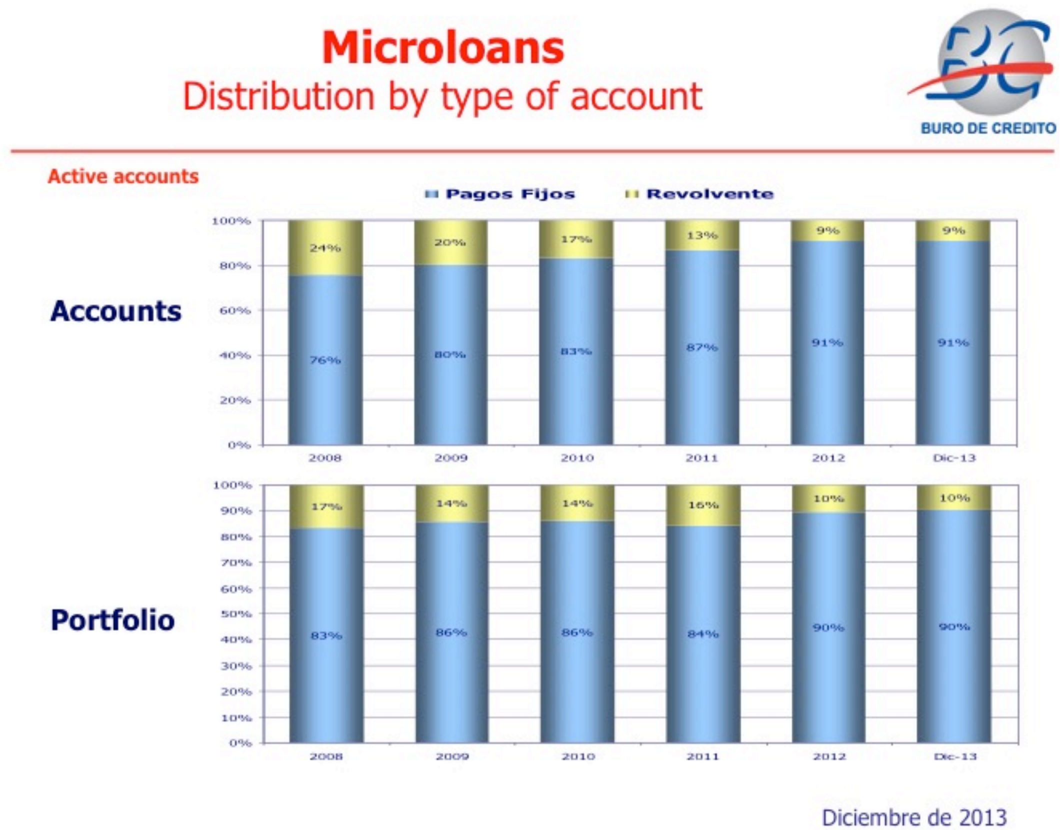
Active Accounts

Accounts

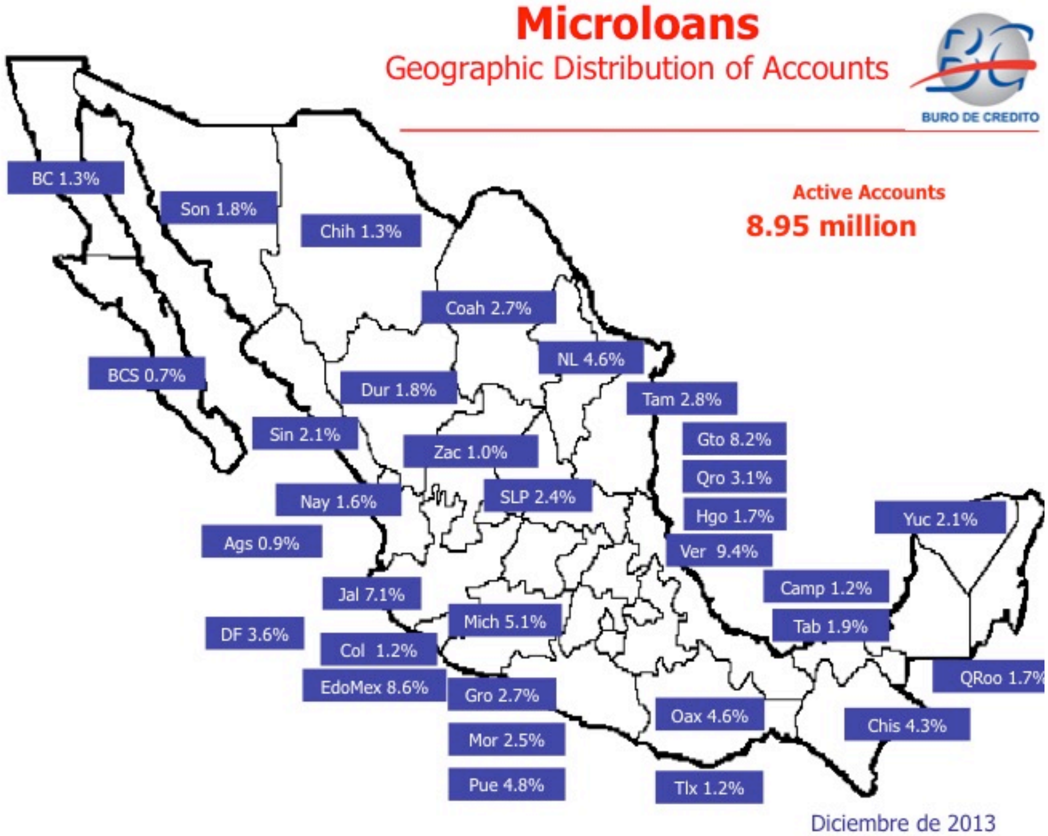
Portofolio

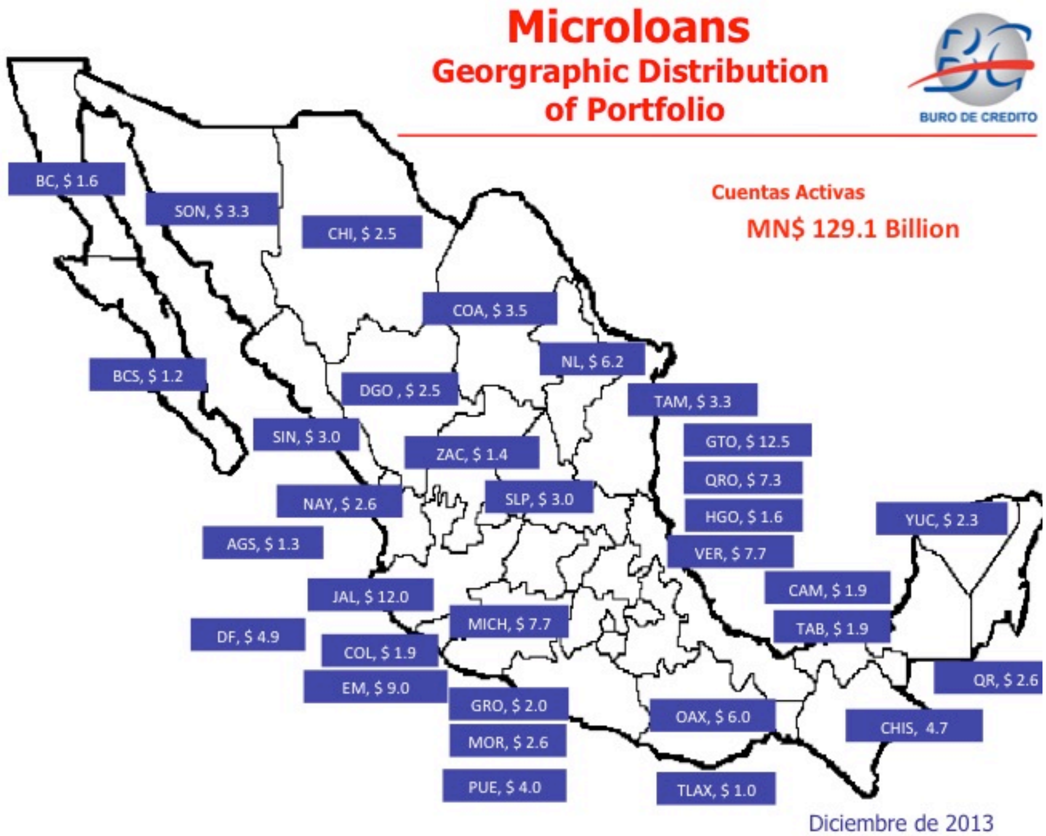


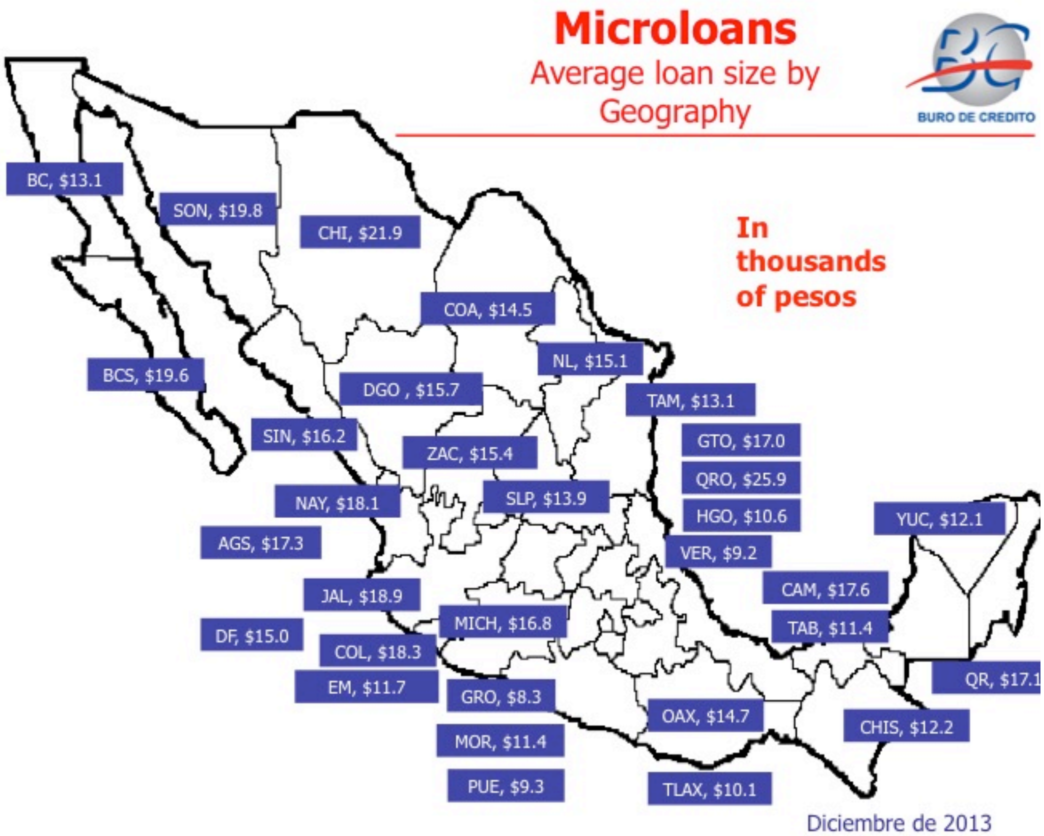
Diciembre de 2013



Note: "Pagos fijos" refers to "Fixed Payments" or instalment loans."Revolente" refers to revolving loans.


Microloans
Geographic Distribution of Accounts
BURO DE CREDITO
Active Accounts
8.95 million
BC 1.3%
Son 1.8%
Chih 1.3%
Coah 2.7%
NL 4.6%
BCS 0.7%
Dur 1.8%
Tam 2.8%
Sin 2.1%
Zac 1.0%
Gto 8.2%
Qro 3.1%
Nay 1.6%
SLP 2.4%
Hgo 1.7%
Yuc 2.1%
Ags 0.9%
Ver 9.4%
Jal 7.1%
Camp 1.2%
DF 3.6%
Mich 5.1%
Tab 1.9%
Col 1.2%
EdoMex 8.6%
Gro 2.7%
QRoo 1.7%
Oax 4.6%
Chis 4.3%
Mor 2.5%
Pue 4.8%
Tlx 1.2%
Diciembre de 2013

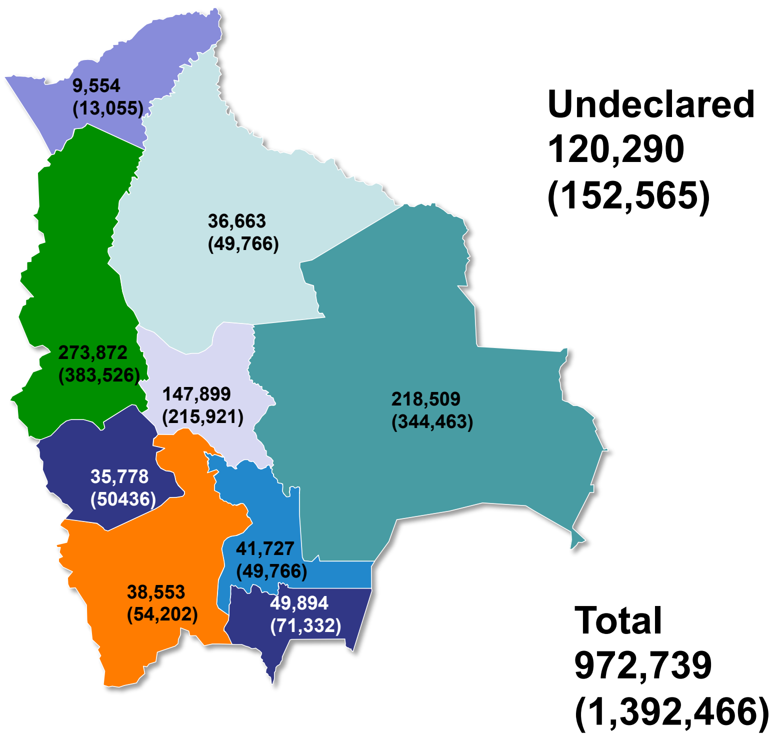

Microloans
Georgraphic Distribution
of Portfolio
BURO DE CREDITO
Cuentas Activas
MN$ 129.1 Billion
BC, $ 1.6
SON, $ 3.3
CHI, $ 2.5
COA, $ 3.5
NL, $ 6.2
BCS, $ 1.2
DGO , $ 2.5
TAM, $ 3.3
SIN, $ 3.0
ZAC, $ 1.4
GTO, $ 12.5
QRO, $ 7.3
NAY, $ 2.6
SLP, $ 3.0
HGO, $ 1.6
YUC, $ 2.3
AGS, $ 1.3
VER, $ 7.7
JAL, $ 12.0
CAM, $ 1.9
DF, $ 4.9
MICH, $ 7.7
TAB, $ 1.9
COL, $ 1.9
EM, $ 9.0
QR, $ 2.6
GRO, $ 2.0
OAX, $ 6.0
CHIS, 4.7
MOR, $ 2.6
PUE, $ 4.0
TLAX, $ 1.0
Diciembre de 2013


Microloans
Average loan size by Geography
BURO DE CREDITO
In thousands of pesos
BC, $13.1
SON, $19.8
CHI, $21.9
COA, $14.5
NL, $15.1
BCS, $19.6
DGO , $15.7
TAM, $13.1
SIN, $16.2
ZAC, $15.4
GTO, $17.0
QRO, $25.9
NAY, $18.1
SLP, $13.9
HGO, $10.6
YUC, $12.1
AGS, $17.3
VER, $9.2
JAL, $18.9
CAM, $17.6
MICH, $16.8
TAB, $11.4
DF, $15.0
COL, $18.3
QR, $17.1
EM, $11.7
GRO, $8.3
OAX, $14.7
CHIS, $12.2
MOR, $11.4
PUE, $9.3
TLAX, $10.1
Diciembre de 2013

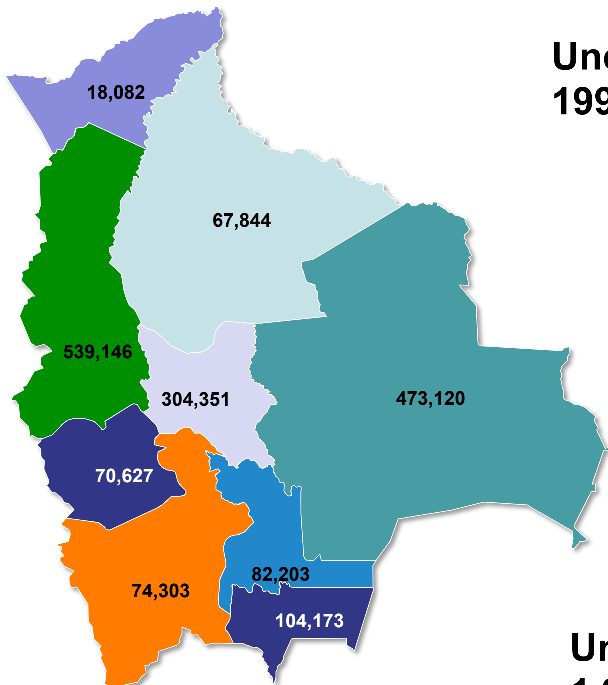
Appendix D: Bolivia, Microfinance Sector

The Bolivia MFI sector tracking data presented in this section were produced by Infocred Servicios de Información BI S.A. These data were requested by PERC in 2013 and represent figures as of 2013

Active Borrowers (Total Borrowers)



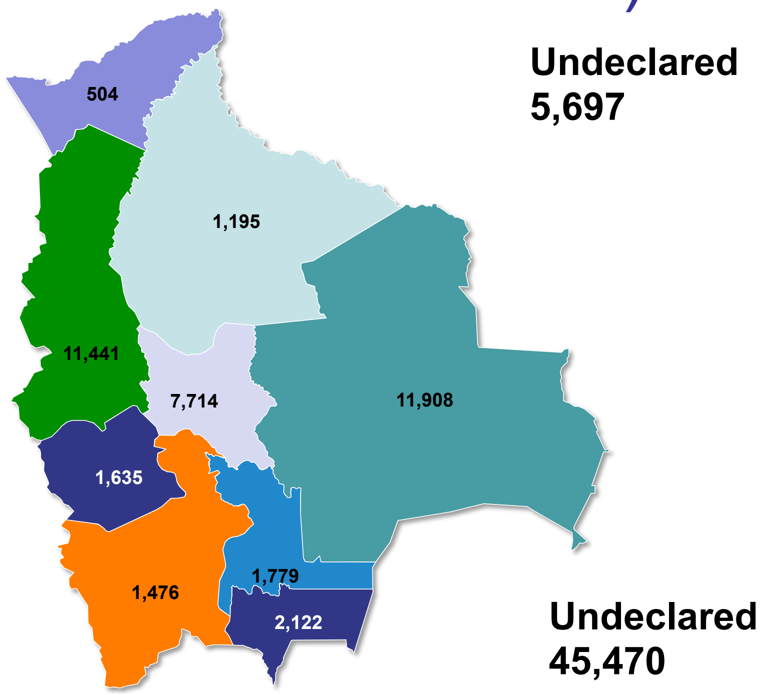
Total Number of Active Loans



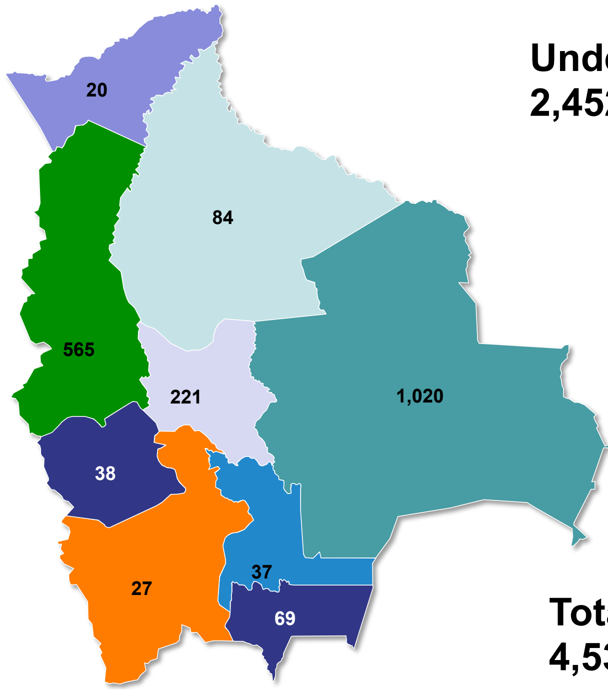
**Undeclared
199,032**

**Undeclared
1,932,881**

Total Amount Outstanding (in millions of Bolivianos)



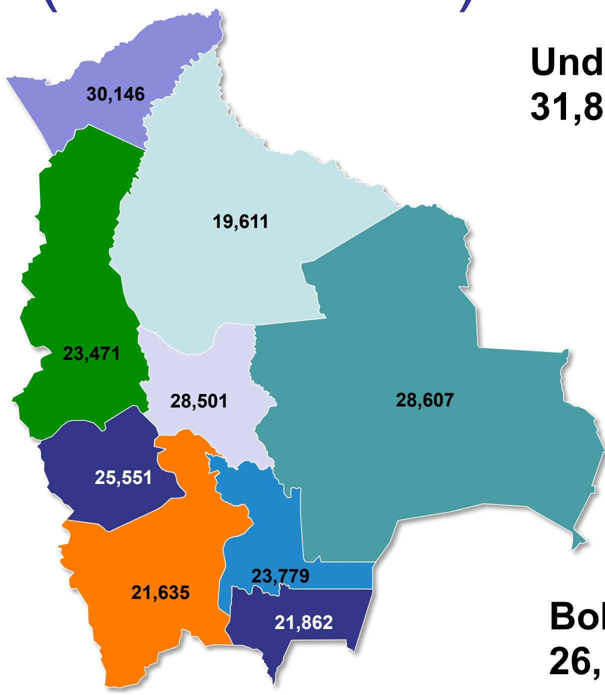
Total Amount Overdue
(in millions of Bolivianos)



Undeclared
2,452

Total
4,532

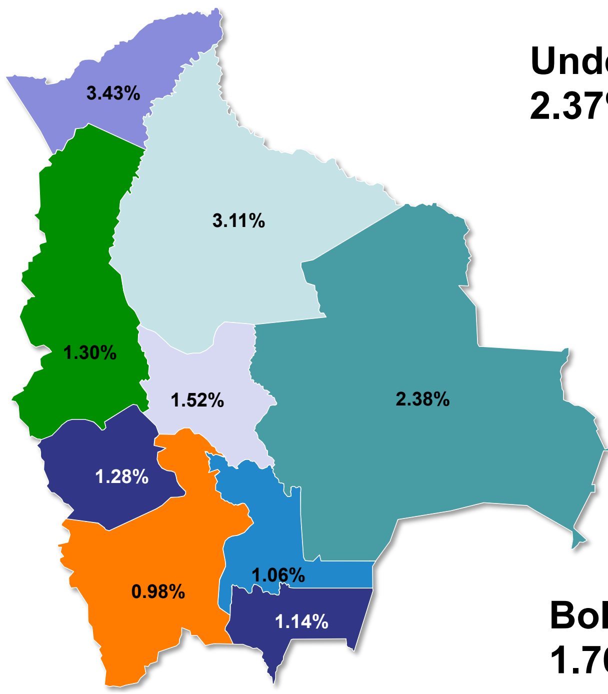
Average Loan Size (in Bolivianos)



Undeclared 31,894

Bolivia wide 26,121

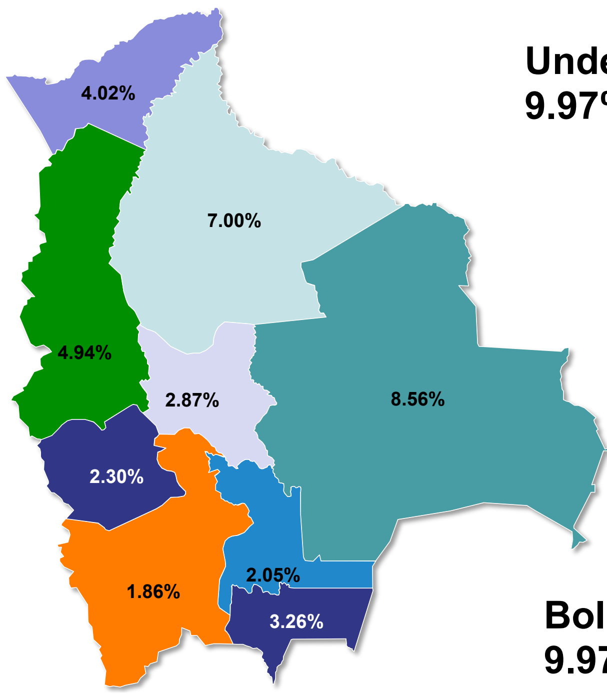
Percent of Loans Overdue



Undeclared
2.37%

Bolivia wide
1.76%

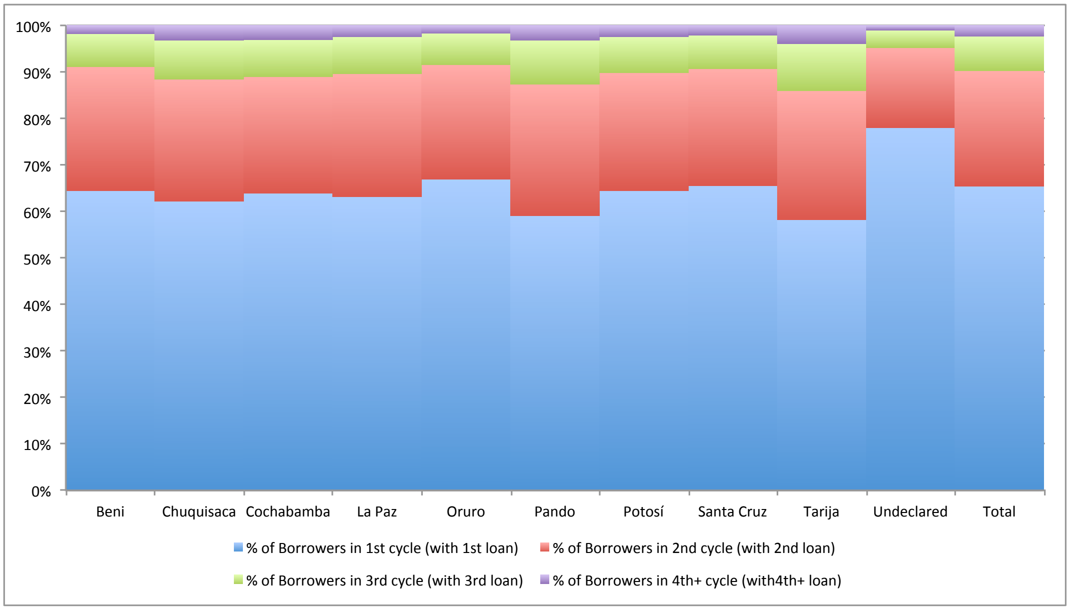
Percent of Portfolio Overdue



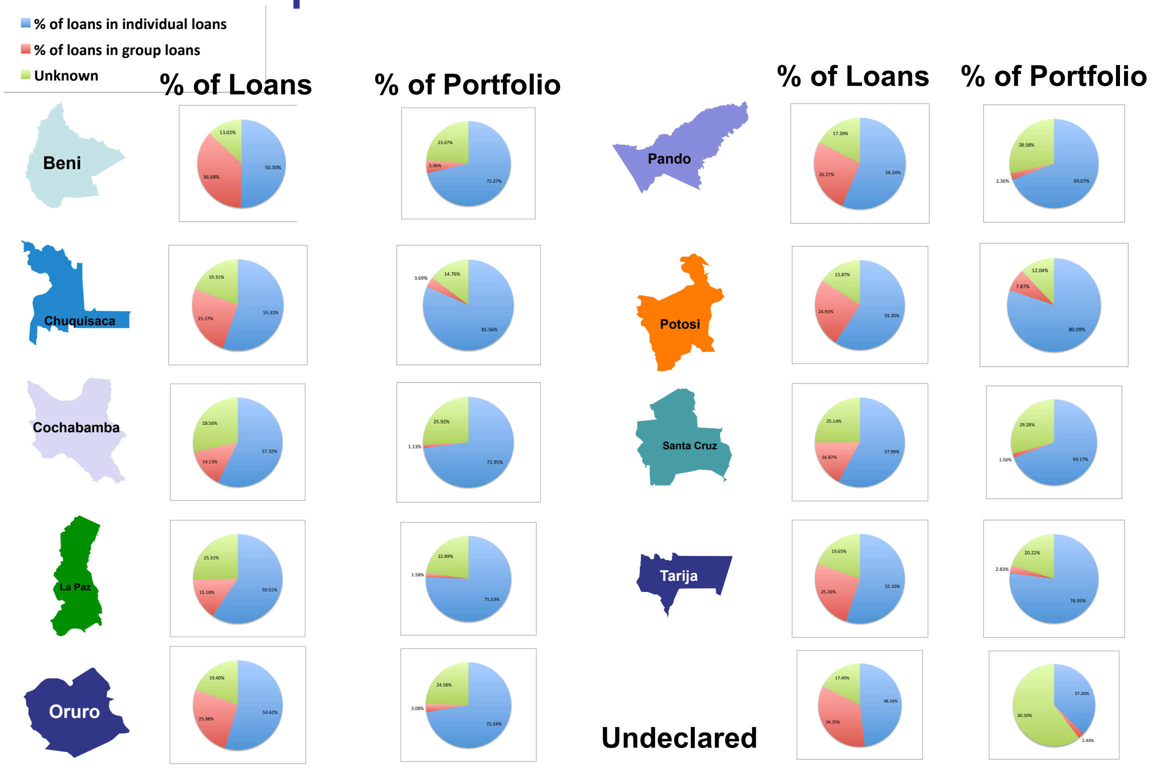
Undeclared
9.97%

Bolivia wide
9.97%

Portfolio by Loan Cycle



Group and Individuals Loans



Notes for Appendices

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[1] Non-Banking Financial Company-Micro Finance Institutions (NBFC-MFIs) – Directions – Modifications RBI/2012-13/161 DNBS (PD) CC.No.300 /03.10.038/2012-13 August 03, 2012 https://rbi.org.in/scripts/NotificationUser.aspx?Id=7493&Mode=0#3. In April 2015, the total indebtedness ceiling was raised to INR 100,000 from 50,000. Monetary and Credit Information Review Date: Apr 30, 2015. https://www.rbi.org.in/scripts/PublicationsView.aspx?id=16222.

[2] For example, a report released in 2009 was full of red flags about the Morales regime. See Douglas Farah, “Into the Abyss: Bolivia Under Evo Morales and the MAS,” International Assessment and Strategy Center. Accessed from http://www.hacer.org/pdf/Farah00.pdf.