*IOSR Journal of Economics and Finance (IOSR-JEF)*
*e-ISSN: 2321-5933, p-ISSN: 2321-5925.Volume 8, Issue 3 Ver. IV (May - June 2017), PP 15-25*
*www.iosrjournals.org*

# Applying Financial Engineering towards Mitigating Microfinance Risks

Saumya Swaroop
*540 E 20th Street, Apt 6F New York, NY 10009*

***Abstract**: Microfinance firms cater to the financial needs of underprivileged people, who because of their unstable and uncertain sources of income cannot avail these services through banks. By virtue of the nature of their clientele, these firms are exposed to a lot of credit risk. Using primary data from Indian MFIs, a region that witnessed a major crisis in the microfinance sector in the year 2010, this research paper has attempted to devise hedging strategies for these firms to help mitigate risk and enhance operational efficiency. While discussing various possible hedging instruments, the main focus of this paper is insurance contracts. Using Importance Sampling techniques, we were able to simulate the expected number of defaults helping us gauge the number of insurance contracts needed. Applying the simulation to Future Financial Services Ltd., an MFI in India, we found that had this firm purchased insurance contracts based on the default predictions made by our model, its loan loss for the worst crisis year would have been reduced by almost 36%. Another major finding of this research was that the insurance contracts would be cheaper if the MFI charges lower interest rates from its clients. This would help counteract one of the major criticisms of MFIs- that they push the clients into debt traps by charging extremely high interest rates. We hope that this research reiterates the need for the MFIs to start managing their risks as financial firms and to make adequate investments in hedging schemes. This is intended so that the aim of economic empowerment of the poor can be met in a way that is sustainable for these firms.*

## I. Introduction

Microfinance has come a long way since its inception in the 1970s. While the pioneers of MFIs were originally founded to provide credit to the poor who could not qualify for formal bank loans because of lack of acceptable collateral, MFIs today offer a variety of services to the poor[1]. For the purposes of this research paper, we will focus on micro-lending only.

- *Loans:* The practice of providing small loans to the poor is called micro-lending. This still remains the major function of MFIs across the globe. Micro-credit is important for the poor as it is lent without demanding any collateral. Lack of collateral is the primary reason why the poor are unable to avail the services of banks.
- *Savings:* MFIs allow poor people to save small amounts of money with them in micro-savings accounts, which do not have a minimum balance requirement and therefore, the families save money and withdraw their savings when the need arises.
- *Insurance:* Small entrepreneurs, who are in initial stages of developing their businesses, often make small payments to MFIs as a premium to avail insurance services. This service is called micro-insurance.
- *Money Transfer Services:* A lot of people from rural or economically underdeveloped areas travel to different regions and countries in search of employment. They can transfer money back home using an MFI's money transfer services.

Thus, the MFIs differ in a lot of ways in which they function and the type of services that they provide, the end goal remains the same: the financial empowerment of such people for whom banks have always been a faraway dream. By lending to such clients, the MFIs are also undertaking a lot of risk because of the very nature of their clientele who may have no choice but to default on their loans because of their uncertain incomes. The high operational costs also introduce a lot of challenges for this sector.

Need to Devise Hedging Strategies for Microfinance Firms in India

The size of the loans that MFIs give out is meager compared to what formal banks deal with on a day-to-day basis. However, the risks associated with micro-credit are as high, if not higher, as that of borrowers from formal banks. This is because the MFI clients do not have enough income or assets to be eligible for bank loans. Moreover, their income sources are insufficient and often uncertain (for instance, farmers in rural areas whose income may be highly seasonal). In order to maintain their services, MFIs need to ensure that clients repay their loan installments continually. These institutions in turn, need to repay the banks that they borrow from or the

[1]Gaurang C. Barot and Sandip K. Bhatt, "Microfinance in India," in *Micro Finance in India,* ed. A.K. Agarwal and Bhartendu Singh (Guwahati: DVS Publishers, 2013), 17.

investors who have put in their money in the MFIs. Therefore, the inherent and higher chances of default because of the nature of their clientele expose the MFIs to a lot of risk. It is articulated as, "MFIs especially as compared to commercial banks must have higher loan loss provision as they don't have collaterals against the loans that they offer."[2]

The Indian microfinance sector has witnessed great turmoil in the recent years. Perhaps in an effort to maintain investor confidence and to be able to borrow money from banks, the MFIs followed a policy of "zero tolerance for defaults"[3], thereby increasing the pressure on their workers to collect repayments at any cost. It is said that "lapses in repayment led to an exchange of words between staff and clients... coercive behavior from some of the staff was resented by defaulting clients and their families, resulting in unfortunate exchanges and incidents, some of which drew the attention of district authorities, religious groups and the media."[4]The biggest upheaval took place in the state of Andhra Pradesh in October 2010, where faced by increasing number of client suicides in light of defaulting on their microcredit, religious groups led a movement and propagated that no client repay their loans to the MFIs. MFI workers are said to have behaved coercively with their clients not just when they were unable to repay their loans, but also when they were in a rush to leave the meetings to go earn their daily wages. A large number of clients were women, and anecdotal evidence exists that they were pushed into clutches of prostitution to procure money to repay loan installments[5].They felt that disrespecting themselves by selling their dignity was 'better' than being abused by a stranger in front of their known ones. It also appears that the public resented the IPO of an MFI, SKS Microfinance, as the media coverage saw it against the philanthropic principles of MFIs. It was believed that operating akin to corporate firms, the IPO highlighted "potential high profits and lavish executive compensation."[6]The state government, in what seems to be in support of this movement against the MFIs, issued ordinance that severely curbed the operations of all MFIs in the state. The crisis was especially big because the largest number of MFIs in India is based in Andhra Pradesh. The effect of this crisis also spread to other parts of the country where other MFIs witnessed an increasing rate of default on their loans as well, or the loss from Andhra Pradesh was so high that the firms found themselves in a crunch for funds. Growth rates for both loan portfolios and clients was a mere 17% in fiscal year 2010, compared to respective growth rates of 95% and 57% in 2009[7].The situation turned so bad that one branch manager despaired that the whole year's collection in that year had been less than the average amount due every day[8].In response to the crisis, the Reserve Bank of India (RBI) formalized a Microfinance Industry Code of Conduct in January 2011, some of whose provisions were[9]:

- Upper limit of income at $1000 for rural areas and $2000 for urban areas
- Maximum first loan of $580 and subsequent maximum loans of $830
- The indebtedness of the borrower capped at $830
- Minimum 2 years of tenure for credits exceeding $250
- The borrower decides the repayment frequency- weekly, fortnightly or monthly
- The interest rate that an MFI can charge was limited such that the difference between the borrowing rate from banks and the lending rates to clients does not exceed 12% and the interest rates on loans cannot exceed 26%
- The clients cannot be treated coercively

The RBI also indicated that the failure to abide by any of the provisions of the Code of Conduct would be penalized severely. In February 2014, the RBI modified these provisions and removed the 26% interest rate

[2]Ibid, 35.

[3]Berenice da Gama Rose and Alok Misra, "Fair treatment of clients, code of conduct and institutional response-intense scrutiny?," in *Microfinance India: The Social Performance Report 2012,* Girija Srinivasan (New Delhi: Sage Publications India Pvt. Ltd, 2013), 43.

[4]Ibid, 43.

[5]Nithya Joseph, "Mortgaging used sari-skirts, spear-heading resistance," in *Microfinance, Debt and over-Indebtedness,* ed. Isabelle Guerin, Solene Morvant-Roux and Magdalena Villarreal (Oxon: Routledge, 2014), 279.

[6]"Andhra Pradesh 2010: Global Implications of the Crisis in Indian Microfinance," CGAP Focus Note, No. 67 November 2010, accessed February 2017.

[7]Rahul Shyamsukha, "India: post microfinance crisis results," in *India: Post microfinance crisis results,* November 2011, accessed February 2017, http://www.themix.org/publications/mix- microfinance-world/2011/11/india-microfinance-post-crisis-results.

[8]Nithya Joesph, "Mortgaging used sari-skirts, spear-heading resistance," in *Microfinance, Debt and Over-Indebtedness,* 279.

[9]Berenice da Gama Rose and Alok Misra, "Fair treatment of clients, code of conduct and institutional response-intense scrutiny?," in *Microfinance India: The Social Performance Report 2012,* 46.

cap, suggesting instead of mandating, a 10% margin between rates of borrowing and lending to clients[10].The intense scrutiny of MFIs post the Andhra Pradesh crisis led many banks as well as investors to withdraw their funding from these institutions. This led to a liquidity crunch characterized by a "dearth of fund flow to the sector."[11]A social investor observes: "Two years ago we could find 50 MFIs for potential investments but today there are less than 10. When pricing restrictions are applied, many of them are not profitable any more."[12]Combined with the fact that MFIs only cover about 10% of the total requirements and that almost 87% of the Indian population is ineligible to avail banking services, there is a need to work towards the sustainability of MFIs.

Risk Measures for Microfinance Firms

The most common types of risk measures used for MFIs are as follows[13]:

*Write-Off Ratio:* When a particular loan is deemed uncollectable, the outstanding loan balance is removed from the loan portfolio. The ratio of this loan write-off to the loan portfolio is called the write-off ratio.

$$Write - Off\ Ratio = \frac{Write - Offs}{Gross\ Loan\ Portfolio}$$

*Portfolio-at-Risk Ratio:* The portfolio-at-risk is the value of all loans outstanding that has one or more installments of principal due for more than a particular number of days. This includes the entire unpaid principal balance, including both the previous due and future installments, but no accrued interest. It also includes loans that have been restructured or rescheduled. The portfolio-at-risk ratio is the ratio of the value of portfolio-at-risk with respect to the gross loan portfolio value.

$$Portfolio - at - Risk\ Ratio\ (> X\ Days) = \frac{Portfolio - at - Risk > X\ Days}{Gross\ Loan\ Portfolio}$$

Based on a preliminary data analysis, we see that the risk measures of Indian MFIs increased significantly during crisis and have not come back to the pre-crisis levels. The portfolio-at-risk measure (over 30 days) saw a sharp spoke from 2010 onwards, concurrent with the Andhra Pradesh MFI crisis. The loan write-offs also echo the rise in portfolio-at-risk.

**Devising Risk-Hedging Strategies**

Innovative financial solutions are imperative for the overall economic development of a country. In a country like India, where a majority of its citizens still live under poverty and do not qualify to avail these services formally, these facilities become all the more important. Let us look at some of the probable strategies and how they can be used by the MFIs.

***Insurance:*** Client defaults will cause a loss to microfinance firms and create pressure in meeting the costs of loans. In the event that the default becomes big and converts into a major crisis, it can put the very existence of a firm in jeopardy. Since there are two possibilities here, one that a client is able to repay the loan and other that he defaults, there is an expected payoff which is a probability weighted average of the amounts received in either of the two scenarios. More specifically, if the two scenarios are *repay* and *default* with respective probabilities $p_1$ and $p_2$, the expected payoff is:

$$EP = p_1 * Payoff_{repay} + p_2 * Payoff_{default} \qquad (1)$$

This is what the MFI will definitely like to receive should a default occur and it needs to claim its insurance. If the client is able to repay the loan, the MFI will receive the principal amount plus the interest rate on that particular loan and will be able to cover the costs of servicing that loan. Thus, if $S_t$ is the principal amount that is being lent out at an interest rate *r* for *T* years and the total expense incurred by the MFI for this client is *C*, the payoff for the MFI if the client successfully repays the loan will be,

$$Payoff_{repay} = S_t * (1 + r)^T - C \qquad (2)$$

The data for our MFIs are organized on an annual basis, giving us the number of loan the MFI makes, the amount it has to write off, as well as total expenses every year. Since the MFI, like any other financial firm, updates its financial statements every year, for the purpose of this research we would like to study hedging instruments with a time period of one year. Of course, the loans may have maturities greater than a year as well. If, on the other hand, the client defaults on his loan, the MFI has to bear the expenses of that borrower without having the repayments to rely on to cover this cost. Thus, if the expense of servicing the loan amount is *C* (as

[10]"RBI Removes 26% Interest Rate Cap on MFI Loans," in *The Economic Times,* February 8, 2014, accessed April 2015, http://articles.economictimes.indiatimes.com/2014-02- 08/news/47127322_1_margin-cap-lending-rate-interest-rate.

[11]Girija Srinivasan, "Lenders, Investors and Donors-Are They Responsible?" in *Microfinance India: The Social Performance Report 2012, 60.*

[12]Ibid, 61.

[13]"Glossary," in MIX Publications, accessed February 2017.

before), the payoff will be,

$$Payoff_{default} = -C \qquad (3)$$

Strangely, when MixMarket reports data, there is no line item for the total loan costs. Rather it reports total costs over total assets. But since total assets are reported, we can obtain the total costs by multiplying this ratio by the total asset amount. The active clients per year are a part of the MixMarket report and from here it is easy to obtain the total costs per client. Thus,

$$C = \frac{Asset * \frac{Total\ Cost}{Asset}}{Number\ of\ Active\ Borrowers} \qquad (4)$$

The insurer (details of who the insurer will be is discussed further) will also charge a certain risk premium to bear the risk. If the volatility is measured by the standard deviation of the expected payoff, it can be calculated as follows:

$$\sigma_{EP} = \sqrt{p_1 * \left(Payoff_{repay} - EP\right)^2 + p_2 * \left(Payoff_{default} - EP\right)^2} \qquad (5)$$

This premium will depend on what type of client the MFI is lending to. Clients with a higher risk of default will need to have their loans insured with higher premiums. The total price that the MFI pays to the insurer is the sum of the risk premium plus the expected payoff. Hence, if t$\lambda_j$ is the risk factor associated with a borrower of type *j*,the total cost of insurance for the firm would be,

$$P = \lambda_j * \sigma_{EP} + EP \qquad (6)$$

Using Importance Sampling Theory to Simulate MFI Portfolio

While individual client defaults are more frequent and have been rising (as evident from the increasing write-off ratio in recent years), defaults on a scale as large as that resulting from the Andhra Pradesh crisis are less common. We are going to assume that if the method works in an extreme case scenario, it will also work under a more regular/expected outcome. Using the theory from Importance Sampling (IS), we shall find out the appropriate default probabilities and use these to simulate the portfolio and further, to price the insurance. Defined by Paul Glasserman, Wanmo Kang and Perwez Shahabuddin, portfolio credit risk is measured through probabilities of large losses, which are typically due to defaults of many obligors (who are sources of credit risk) to which a portfolio is exposed. One challenge in simulating such a portfolio is that for a large default to occur the sources of credit risk share some common factor between them and hence there is factor dependence in this model[14].The dependence between these factors that trigger client default is definitely a challenge. However, for the purpose of this paper, we shall make a simplifying assumption and use single factor models.

Proved in the same paper by Glasserman, Kang and Shahabuddin, IS techniques can be used to increase efficiency in rare-event simulation where Monte-Carlo simulation might not be the most optimal option to use. The reason for using IS techniques are twofold: (i.) We do not have access to the data about individual default rates. In fact, MFI's do not provide us a number for the client defaults. Rather we need to infer it from the loan write-offs and portfolio-at-risk. Therefore, we would like to use this technique to help us see a worst-case scenario. (ii.) The latent factors that trigger default are rare and hard to quantify mathematically. These factors could be weather-related leading to mass farmer defaults; as we saw in the case of the Andhra Pradesh crisis, this factor could also be related to an external agency wherein they can pressurize clients not to repay their loans. Following are the parameters that we need in order to be able to proceed with this modeling exercise[15]:

- *m* = The number of obligors to which the portfolio is exposed. In our case, it will be the total number of active borrowers of an MFI.
- $Y_k$ = A binary variable which is 1, indicating default, and 0 otherwise for the *k-th* borrower.
- $p_k$ = Probability that the *k-th* borrower defaults. For simplicity, we will consider that this probability is the same across all borrowers.
- $l_k$ = Loss resulting from default of the *k-th* borrower. This will be the value of the gross loan portfolio per borrower. Hence, for this exercise it will be the same deterministic value across all borrowers.
- $L_m = l_1Y_1 + l_2Y_2 + ... + l_mY_m$ = Total loss from defaults.

Simulation will need to be done to approximate how many clients will default and thus, to determine how many insurance contracts the MFI needs to purchase. In our case, the payoffs in the two different scenarios are deterministic. Since an external factor causes clients to default, we will assume that the latent variable that causes the default indicator to be one has a normal distribution. These latent factors exist but are hard to quantify mathematically. We assume that these are normally distributed. The normal distribution has a bell-shaped curve that peaks around the mean and tapers off for extreme values in either direction. The assumption

[14]Paul Glasserman, Wanmo Kang and Perwez Shahabuddin, "Fast Simulation of Multifactor Portfolio Credit Risk," last modified January 2007,1.
[15]Ibid, 3.

of the normal distribution helps us take into account all these latent variables, those that will be more frequent (such as erratic weather) and lie in the bell-region of the distribution and those like external pressure that are rare and lie at either extreme ends. Let us represent these latent variables by $X_k$, that is, the latent variable for the *k-th* borrower. The default indicator for the *k- th* borrower can then be expressed as[16]:

$$Y_k = \mathbf{1}\left(X_k > \phi^{-1}(1-p_k)\right) \qquad (7)$$

$\phi$ is the cumulative normal distribution, $X_k$'s are the (correlated) standard normal variables. Correlations between these latent random variables represent the correlations of the default indicators. As mentioned before, we shall assume single-factor models where the default is triggered by one factor only. From derivations in the paper by Glasserman, Kang and Shahabuddin, if the *k-th* borrower is of type *j* then the latent variables can be expressed as:

$$X_k = a_j \boldsymbol{Z} + b_j \epsilon_k \qquad (8)$$

$a_j \in$ R and $0 < |a_j| < 1$, $Z$ is a standard normal variable representing the systematic risk factors, $b_j = \sqrt{1-a_j^2}$ and finally, $\varepsilon_k$ is a vector representing the idiosyncratic risk factors. We shall also divide the borrowers into three categories: high risk
($a_h \in$ 0, 0.35 ), medium-risk ($a_m \in$ 0.35, 0.65 ), and low-risk ($a_l \in$ (0.65,1)). We can understand the $a_j$'s to be some sort of a credit score, where the best clients get the highest score, similar to the way credit-card companies provide a credit score to cardholders. For the case of Indian microfinance, this is easy to determine: post the Andhra Pradesh crisis, the government mandates the issue of something called a Hallmark Report. This report is electronically generated for every MFI borrower and indicates his/her credit history, how many other MFIs the borrower has taken loans from, and so on. MFIs are finding this report to be very useful and besides the loan officer's own checks and judgment, can refer to it as an extra source of credit check before lending money[17].From the given values of $a_j$'s, we can determine the corresponding values of $b_j$'s. The next step in utilizing the Importance Sampling theory is to express the default events as independent Bernoulli random variables, if we can. This can be done if we condition the default probability on the systematic risk, *Z*. Thus, the conditional default probability of the *k-th* obligor of type *j*, is given by[18]:

$$p_k^j(Z) = P(Y_k = 1|Z) = P(X_k > \phi^{-1}(1-p_k)|Z) = \phi\left(\frac{a_j Z + \phi^{-1}(p_k)}{b_j}\right) \qquad (9)$$

In the above equation, we utilized the expression for $X_k$ from Equation (8) and the fact that $\phi^{-1}(1-p_k)$ is $-\phi^{-1}(p_k)$. We will get three different values of this probability, one for each type of borrower.
We use the ratio of loan write-off over the gross loan portfolio value as an indicator of the default probability. Since we are working in per-borrower terms for our model, we would like to find the default probability for every borrower on an average. Thus, we take the ratio of write-off per borrower and the gross loan portfolio per borrower. This cancels out the number of borrowers from the numerator and the denominator. Thus, the default probability for the *k-th* obligor is:

$$p_k = \frac{Write-Offs}{Gross\ Loan\ Portfolio} \qquad (10)$$

The fact that the default probability is the same for every borrower is counterintuitive to the fact that we have divided the borrowers into three categories: low, medium and high risk. However, we see from Equation (9) above that we are able to find the default probabilities for the borrowers belonging to different categories by applying the factors $a_j$ and $b_j$. Once the MFI has determined the category of the borrower using the Hallmark Report as well as the loan officer's judgment, the default probability of the borrower in a particular category can be determined using Equation (9). Let us enlist step-wise how to simulate the default of clients.

1. Determine the value of the default probability of the *k-th* borrower as in Equation (10). We would like to use the risk neutral value here and therefore, determine the industry average. We take the historical average of the default probabilities for each MFI. We then take the average of these default probabilities to try and get an industry-wide metric. The value of this default probability for the Indian MFIs is 11.6%. Thus, independent of the client categorization, on an average there is 11.6% chance that a particular borrower will default.
2. Based on the score that the MFI has assigned to the client, it can be determined whether the borrower is deemed to be a low, medium or a high-risk borrower. For instance, if the MFI assigns a score of 0.5, we know that the borrower is considered to be a medium-risk borrower. The value of $a_j$ that we will use to

[16]Ibid, 4.
[17]Shailendra Pratap Singh (State Head, Bhartiya Samriddhi, Bihar, India), in discussion with the author, December 2014.
[18]Glasserman, Kang and Shahabuddin, "Fast Simulation of Multifactor Portfolio Credit Risk," 5.

determine the default probability in any category should be the average of the boundary values of that category. Thus, the values of $a_j$ to be used are 0.175, 0.5 and 0.825 for high, medium and low-risk borrowers respectively. Thus, in the above example, the value of $a_j$ to be used is 0.5 since the borrower is deemed to be a medium- risk client. Corresponding to the $a_j$'s, the values of $b_j$ can be determined as 0.985, 0.866 and 0.565.

Now, using Equation (9) we can find the values of default probabilities for each type of client under a risk-neutral measure. We will do this by simulating standard normal random variables ($Z$) for this purpose and take an average of 100 trials. These trials represent different realizations of the systematic risk that have the standard Gaussian distribution. Table 1 lists the values so obtained. Risk-neutral probabilities, as the ones we have obtained below, are risk-adjusted. They take into account the industry risk metrics so that one does not have to compute different probabilities for every firm in the industry based on its individual risk profile. We will use these probabilities to determine the expected payoffs for insurance pricing.

| Risk Profile | Probability of Default |
|---|---|
| Low-Risk | 6.9% |
| Medium-Risk | 9.1% |
| High-Risk | 10.8% |

**Table 1**

3. While the above parameters will be sufficient to price the insurance, we need to simulate the portfolio to gauge a measure of how many clients are expected to default. For this, we first use Equation (8) and find a measure for the latent variable $X_k$, that triggers defaults. We need another simulation of the systematic risk, $Z$ that affects all the borrower of a particular category $j$ with corresponding probability of default, $p^j_k$. Let us use $Z_{avg}$ as the value for the systematic risk, where we have taken the average of $n^j$simulated standard normal random variables, where $n^j$is the number of borrowers in category $j$. We simulate a separate set of standard normal random variables representing the idiosyncratic risk, the size of this set being equal to the number of active borrowers of the MFI belonging to a particular category. We simulate as many of these latent variables for each category as there are the number of active borrowers of an MFI.
4. Finally, we should be able to predict whether a particular client will default based on whether the default indicator is 1. Having found out the latent variables, we can use Equation (7) and determine these indicators. The category assigned to an individual borrower is based on his prior credit metrics, using which the borrower is assigned a credit score. Since we cannot determine an individual borrower's credit score, we go about determining what the distribution for defaults would look like for each category. This is a simple RStudio calculation. The purpose of predicting how many clients default is to see how many insurance contracts the MFI should purchase. We do this prediction for Future Financial Services Ltd, an MFI in India. The calculations yield that if we assumed that *all* of its 2,12,136 borrowers in 2011 belonged to a particular category, 749 of them would default if all the borrowers were low-risk; 11,973 would default if they were medium-risk and 21,412 of them would default if they were all high-risk. This translates to corresponding defaults amounting to \$123,616, \$1,976,043 and \$3,533,871 for low, medium and high-risk borrowers. We obtain these values by multiplying the expected number of defaults by the gross loan portfolio value per borrower in 2011. The actual write-off for this year was \$3,78,151.

These values give us confidence in our procedure and indicates that with access to credit scores for the borrowers, an MFI should be able to predict how many of its borrowers are going to default, and thus, how many hedging contracts it should invest in.

**Pricing Insurance Contracts**

We now need to determine the exact expressions for the parameters that we should use to find a value of the contract. It is clear that the loan amount repaid is the principal plus some interest. The principal is thus, the gross loan portfolio value per borrower. As discussed before, this does not include the interest amount. Therefore,

$$S_t = \frac{Gross\ Loan\ Portfolio}{Number\ of\ Active\ Borrowers} \qquad (11)$$

where, $S_t$ is the principal amount mentioned in Equation (2). The expense incurred per borrower is another parameter that we need, available from Equation (4). The risk premium is the final parameter that we have to determine. From Equation (6), we know that it is the standard deviation of the expected payoff times some factor, which we call $\lambda$. Determining an expression for this factor is our next and final step towards pricing these insurance contracts. The risk premium paid should be higher for the riskier clients and this should be related to

the credit score that the MFI assigns to the clients during borrower screening. A good factor to use here could be $b_j$. From the expression of determining $b_j$, we know that the riskier borrowers will have a lower associated value for this parameter. If this factor were to be multiplied with the measure of volatility of the expected payoff of that particular category of client, the volatility would be penalized more for the least risky client, leading to lower risk premiums for the safest borrowers. While the MFI will definitely need to pay the amount equivalent to the expected payoff given the two different scenarios (no arbitrage), the risk premium is something that we have more control on when pricing the contract. If we use the square of $b_j$ as a factor to penalize the volatility, it will provide the MFIs lower risk premiums for thecorresponding clients. It is implied from the fact that $\|b_j\| < 1$ so the square of this value will be lower than the original value of this factor. Since the counterparty of the contract is getting involved as a socially conscious entity, the slight reduction in the premium should not hamper the intent to get involved. The risk premium can be considered analogous to the return an investor would receive had he put in money in the MFI to receive some return. The risk premium is an excess amount received over the expected payoff value and provides the counterparty an incentive to bear the risk. Since the time horizon that we consider is for a year, the counterparty also receives this amount in much less of a time period.
To update our expression for the price of the insurance contract, we use all the analysis above so that the pricing equation to purchase a contract for a borrower of type $j$ is as follows:

$$P_j = b_j^2 * \sigma_{EP} + \left(1 - p_j\right) * (S_t * (1 + \tau) - C) - p_j * C \qquad (12)$$

The above equation can be used to determine the price that the MFI has to pay to insure itself against the risk of default. Let us use the above to determine the price of the insurance contract for each type of borrower for Future Financial Services Ltd. for the year 2012. This MFI charges an interest of 20.8%[19]from its clients. So let us use this interest rate in the pricing formula of Equation (12). The value of $b_j$ for each borrower, as previously derived are, 0.985, 0.866 and 0.565 for high, medium and low-risk borrowers, respectively. At a gross loan portfolio value of \$209.40 and cost per borrower of \$55.13, the price of the contract for each type of borrower is listed in Table 2.

| Type of Borrower | Expected Payoff (in \$) | Risk Premium (in \$) | Price of the Contract (in \$) |
|---|---|---|---|
| Low-Risk | 180.38 | 20.47 | 200.85 |
| Medium-Risk | 174.81 | 54.56 | 229.37 |
| High-Risk | 170.51 | 76.18 | 246.69 |

**Table 2**

As predicted, the expected payoff decreases with the riskiness of the borrower while the risk premium increases. A probable payment schedule to enter this insurance contract is to make a certain amount of payment monthly. Therefore, the first payment could be the risk premium plus one-twelfth of the expected payoff, which is included in the price of the contract. The next eleven payments would then be the same fraction paid very much like the insurance premiums under a conventional scenario.

Now that the price of the insurance contract has been determined, let us determine how many of these contracts the MFI would actually need to purchase. Naturally, the number of contracts purchased would be in the ballpark of number of defaults expected. The latter can be determined using the simulation techniques previously devised. One minor setback before proceeding on this is the fact that we do not have access to individual credit scores of the borrowers, and therefore, we do not have the exact number of borrowers in each category. One way to work around this is to proceed based on an assumption that echoes real-world functioning of financial firms. Formal banks in India usually cap their high-risk clients at 20% of the total number of borrowers[20].Since any firm would like to have more of the lowest-risk borrowers, let us assume that the composition between the low, medium and high-risk borrowers is 45%, 35% and 20% of the total number of borrowers in any given year. Using the simulation techniques from the previous chapter, following is the expected number of defaults of clients in each category.

| Year | Total Borrowers | Predicted Number of Defaults | | | Total Number of Defaults |
|---|---|---|---|---|---|
| | | *Low-Risk* | *Medium-Risk* | *High-Risk* | |
| 2009 | 2,57,991 | 520 | 5,611 | 5,401 | 11,532 |
| 2010 | 2,99,919 | 569 | 6,416 | 6,385 | 13,370 |
| 2011 | 2,12,136 | 384 | 4,548 | 4,407 | 9,339 |
| 2012 | 1,79,620 | 312 | 3,890 | 3,773 | 7,975 |

**Table 3**

Note that even though the total number of defaults for the medium-risk borrowers is shown to be higher than the

[19]"Future Financial Services ltd., Audited Financial Statements," last accessed April 2015, 33, http://www.mixmarket.org/sites/default/files/ffsl_financials_-_fy_2013-14.pdf.
[20]Shailendra Pratap Singh, in discussion with the author, December 2014.

number of defaults of high-risk borrowers, the percentage of defaults amongst the high-risk borrowers is greater, since the number of borrowers in this category was assumed to be lesser to begin with. Let us see how these compared to the actual defaults. The loan portfolio value per borrower for Future Financial Services Ltd. was \$210.60, \$173.31, \$165.04 and \$209.40, corresponding to the years 2009, 2010, 2011 and 2012. We have access to the total loss amount in the form of loan write-offs for each year. We can also see the predicted loan default amount by taking the product of the total expected default and the loan portfolio value per borrower. Table 4 gives us these values.

| Year | Predicted Default (in \$) | Realized Loan Write-Off (in \$) | Predicted Default/Write-Off |
|---|---|---|---|
| 2009 | 24,28,639 | 5,02,009 | 4.84 |
| 2010 | 23,17,155 | 37,35,308 | 0.62 |
| 2011 | 15,41,309 | 3,78,152 | 4.08 |
| 2012 | 16,69,965 | 23,99,305 | 0.70 |

**Table 4**

Thus, during non-crisis years, we are over- predicting the number of defaults. So if the MFI were to invest in the number of insurance contracts predicted via simulation, it would be over-insured, if nothing else. Importance Sampling relies on weighing those values in the distribution that have a greater impact on the parameter being estimated, and simulate those values more frequently. Thus, when we are using this technique to simulate client defaults, we can infer from the theory that the defaults will be overestimated at the input parameters. Therefore, the parameters that overestimate the default for non-crisis years might be in line with actual defaults or even underestimate them for the crisis year. We can expect this to happen when we use an assumption on the categorization of the MFI clients. This is because the categorization that works for the more regular scenarios might not hold for the crisis scenarios. During the years of crisis, such as 2010 and 2012 (the funding to the MFI sector had reduced in 2012 post the release of RBI regulations), the predicted default amount is about 60%-70% of the actual number of defaults. A possible reason behind under-estimating the number of defaults during the crisis-years is that a lot of clients that may have been perceived to be low or medium-risk borrowers turn out to be high-risk borrowers, because of the effect of some external factor. Thus, the 20% of the high-risk borrowers becomes a very conservative number. However, we believe that MFIs will have access to better credit reports (via the Hallmark Report) and will have more accurate estimate of the percentage of borrowers in each category. For now, we will continue working with the 45-35-20 percent categorization, for even though the 20% cap of high-risk borrowers may turn out to be conservative during crisis years, we are able to insure a significant value of the loan portfolio against defaults.

The next step in this analysis is to determine the number of insurance contracts and hence the total amount the MFI will need to invest in purchasing these contracts. We have already determined the price of these contracts for Future Financial Services Ltd. for the year 2012. Note that the price will be different each year based on the gross loan portfolio value, the interest rate charged and the expense incurred per borrower. For the year 2012, the predicted default amount is \$1,669,965.00. We assume that the MFI is going to follow the simulation results and buy the number of insurance contracts as there are defaults for each category. Therefore, it would be buying 312 contracts for low-risk borrowers, 3890 contracts for medium-risk borrowers and 3773 contracts for high-risk borrowers (Table 5.2). Given that the respective expected coverage is \$180.38, \$174.81 and \$170.51, the MFI will receive \$1,379,623.69 in total of insurance coverage and it will pay \$1,885,675.87 in total of insurance premiums (including risk premium). Therefore, if FFSL had purchased insurance contracts for the year 2012 based on the simulation carried out here, instead of \$2,399,304.81, its write-off value would have been \$1,019,681.12 (difference between actual write-off and the amount received from exercising insurance contracts). If we include the risk premiums paid, the loss would have been \$1,525,733.30. Thus, the loss amount is reduced by 36.4%, including all premiums paid! In the real-world application of the simulation technique to determine the number of defaults, the MFI will hopefully have a better understanding of the credibility of the borrower through Hallmark Report and thus, the estimation of the expected number of defaults in each category will be more accurate.

The question following this analysis is that how exactly will the MFI pay for the insurance and where does it bring in the investment amount from. For this, we first price the insurance contracts for each year and for each borrower category using an interest rate of 20.8% to see the range of prices needed to purchase insurance contracts. Using the similar calculations as before, the prices for the contracts (including the risk premium) for each category of borrower are listed below in Table 5.

| Year | Price of the Insurance Contract (in $) | | |
|---|---|---|---|
| | *Low-Risk* | *Medium-Risk* | *High-Risk* |
| 2009 | 226.28 | 254.96 | 272.30 |
| 2010 | 151.52 | 171.06 171.06 | 182.87 |
| 2011 | 115.68 | 133.97 133.97 | 145.03 |

**Table 5**

A possible way to pay for the insurance contracts is to use the liquid assets to pay for purchasing these contracts. When a crisis occurs, firms usually liquidate their assets for extremely low prices and use the cash so obtained to pay off existing debt or any immediate expense. The difference here is that the cash obtained from liquidating the requisite amount of these assets would be used to hedge the MFI against defaults, and thus, the value for the assets obtained would be in line with the market value. As Table 5 shows us for the case of Future Financial Services Ltd,, purchasing these contracts would amount to liquidating only a very minor percentage of assets. The fact that it helps the MFI to hedge itself against major defaults makes the minor liquidation worth it. Of course, if the MFI has cash ready to finance the purchase of these contracts, the asset liquidation is not even necessary.

| Year | Total Price of Insurance Contracts (in | Total Asset Value (in $) | Insurance Contract Price as %age of Asset Value |
|---|---|---|---|
| 2009 | 3,018,938.46 | 63,535,654.70 | 4.7 |
| 2010 | 2,351,360.79 | 52,927,678.10 52,927,678.1034 | 4.4 |
| 2011 | 1,112,762.61 | 34,348,749.00 34,348,749.00 | 3.2 |
| 2012 | 1,885,675.87 | 31,187,084.90 | 6.0 |

**Table 6**

One possible hindrance towards the application of this technique is that defaults are over-estimated between two to five times for the years that experienced no major defaults. A possible way to work around this is to leverage the fact that the MFIs have a philanthropic aspect attached to their operations, and that the counterparties will be socially conscious entities as well. We have already discussed a possible payment schedule of the insurance premiums. The MFI could establish a checkpoint (at six month, say) during the validity of the insurance contract. At this checkpoint, if it seems that an insurance contract might not even be necessary for a client because he has been regular with his loan payments, the counterparty should return the premiums paid as part of the expected payoff, keeping the risk- premium paid as compensation for sharing the client default risk with the MFIs. Alternatively, if another client, originally perceived as safe and therefore uninsured, has been unable to make timely payments, the insurance contract can be transferred to hedge against the risk of this new high-risk client.

Since the major motive of this research is for the MFIs to be able to expand their operations by reducing the risks that they are exposed to, let us see how the price of the insurance contract would be affected with the change in their important parameters. Tables 7-9 show the direction of movement of the price of the insurance contract with changes in the interest rate and the expense per borrower of the same MFI, Future Financial Services Ltd.

| | **$50** | **$51 $$51** | **$52 $52** | **$53 $53** | **$54 $54** | **$55.13** | **$56 $56** | **$57 $57** |
|---|---|---|---|---|---|---|---|---|
| **17.0%** | 197.92 | 196.25 195.2619 | 195.26 195.26 | 194.26 194.26 | 193.26 193.26 | 192.13 | 191.26 191.26 | 190.26 190.26 |
| **18.0%** | 199.37 | 198.37 | 197.37 | 196.37 | 195.37 | 194.25 | 193.37 | 192.38 |
| **19.0%** | 201.48 | 200.48 | 199.48 | 198.48 | 197.48 | 196.36 | 195.49 | 194.49 |
| **20.0%** | 203.59 | 202.59 | 201.59 | 200.60 | 199.60 | 198.47 | 197.60 | 196.60 |
| **20.8%** | 205.28 | 204.28 | 203.28 | 202.29 | 201.29 | **200.16** | 199.29 | 198.29 |
| **21.0%** | 205.70 205.70 | 204.71 | 203.71 | 202.71 | 201.71 | 200.58 | 199.71 | 198.71 |
| **22.0%** | 207.82 207.82 | 206.82 | 205.82 | 204.82 | 203.82 | 202.70 | 201.82 | 200.83 |

**Table 7:** Low-Risk Borrowers

| | **$50** | **$51** | **$52** | **$53** | **$54** | **$55.13** | **$56** | **$57** |
|---|---|---|---|---|---|---|---|---|
| **17.0%** | 225.55 | 224.55 | 223.55 | 222.55 | 221.55 | 220.42 | 219.55 | 218.55 |
| **18.0%** | 227.90 | 226.90 | 225.90 | 224.90 | 223.90 | 222.78 | 221.90 | 220.90 |
| **19.0%** | 230.26 | 229.26<br>229.26 | 228.26<br>228.26 | 227.26<br>227.26 | 226.26<br>226.26 | 225.13 | 224.26<br>224.26 | 223.26<br>223.26 |
| **20.0%** | 232.62 | 231.62 | 230.62 | 229.62 | 228.62 | 227.49 | 226.62 | 225.62 |
| **20.8%** | 234.50 | 233.50 | 232.50 | 231.50 | 230.50 | **229.37** | 228.50 | 227.50 |
| **21.0%** | 234.97 | 233.97 | 232.97 | 231.97 | 230.97 | 229.84 | 228.97 | 227.97 |
| **22.0%** | 237.33 | 236.33 | 235.33 | 234.33 | 233.33 | 232.20 | 231.33 | 230.33 |

**Table 8:** Medium-Risk Borrowers

| | **$50** | **$51** | **$52** | **$53** | **$54** | **$55.13** | **$56** | **$57** |
|---|---|---|---|---|---|---|---|---|
| **17.0%** | 242.32 | 241.32 | 240.32 | 239.32 | 238.32 | 237.19 | 236.32 | 235.32 |
| **18.0%** | 244.82 | 243.82<br>243.82 | 242.82<br>242.82 | 241.82<br>241.82 | 240.82<br>240.82 | 239.69 | 238.82<br>238.82 | 237.82<br>237.82 |
| **19.0%** | 247.32 | 246.32<br>246.32 | 245.32<br>245.32 | 244.32<br>244.32 | 243.32<br>243.32 | 242.19 | 241.32<br>241.32 | 240.32<br>240.32 |
| **20.0%** | 249.81 | 248.81<br>248.81 | 247.81<br>247.81 | 246.81<br>246.81 | 245.81<br>245.81 | 244.69 | 243.81<br>243.81 | 242.81<br>242.81 |
| **20.8%** | 251.81 | 250.81 | 249.81 | 248.81 | 247.81 | **246.69** | 245.81 | 245.81 |
| **21.0%** | 252.31 | 251.31<br>251.31 | 250.31<br>250.31 | 249.31<br>249.31 | 248.81<br>248.31 | 247.19 | 246.31<br>246.31 | 245.31<br>245.31 |
| **22.0%** | 254.81 | 253.81 | 252.81 | 251.81 | 250.81 | 249.68 | 248.81 | 247.81 |

**Table 9:** High-Risk Borrowers

From the sensitivity analysis presented above, we see that for a given cost, the insurance contract becomes cheaper for a lower interest rate. Thus, at the given cost per borrower the MFI will be able to hedge its risk more cheaply if it reduced the interest rate that it charges from its clients. This is a very important observation. This will help counteract one of the biggest criticisms of MFI operations, that it charges extremely high interest rates from its borrowers and pushes them into debt traps. We also see that the cheapest insurance contracts are realized at the lowest interest rates and the highest expense per borrower. This may seem strange initially because this seems to be pushing towards the conclusion that the MFI should increase its expenses to obtain the lowest cost insurance. However, we must remember that hedging is just one of the many aspects of sustainable MFI operations. Increased expenses will lead to lower margins adversely affecting its financial statements. If we look at the sensitivity tables, we see that the extra dollar we save on the insurance contract is the dollar that we increase on our expense per borrower. Therefore, our interpretation from the sensitivity analysis of the insurance contract prices is that lowering the interest rates for the MFIs is beneficial for both the client and the firm: the former, because they have to pay lesser on the interest on their principal amount; the latter, because with reduced interest rate on lending, credit will be accessible to more clients and the cost of hedging for the firm is reduced.

Despite the perceived benefits of having hedging instruments in place, the MFI cannot be fully efficient unless it reduces costs. In fact, the higher cost of operation has often been cited as a reason for the unsustainability of microfinance firms. Following are the three major reasons for these expenses[21]:

- Cost of delivery of services is high because of remoteness of the areas where clients live.
- Client defaults add to increased expenses as it amounts to rigorous follow-up and strict supervision by staff, who in turn need to be compensated more.
- Trained staff usually tends to leave in search of better employment opportunities and expense has to be incurred in training new staff.

While it is easier to cut certain expenses, there are some investments that need to be increased for longer run cost effectiveness. For instance, MFIs can look into the modes of transport used by their employees to travel to the areas where the clients are based and see if there is a potential to cut costs. On the flip side, MFI employees need to be compensated at par with formal bank employees, otherwise they will leave in search of better job opportunities. Increasing their salaries along with a certain binding work contract are possible solutions to help the MFI save on training costs for new staff. These are just possible solutions and more solid

[21]Krishan Jindal, K.C Ranjani and K.C. Sharma, "Sustainability of MFIs in India- A Sectoral Perspective" in *Microfinance Institutions- Issues in Sustainability*, ed. Krishan Jindal and K.C. Sharma (Lucknow: Bankers Institute of Rural Development, 2001), 11.

cost-effective strategies are a firm-specific problem, because the distribution of expenditures and potential areas of savings are best known to the firm and its employees. Perhaps the most important part of training MFI workers would involve training them in the best practices of client interaction. MFI employees exacerbated the Andhra Pradesh crisis because of the abusive treatment of the clients. This also had adverse social contexts as we have previously seen. What needs to be understood here is that sometimes even the best clients may find it difficult to repay their loans because of unavoidable circumstances. Coercive treatment will only make the situation worse and the MFI workers need to be trained in handling situations of client defaults more pragmatically. Therefore, investment in the training of and retention of MFI employees is extremely important.

The mission of the microfinance sector across the globe is the same: economic empowerment of the poor by providing them the necessary financial services that they are otherwise unable to access. The sector functions in a way, which shows that working with the poor is not equivalent to running a non- profit. Some firms have done exceptionally well and are the quoted examples of model MFIs. BRAC in Bangladesh, Alexandria Business Association in Egypt, and BancoSol in Bolivia are such examples. A common element between all of these institutions is that they have internal early warning systems and management responses that preventing small problems from exploding into large ones[22].This reiterates the fact that it is imperative for other firms to manage their risks as the traditional financial sector to ensure sustainability in operations.

While this research has focused on the Indian microfinance sector to build upon and test the applicability of this research, we hope that the underlying theories can be applied to further improve the MFI sector in other countries as well. As mentioned previously, this may involve the consideration of different factors than that affecting the Indian poor and the usage of multifactor models. The developing nations, where MFI services are most needed, have boasted consistent growth over the past few decades. But economic empowerment is never exclusive. As the developing nations progress through on the path of greater economic development, it is a humanitarian responsibility that the underprivileged, who form a significant part of the population in these nations, are not left behind. Microfinance services are integral for providing these people the opportunities for economic growth and security. The rich and privileged cannot be the sole yardstick for economic growth and stability. It is those crushed by their circumstances and limited by their means who need these microfinance services to be strengthened and for their strategies to be revamped to truly achieve the goal of prosperity. These are not egalitarian measures but the need of the hour to be able to prevent greater crises. And the clock is ticking away. It is time to act.

## References


[1]. Agarwal, A.K., and Bhartendu Singh, eds. *Micro Finance in India.* Guwahati: DVS Publishers, 2013.

[2]. Bhandari, Amit, and Ashok Kundu, eds. *Microfinance, Risk-Taking Behaviour and Rural Livelihood.* New Delhi: Springer Publications, 2014.

[3]. Bramono, Dewi, Ming Chung, Yoonmi Eom, Kevin Lam, and Yenn Khan, “Microfinance in Indonesia,” Economics and Management in Developing Countries.

[4]. Consultative Group to Assist the Poor (CGAP). “Andhra Pradesh 2010: Global Implications of the Crisis in Indian Microfinance,” CGAP Focus Note, No. 67 November 2010. Accessed February 2017. http://www.cgap.org/sites/default/files/CGAP-Focus-Note-Andhra- Pradesh-2010-Global-Implications-of-the-Crisis-in-Indian-Microfinance-Nov- 2010.pdf.

[5]. Deutsche Gesellschaft für Technische Zusammenarbeit. “A Risk Management Framework for Microfinance Institutions,” July 2000.

[6]. Fisher, Thomas and M.S. Sriram. *Beyond Micro-Credit: Putting Development Back into Micro-Finance*. Oxford: Oxfam Publishing, 2002.

[7]. “Future Financial Services Ltd., Audited Financial Statements,” accessed April 2015. http://www.mixmarket.org/sites/default/files/ffsl_financials_-_fy_2013-14.pdf.

[8]. Giné, Xavier, Lev Menand, Robert Townsend, and James Vickery. “Microinsurance: A Case Study of the Indian Rainfall Index Insurance Market,” The World Bank Development Research Group, Finance and Private Sector Development Team. October 2010.

[9]. Glasserman, Paul, Wanmo Kang, and Perwez Shahabuddin. “Fast Simulation of Multifactor Portfolio Credit Risk,” last modified January 2007.

[10]. Guérin, Isabelle, Solène Morvant-Roux, and Magdalena Villarreal, eds. *Microfinance, Debt and Over-Indebtedness*. Oxon: Routledge, 2014.

[11]. Jena, Sanjeeb K. *Micro Finance and Micro Enterprises in India.* New Delhi: New Century Publications, 2013.

[12]. Jindal, Krishan, and K.C. Sharma, eds. *Microfinance Institutions- Issues in Sustainability.* Lucknow: Bankers Institute of Rural Development, 2001.

[13]. “MixMarket Bangladesh Market Profile,” accessed February 2017. http://www.mixmarket.org/mfi/country/Bangladesh.

[14]. “MixMarket India Market Profile,” accessed February 2017. http://www.mixmarket.org/mfi/country/India.

[15]. “MixMarket MFI Report,” accessed March 2017, http://www.mixmarket.org/node/34436/report.

[16]. “Mix Microfinance World: India Post-Crisis Results,” accessed March 4, 2015. http://www.themix.org/sites/default/files/MMW-%20India%20Post%20Crisis%20Results.pdf.

[17]. Shyamsukha, Rahul. “India: post microfinance crisis results,” in *India: Post microfinance crisis results.* November 2011. Accessed February 2017. http://www.themix.org/publications/mix-microfinance- world/2011/11/india-microfinance-post-crisis-results.

[18]. Srinivasan, Girija. *Microfinance India: The Social Performance Report 2012*. New Delhi: SAGE Publications, 2013.


[22]“A Risk Management Framework for Microfinance Institutions,” July 2000, 8.