Centre Emile Bernheim
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H. Marrez and M. Schmit

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JEL Classifications: G21; G28; O16

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Credit risk analysis in microcredit: How does gender matter?

by

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Abstract

This paper is the first to analyze the credit risk of a microfinance institution based on the loan portfolio of a leading Maghrebian microfinance institution, both in terms of number of clients served and of portfolio size. This allows us to work with a proprietary data set of 1,144,770 contracts issued between 1997 and 2007. Using a resampling technique, we estimate the probability density function of losses and value-at-risk measures for a portfolio of loans granted to female and male microfinance clients separately. Results show that loss rates are higher for a male client population than for a female client population, both on average as for percentiles 95 to 99.99. We find that this difference is due to lower default probabilities for female clients, while recovery rates for male and female clients are similar. We also analyze diversification effects, where we find that the proportion of diversifiable risk in total risk is bigger for portfolios of loans granted to female clients than for portfolios of loans granted to male clients. Finally we show that capital requirements determined by the 99.9 percentile remain below those required by the Basel 2 Accords, which opens perspectives for a specific treatment of microfinance if financial regulation becomes applicable to the sector.

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1. Introduction

During the last two decades, microfinance has evolved from an informal sector into a semi-mature, professional industry. Microfinance institutions begin to face some of the main challenges of regular retail banks: dealing with competition, offering good services at low cost and monitoring risks. The latter is particularly important when microfinance institutions become big or start to accept savings. Nevertheless, little research has been done on the analysis of credit risk and loss distributions of microfinance loan portfolios. One of the topics in relation to this subject is the idea that women have better repayment records than men, explained by for example Armendariz and Murdoch (2005, p. 183). Studies with large amounts of data that give proof for this hypothesis are not available yet. Studies on small data sets include a survey of 358 micro-entrepreneurs in Guatemala by Kevane & Wydick (2001). A report on the Grameen bank (Khandker, Khalily & Kahn, 1995, p.76) finds that men are more likely to default than women.[2]

We use a large data sample over a time frame of 10 years to calculate the loss distribution for two portfolios of loans, one consists of loans granted to male clients, the other comprises loans granted to female clients. The loss distributions are calculated with a re-sampling technique similar to the one used by Carey (1998), Calem and LaCour-Little (2004) and Schmit (2004) to estimate credit risk in private debt portfolios, in mortgage loan portfolios and in the leasing industry respectively. To our knowledge this is the first study that applies the technique on microfinance loan portfolios. Our results can be used to show a difference between the credit risk of loans granted to female clients versus male clients. We also compare the obtained loss

[2] It has to be mentioned that 95% of the client population of Grameen bank are women.

distributions with those obtained by Carey (1998) for private debt portfolios, in order to discuss the level of credit risk of microfinance compared to that of retail banking.

The next section of this paper explains the methodology used. Thereafter we discuss in detail the data set used in the study, followed by the results of our analysis. Section 5 consists of a discussion of the results and is followed by a comparison between capital requirements derived from the proposed internal model and the requirements derived from the Basel II accord. In the final section we highlight the conclusions drawn from our analysis.

2. Methodology

2.1 Measuring default probabilities

Default probabilities are defined as the probability the contract will default somewhere between issuance date and date of maturity.

A loan contract is defined as defaulted when the lender has unilaterally cancelled the agreement because the borrower did not pay one or more scheduled amounts due. The microfinance institution under consideration defines a contract as defaulted when one or more payments remain unfulfilled 30 days after the date they were due. In the database contracts are given the status ‘active’, ‘completed’ or ‘defaulted’. For the contracts where the client did not satisfy certain payments but managed to reimburse the full amount afterwards, the status ‘defaulted’ is set to ‘completed’. Hence we cannot distinguish between contracts with all payments settled on payment date and contracts with one or more payments fulfilled afterwards. We thus consider all contracts with the status ‘completed’ as satisfactory fulfilled.

2.2 Measuring loss given default and recovery rates

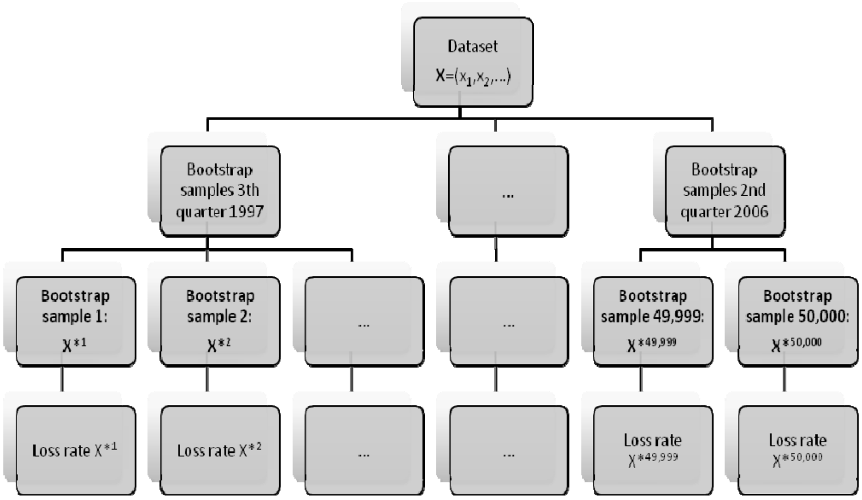
Loss given default is measured as the sum of all capital payments not fulfilled within 30 days, minus the recovered payments, divided by the total amount issued.[3,4] The loss rate for a given sub-portfolio is the sum of all losses incurred divided by the total amount granted. The recovery rate of a defaulted contract equals 1 minus the loss given default.

2.3 Bootstrap calculation of loss distribution

The data sample is subdivided into one subportfolio of loans granted to male clients and another one of loans granted to female clients. Subportfolio loss distributions are then estimated with a non-parametric resampling technique, similar to the one used by Carey (1998) to estimate credit losses in private debt portfolios. This technique is also known as 'bootstrapping'. As explained by Mooney and Duval (1993, p.1) "*bootstrapping differs from the traditional parametric approach to inference in that it employs large numbers of repetitive computations to estimate the shape of a statistic's sampling distribution, rather than strong distributional assumptions and analytical formulas*". The advantage of using a bootstrap technique thus lies in the fact that no parametric assumptions need to be made. Figure 1 represents the bootstrap process for estimating loss distributions.

[3] The institution does not charge interest on arrears.
[4] Administrative costs of recovering late payments are not taken into account in this analysis.

Figure 1: The bootstrap process for estimating loss distributions[5]



The basic process consists of choosing randomly, with replacement, a portfolio of *n* loans issued during a randomly chosen period of time, i.e. a quarter, in our study.[6] The draw of a quarter can be interpreted as a draw from the best available representation of the possible macroeconomic conditions influencing the risk factor. When a non-defaulted loan is drawn, the associated loss is zero, whereas when the process selects a defaulted loan, the associated loss is the loss given default as explained above. By dividing the sum of all losses with the sum of the full amounts granted, we obtain the loss rate of that particular bootstrap sample.

The process is iterated 50,000 times in order to obtain 50,000 bootstrap samples and thus 50,000 corresponding loss rates. The final step is the calculation of the average loss rate and the percentiles at 95%, 99.5%, 99.9%, and 99.99% in order to obtain the VaR95, VaR99.5, VaR99.9 and the VaR99.99 respectively.

By performing the draw procedure in two stages (i.e. first drawing a quarter, then a portfolio of *n* loans), we avoid the understating of tail loss rates. Otherwise, the combination of default

[5] Adapted from Efron, B & Tibshirani, R. (1997, p.13).
[6] In our research *n* equals 500 to 20,000.

experiences from different periods would lead to a tricky mixture of the underlying systematic factors and hence to over-diversification.

3. The data

3.1 The sample

Our database consists of a set of group loans issued by a Maghrebian microfinance institution. It is one of the leading MFIs in its country, both in terms of number of clients served and of portfolio size. The institution was founded in 1997 and has known a compounded annual growth rate of 71.83% between 1997 and 2007 included.

All loans have a maturity between 3 and 18 months. Amounts vary from 44 to 2692 Euros[7] and weekly, bimonthly or monthly repayment schemes are offered. Clients can apply for a group loan in groups of four to five persons. When the loans are approved, each client receives its own client code and detailed information on the client and his or her loan is treated individually in the institution's database. For this reason, we consider a loan to a client as one contract; hence one group represents four to five contracts. The database comprises detailed information concerning the loans granted, belonging to three categories. The first category consists of client details like his or her unique client code, gender, age and sector of his or her microenterprise. The second category encompasses the ex ante loan variables, which are the origination date of the contract, the amount granted, the maturity of the loan and the amount and the periodicity of forecasted payments. The third category groups the ex post loan variables, namely all effective payments, amounts remaining unpaid and the final status of the contract.

[7] Conversion to Euros based on the exchange rate of 31 March 2009.

Table 1 shows that in total 1,657,765 loans were issued between the 1st of January 1997 and the 30th of June 2007. We subdivide this portfolio into the segments started in 1997, which comprise 1,353,905 contracts, and the segments active since 2004, which comprise 303,860 contracts. Our analysis focuses on those segments launched in 1997, this to work with a sufficiently long time period of data. As the analysis needs to be performed on finished contracts only, we eliminate all loans still active on the 30th of June 2007. Furthermore we decide to limit our scope to those contracts with a maturity between 175 and 360 days, which represents over 99.5% of all contracts in the database. This leaves us with a sample of 1,144,770 loans.

Table 1: number of loans issued

	Total	**Segments launched in 2004**	**Segments launched in 1997**	**Of which maturity 175-360 days**
Completed	1,240,099	92,052	1,148,047	1,142,564
Defaulted	2359	36	2323	2206
Active	415,307	211,772	203,535	/
Total	1,657,765	303,860	1,353,905	1,144,770

3.2 Descriptive statistics

Descriptive statistics of our sample are shown in table 2. Panel A provides the frequency distribution by client's gender and issuance date of the contract. Panel B shows the frequency distribution by amount granted. Panel C indicates the number of contracts in our sample in comparison with the total number of loans granted between 1997 and 2007.

Table 2: Descriptive statistics of a sample of 1,144,770 completed contracts issued between 1997 and 2007.

Panel A: Frequency distribution by client's gender and issuance date of the loan

Year of issuance	Number of loans			Percent of total (%)	Cumulative percent (%)
	Women	Men	Total		
1997	272	1.053	1.325	**0,12%**	**0,12%**
1998	4.967	5.048	10.015	**0,87%**	**0,99%**
1999	17.609	14.986	32.595	**2,85%**	**3,84%**
2000	32.177	27.533	59.710	**5,22%**	**9,05%**
2001	52.214	40.636	92.850	**8,11%**	**17,16%**
2002	68.473	46.832	115.305	**10,07%**	**27,24%**
2003	87.446	58.613	146.059	**12,76%**	**40,00%**
2004	121.497	91.725	213.222	**18,63%**	**58,62%**
2005	161.776	158.621	320.397	**27,99%**	**86,61%**
2006	90.411	62.839	153.250	**13,39%**	**100,00%**
2007	11	31	42	**0,00%**	**100,00%**
Total	636.853	507.917	1.144.770	**100,00%**	**100,00%**

Panel B: Frequency distribution by amount granted

Amount in Euros	Number of loans	Percent of total (%)	Cumulative percent (%)
0-100	32.265	2.82%	2.82%
101-200	212.566	18.57%	21.39%
201-300	305.217	26.66%	48.05%
301-400	210.663	18.40%	66.45%
401-500	246.855	21.56%	88.01%
501-1000	129.623	11.32%	99.34%
1001-3000	7.581	0.66%	100.00%

Minimum: 44 Maximum: 2692 Mean: 344 Median: 314

Panel C: Proportion of loans in the sample in comparison with the number of loans issued by the MFI

Year of issuance	Proportion (%)	Year of issuance	Proportion (%)
1997	70.48%	2003	99.94%
1998	99.16%	2004	99.97%
1999	99.25%	2005	99.43%
2000	99.56%	2006	57.73%
2001	99.78%	2007	0.04%
2002	99.90%		

4. Results

4.1 Cohorts

We group all contracts of our sample into one sub-portfolio of loans issued to female clients and another sub-portfolio of loans issued to male clients. Because we analyze short term loans, with a maturity between 175 and 360 days, we subdivide our sample into cohorts of one quarter, where each cohort contains all loans of the sub-portfolio issued between start and end date of that particular quarter. Loss distributions for a given sub-portfolio can be calculated only if all the data for a given cohort are available. Therefore, we only allow the simulation procedure to draw contracts from the third quarter of 1997 up till the second quarter of 2006.

4.2 Loss distribution

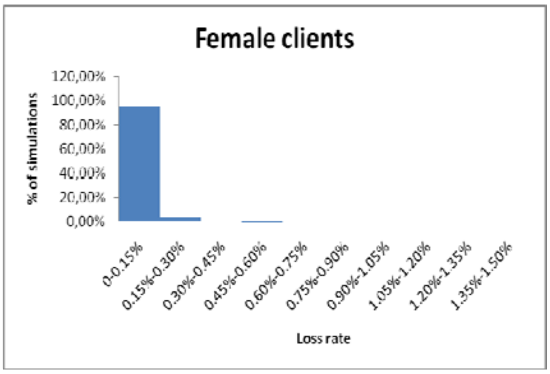
Table 3 provides summary statistics on loss distributions for portfolios of 5000 contracts from a female and a male client population respectively. Results are obtained by running 50,000 iterations. The average expected loss lies higher for male clients than for female clients: 0.04% versus 0.20%. The loss rate at the 99.99th percentile is 0.42% versus 1.48%, demonstrating that bad tail loss rates are also higher for the male segment than for the female segment. The difference is also illustrated by figure 3 and 4, which present the loss distribution for female clients and for male clients for portfolios of 5000 contracts respectively.

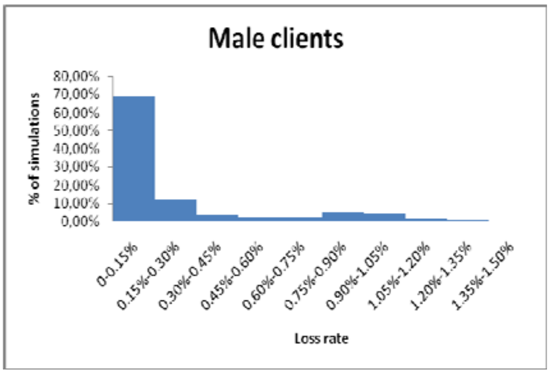
Since loss rates at the 99.99th percentile remain below 2%, we can also conclude that big, well-managed microfinance institutions behave like retail banks in terms of credit risk. The loss distribution for the female segment resembles the one of AAA- to A-rated private debt found by Carey, while the male segment depicts a loss distribution similar to the one of BBB-rated private debt.

Table 3: summary statistics on loss rate distributions (50,000 iterations)

		Simulated portfolio loss rates at loss distribution percentiles:			
	Mean	95	99.5	99.9	99.99
Female clients	0.04%	0.15%	0.30%	0.38%	0.42%
Male clients	0.20%	0.95%	1.22%	1.38%	1.48%

Figure 3: Loss distribution for the female segment (portfolio of 5000 contracts)
Figure 4: Loss distribution for the male segment (portfolio of 5000 contracts)

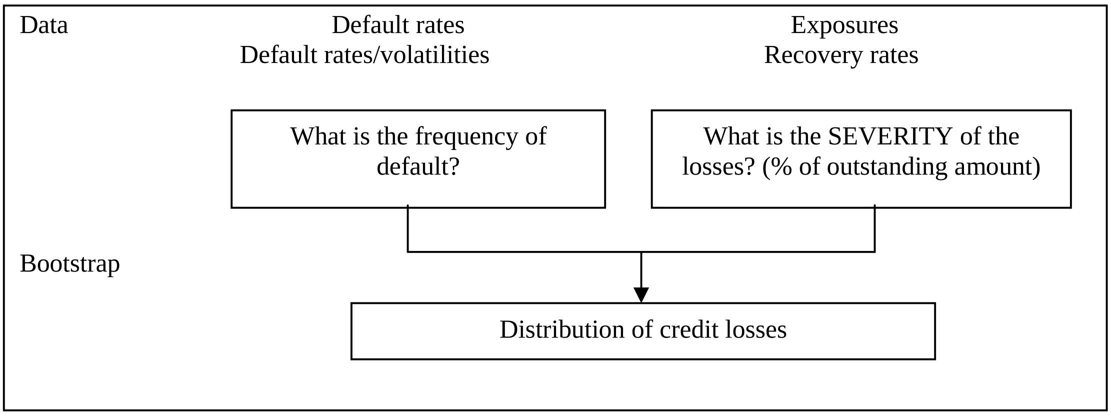




4.3 Observed default rates and recovery rates

A lower default rate does not necessarily entail a lower portfolio loss for the institution because recovery rates might differ. Figure 2 illustrates how both the frequency of default (i.e. default rates) and severity of losses (i.e. 1 minus recovery rate) determine credit losses.

Figure 2: Credit risk measurement framework



We would like to determine whether the difference in loss distributions is caused by a difference in default probability, a difference in loss given default, or both. In order to do so, we look at the observed default and recovery rates in our sample. Default rates are analyzed by cohort and by gender; descriptive statistics are shown in table 4. The default rate of a specific cohort is determined as all defaulted loans which were issued within the corresponding quarter divided by all loans issued within the corresponding quarter.

Table 4: descriptive statistics of observed default rates

	Women	**Men**	**Total**
average	0,00%	0,00%	0,00%
minimum	0,00%	0,09%	0,04%
1st quartile	0,09%	0,18%	0,09%
median	0,12%	0,43%	0,21%
3th quartile	0,38%	4,21%	2,82%
maximum	0,09%	0,50%	0,25%
standard deviation	0,10%	0,86%	0,51%

The figures demonstrate lower probabilities of default for female clients compared to male clients during the period observed; both on average as under adverse circumstances.

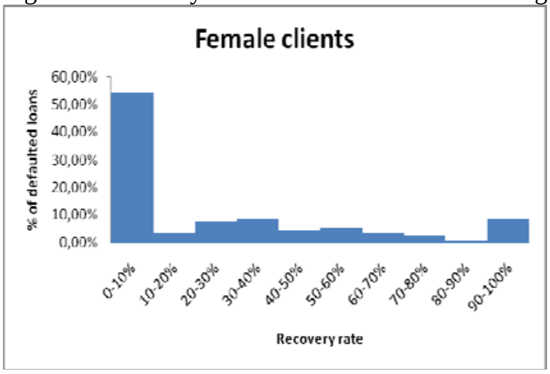
Table 5 provides descriptive statistics on recovery rates for female and male clients. Figure 5 and 6 depict the recovery rate distribution for the female client and male client segment respectively. For both segments, the distribution is bimodal with one mode occurring at a recovery rate of 0% and a smaller mode at recovery rates between 90-100%. The figures show that recovery rates for the two segments are very similar.

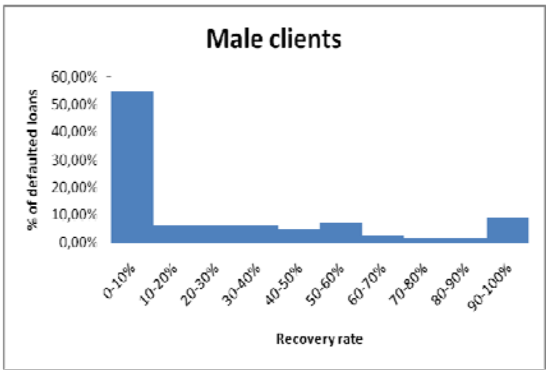
Our analysis of default rates and recovery rates observed in the sample demonstrates lower default rates for female segments compared to male segments; while recovery rates were similarly distributed. Based on this we conclude that the lower loss rates at the different percentiles for the female segment are largely due to a lower probability of default.

Table 5: Recovery rates by client's gender

	Women	Men
	Recovery rate (% of loan amount)	**Recovery rate (% of loan amount)**
Median	0%	0%
Average	23.85%	23.91%
Standard deviation	31.67%	32.39%

Figure 5: Recovery rate distribution for the female segment
Figure 6: Recovery rate distribution for the male segment





5. Discussion

5.1 sample bias

The bootstrap technique is based on the assumption that the sample from which simulated portfolios are drawn is representative for the whole population. However, our analysis is based on a portfolio of contracts from one microfinance institution with all contracts issued between the third quarter of 1997 and the second quarter of 2006. This implies that our simulations have been performed on a limited universe of data. In addition the draw of any particular quarter is equiprobable, which means loss rates can be over- or underestimated if the proportion of good and bad periods in our sample is respectively smaller or bigger than the proportion of good versus bad periods over a long time horizon. The first aspect is difficult to overcome. Long data ranges are rare in microfinance, since the sector's development is quite recent. Also, small microfinance institutions often operate under less than ideal circumstances and might not have the resources to store and retrieve historical data in an efficient way. One way to circumvent this form of sample bias is to take a look at the worst case scenarios included in our data range. Based on the loss distribution results for portfolios of 5000 contracts, we identify a bad period from the first quarter of 2004 up till the first quarter of 2006 for female clients. The portfolio of male clients was least performing from the third quarter of 1997 up till the first quarter of 1999. We isolate in addition the worst period for both segments: the first quarter of 2006 and the third quarter of 1997 for female and male clients respectively. The results summarized in table 6 show that the mean loss varies significantly, but the 99.9th loss distribution percentile is rather similar in each period considered. This suggests that the risk associated with microcredit loan portfolios is more idiosyncratic than systematic in nature. Additionally, because tail loss rates do not vary significantly, we are confident that any over- or underestimation of loss rates due to the equiprobable draws of each quarter will be minor.

Table 6: Loss rate distributions with re-sampling draws originating from different business cycles

Female clients	Number of contracts in the portfolio	Simulated portfolio loss rates				
Cohorts used			At loss distribution percentiles:			
		Mean	95	99.5	99.9	99.99
All	5000	0.04%	0.15%	0.30%	0.38%	0.42%
Bad period: 1st quarter 2004-1st quarter 2006	5000	0.09%	0.24%	0.37%	0.41%	0.47%
Worst case: 1st quarter 2006	5000	0.18%	0.33%	0.43%	0.49%	0.54%
Male clients	Number of contracts in the portfolio	Simulated portfolio loss rates				
Cohorts used			At loss distribution percentiles:			
		Mean	95	99.5	99.9	99.99
All	5000	0.20%	0.95%	1.22%	1.38%	1.48%
Bad period: 3th quarter 1997-1st quarter 1999	5000	0.74%	1.17%	1.38%	1.38%	1.48%
Worst case: 3th quarter 1997	5000	1.13%	1.32%	1.42%	1.48%	1.56%

5.2 Portfolio size and diversification

In order to study the link between portfolio size and diversification, we run the bootstrap procedure for portfolios of increasing size. For both segments, the average expected loss remains at the same level, as can be appreciated in table 7. Nevertheless, increasing the portfolio's size has an effect on the bad tail loss rates. A portfolio of 20,000 contracts of the female segment features a loss rates at the 99.9th and 99.99th percentile one-third to one-quarter as large as a small portfolio of 500 contracts. For portfolios in the male segment, the proportion is about two-third. The diversification effect is thus bigger for the female segment than for the male segment. This implies that the proportion of diversifiable risk in total risk is bigger for portfolios of loans granted to female clients than for portfolios of loans granted to male clients.

Table 7: summary statistics on loss rate distributions for increasing portfolio sizes (50,000 iterations)

Female clients	Simulated portfolio loss rates				
		At loss distribution percentiles:			
Number of contracts in the portfolio	Mean	95	99.5	99.9	99.99
500	0.04%	0.20%	0.58%	0.85%	1.26%
1000	0.04%	0.17%	0.44%	0.62%	1.07%
5000	0.04%	0.15%	0.30%	0.38%	0.42%
7500	0.04%	0.14%	0.27%	0.34%	0.38%
10,000	0.04%	0.14%	0.27%	0.31%	0.36%
15,000	0.04%	0.14%	0.24%	0.29%	0.31%
20,000	0.04%	0.15%	0.24%	0.27%	0.30%
Male clients	Simulated portfolio loss rates				
		At loss distribution percentiles:			
Number of contracts in the portfolio	Mean	95	99.5	99.9	99.99
500	0.20%	1.04%	1.55%	1.79%	1.92%
1000	0.20%	0.99%	1.37%	1.66%	1.82%
5000	0.20%	0.95%	1.22%	1.38%	1.48%
7500	0.20%	0.94%	1.22%	1.33%	1.41%
10,000	0.20%	0.93%	1.21%	1.31%	1.38%
15,000	0.20%	0.93%	1.19%	1.27%	1.31%
20,000	0.20%	0.92%	1.17%	1.25%	1.30%

5.3 Database issues

With this study we analyze loss distributions of microfinance group loans based on simulated portfolios. The microfinance institution under consideration does not accept partial repayments, i.e. if one member of the group cannot reimburse his or her loan, the other members are not allowed to reimburse their loan either and all members of the group are considered to have defaulted their loan. In order to promote to bigger loan amounts or individual loans, it is important though not to have defaulted on previous loans. For this reason group members can put pressure on struggling members to keep up with payments and to avoid default. The effect of being in a group thus goes into two directions: sometimes a borrower defaults because one of his or her group members defaults and sometimes a struggling borrower does not default because his or her group members urge him or her to pay. Although the product under consideration is group lending, in the database loans are treated individually by client. Therefore in our analysis we also consider a loan to a client as one contract. This means that our simulation procedure might draw a contract without drawing the other contracts belonging to the same group. In doing so, it might be that for certain simulated portfolios losses are slightly over- or underestimated because we do not take the group effect into consideration.

6. Comparison between capital requirement derived from the proposed internal model and capital requirements derived from the Basel II accord

6.1 Overview of the approaches proposed by the Basel Committee for retail exposures

The Basel Committee, a working group of the BIS[8], released the so-called Basel II accord in June 2004 with a view to establishing a revised capital adequacy framework. The aim is to provide a number of new approaches that are both more comprehensive and more sensitive to risks than the 1988 accord, while maintaining the overall level of regulatory capital.

The “standardized” approach relies mainly on external credit ratings to evaluate risk weights in relation to capital adequacy. Under the standardised approach, exposures qualifying for retail portfolio are assigned a risk weight of 75%. Thus, a 6% (i.e. 75% times 8%) regulatory capital is required when dealing with retail loan portfolios.

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[8] The Basel Committee on Banking Supervision is composed of central banks’ and supervisory authorities’ representatives from Belgium, Canada, France, Germany, Italy, Japan, Luxembourg, the Netherlands, Sweden, Switzerland, the United Kingdom, and the United States.

The IRB approaches are based on a measure of the total losses[9] at a 99.9% confidence level. However, the risk-weight function yields capital requirement for unexpected losses only; expected losses are treated separately. For retail exposure, the capital requirement *K* (per euro of asset) is formulated as a function of loss given default (*LGD*), probability of default (*PD*) and asset return correlation (*R*):

$$K = LGD \times N\left[\frac{N^{-1}(PD) + \sqrt{R} \times N^{-1}(0.999)}{\sqrt{1-R}}\right] - LGD \times PD \qquad [1]$$

where

- *N(x)* denotes the cumulative distribution function for a standard normal random variable and $N^{-1}(x)$ denotes the inverse cumulative distribution function for a standard normal random variable (the confidence level being set at 99.9%).
- *LGD* is the loss given default.
- *PD* is the probability of default and the minimum of *PD* is 0.03%[10]
- Basel II imposes the asset return correlation for “other retail exposures” to be defined as a decreasing convex function of *PD* and takes values between 3% and 16%:

$$R(PD) = 3\% \times \frac{1-e^{-35\times PD}}{1-e^{-35}} + 16\% \times [1 - \frac{1-e^{-35\times PD}}{1-e^{-35}}] \qquad [2]$$

The capital required is *K* times the exposure at default (*EAD*). The risk weighting-ratio is *K* divided by 8%.

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[9] i.e. expected and unexpected losses.

[10] This constraint is applied hereafter in the theoretical and empirical part, although this is not explicitly mentioned.

6.2 Comparison between the capital requirement derived from the proposed internal model and the capital requirement derived from the IRB capital regulation

A comparison between capital requirement calculations resulting from our internal model at the 99.9th percentile (less the expected losses) and capital required under the standardized and advanced IRB approaches are exhibited in Table 8. One can appreciate that the capital requirements obtained through loss distribution simulations are far below the percentages required by banking regulation.

Table 8: Comparison of capital requirements: Internal model vs. Basel Committee's proposals

			Capital requirements at 99.9 confidence level		
	PD inputs	**LGD inputs**	**Standardized approach**	**IRB advanced approach**	**Internal model**
Female segment	0.08%	76.15%	6%	1.36%	0.38%
Male segment	0.62%	76.09%	6%	5.21%	1.38%

7. Conclusion

This paper presents a quantitative analysis that shows that male and female microfinance clients have different loss rate distributions. The difference in loss rates is solely due to the fact that male clients have a higher probability of default than female clients, while recovery rates are similarly distributed. The loss rates we found are similar to those found in private retail banking portfolios, with female clients resembling AAA-A rated private debt and male clients resembling BBB-rated private debt. This indicates that big, well-managed microfinance institutions behave like retail banks in terms of credit risk.

We also investigated diversification effects, which turned out to be larger for portfolios of female clients than for portfolios of male clients. This means the proportion of diversifiable risk in total risk is bigger for portfolios of loans granted to female clients than for portfolios of loans granted to male clients. Finally we show that capital requirements determined by the 99.9 percentile remain below those required by the Basel 2 Accords, which opens perspectives for a specific treatment of microcredit if financial regulation becomes applicable to the sector.

A study of this kind can help microfinance institutions manage credit risk and calculate economic capital. This in turn supports the microfinance institution in case of adverse economic conditions. Further research can test the robustness of our results or add more insights to credit risk in the microfinance industry. One interesting topic would be to repeat the analysis on other data including the period of the worldwide financial crisis (i.e. second half 2007 up till now and beyond) and compare those results with the figures we obtained. Another path that would be worth investigating is an analysis of credit risk by sector or by region.

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