CREDIT RISK IN MICROCREDIT: HOW DOES GENDER MATTER?

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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 MFI, 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. Results show similarities and differences in credit risk between male and female clients with implications in terms of capital requirements.

Keywords: Microfinance; Credit risk; Gender study; Capital requirement; Africa, Morocco.

JEL: G18, G21, O16

1. INTRODUCTION

During the last two decades, microfinance has evolved from an informal sector into a semi-mature, professional industry. Microfinance institutions have begun 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.

In response to the need for transparency and risk monitoring, most large microfinance institutions report aggregated loan loss ratios or repayment

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rates on their portfolios. The well-known Grameen bank reported from the start repayment rates of 98 to 99% (Jansen & Pippard, 1998), rates it still achieves[1]. Robinson (2002, p. 116) reports default rates for rural MFIs in Indonesia, which are, except for one outlier at 12%, between 1% and 5.5%. CrediAmigo (2009) in Nordeast Brazil reports a loan loss ratio below 2% as from 2004, while in 2002 and 2003 this ratio was at respectively 2.70% and 3.30%. Murdoch (2009) argues that most major microcredit programs report loan loss ratios of less than 5%.

Nevertheless, little research has been done on the in-depth analysis of credit risk and loss distributions of microfinance loan portfolios.

One of the few studies on this subject analyzes the annual credit loss distributions of Chilean banks over the period 1999-2005, showing how the distribution of credit losses for portfolios of large loans differs from the credit loss distribution for portfolios of small loans (Adasme, Majnoni & Uribe, 2006). The results have important implications for the level of loan loss reserves and capital requirements to be carried by regular banks versus MFIs.

One of the topics in relation to the subject of credit risk is the idea that women have better repayment records than men, explained by Armendariz and Murdoch (2005, p. 183). Few studies with large amounts of data that give proof for this hypothesis have been conducted.

Agier and Sfaraz (2010) use a dataset of 32,000 loans granted between 1997 and 2007 by Vivacred, a Brazilian MFI. They conclude that "women exhibit a lower probability of delay than men (7.8% against 9.4%), but a similar probability of default (2.9%)". And more importantly, women lead to significantly smaller losses for the MFI, with an average relative loss of 2.8% for male borrowers and 2.3% for female ones.

A study conducted among 2,630 respondents of the Agrobank in Malaysia found that the probability of default is higher for male than for female borrowers (Roslan & Karim, 2009).

Studies on smaller 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].

In-depth analysis of the credit loss distribution of microfinance institutions has not yet been conducted. This paper attempts to fill that gap with estimates of the probability density function of losses and value-at-risk

[1] Grameen Bank. 2009. "Grameen bank at a glance" <http://www.grameen-info.org/index.php?option=com_content&task=view&id=26&Itemid=175> (Consulted on April 12, 2009).

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

measures for a portfolio of loans granted to female and male microfinance clients.

A large data sample over a time frame of 10 years is used 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 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 that 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 satisfactorally fulfilled.

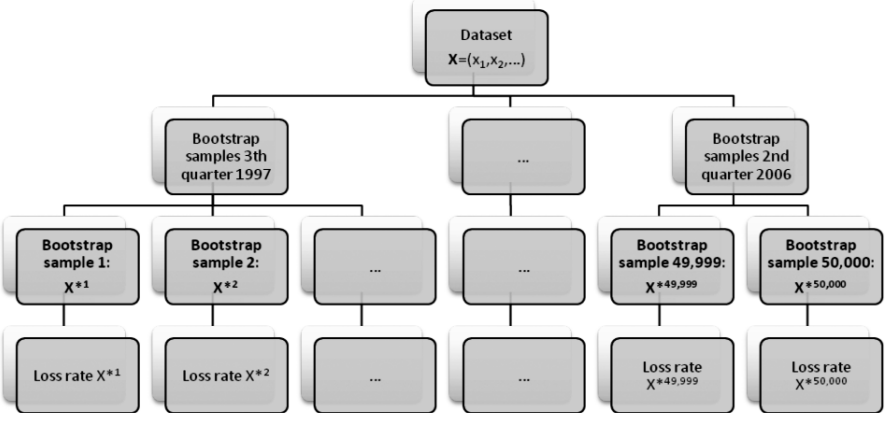
2.2 Measuring loss given default and recovery rates

Loss given default is measured as the sum of all capital payments not fulfilled within 30 days, minus all 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.

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



[3] The institution does not charge interest on arrears.

[4] Administrative costs of recovering late payments are not taken into account in this analysis.

[5] Adapted from Efron, B & Tibshirani, R. (1997, p. 13).

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 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 a two-stage drawing procedure (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 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 the 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 percent between 1997 and 2007 included.

All loans have a maturity between three and eighteen months. Amounts vary from Euro[7] 44 to 2692 and weekly, bimonthly or monthly repayment schemes are offered. Clients can apply for a group loan in groups of four to five persons. When loans are approved, each client receives its own identification code and detailed information on clients and clients' loans are 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 con-

[6] In our research *n* equals 500 to 20,000.

[7] Based on the exchange rate of 31 March 2009.

tracts. The database comprises detailed information concerning the loans granted, belonging to three categories. The first category consists of client's details such as client's identification code, gender, age, region and microenterprise sector. At the start, the MFI mainly operated in urban areas, subdividing its clients' microenterprises into the sector of handicraft, trade or services. As of June 2004, due to the gradual expansion of the MFI, the decision was taken to differentiate between rural and urban regions, thus classifying clients into 6 different segments. The second category encompasses ex ante loan characteristics, which are the origination date of the contract, amount granted, loan maturity and amount and periodicity of installments. The third category comprises the ex post loan characteristics, namely all successful payments, amounts remaining unpaid and the final status of the contract.

Table 1 shows that in total 1,657,765 loans were issued between the 1st of January 1997 and the 30th of June 2007. The portfolio is broken down into segments started in 1997 and segments launched in 2004. The first comprises 1,353,905 contracts in the segments urban handicraft, urban trade and urban services. The latter comprises 303,860 contracts in the segments rural handicraft, rural trade and rural services. The analysis focuses on those segments launched in 1997, this is to work with a sufficiently long time period of data. As the analysis needs to be performed on finished contracts only, all loans still active on the 30th of June 2007 are not included. As said before all loans have a maturity between three and eighteen months, but less than 0.5 percent of these have a maturity below 6 months or over 12. Therefore only contracts with a maturity between 175 and 360 days are considered, which thus represents over 99.5 percent 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	2,359	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 age
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%
501-1,000	129,623	11.32%	99.34%
1,001-3,000	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

All contracts in the sample are split into a sub-portfolio of loans issued to female clients and another sub-portfolio of loans issued to male clients. Because the analysis is based on short term loans, with a maturity between 175 and 360 days, the sample is subdivided 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, i.e. if all loans of the given cohort are completed and data on the status of all contracts is available. Since the 3rd and 4th quarter of 2006 and the first two quarters of 2007 some loans in our sample are still active, the procedure only draws 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 5,000 contracts from female and male client populations respectively. Results are obtained by running 50,000 iterations. The average expected loss lies higher for male clients than for female clients: 0.04 percent versus 0.20 percent. The loss rate at the 99.99th percentile is 0.42 percent versus 1.48 percent, demonstrating that bad tail loss rates are also higher for the male segment than for the female segment. The difference is also illustrated by figures 2 and 3, which present the loss distribution for female clients and for male clients for portfolios of 5,000 contracts respectively.

Since loss rates at the 99.99th percentile remain below 2 percent, one can also conclude that big, well-managed microfinance institutions behave like retail banks in terms of credit risk. The loss distribution for female segment resembles the one of AAA- to A-rated private debt found by Carey (1998), while 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 2: Loss distribution for the female segment (portfolio of 5,000 contracts)

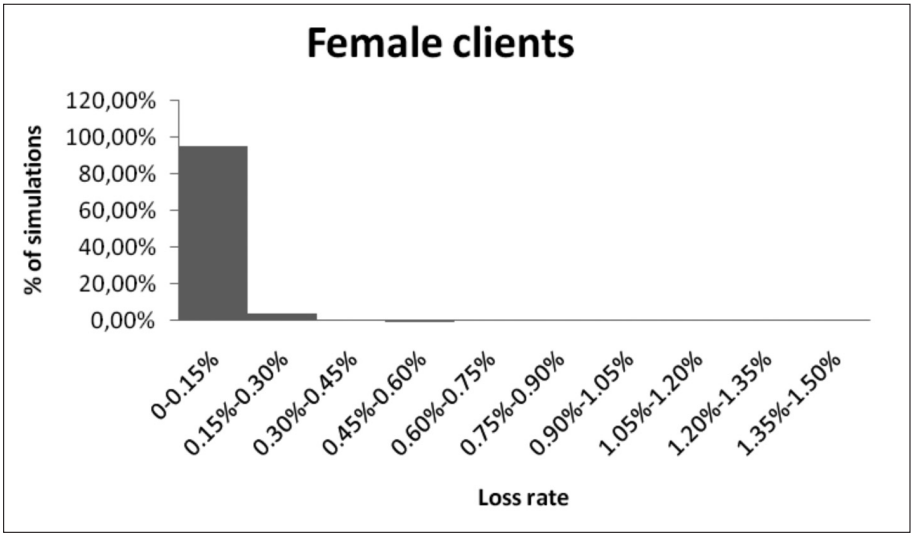
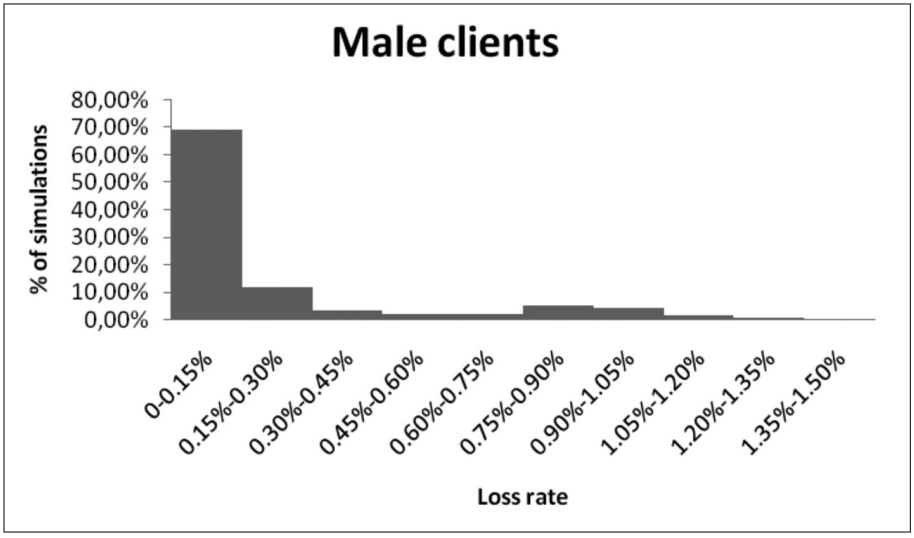


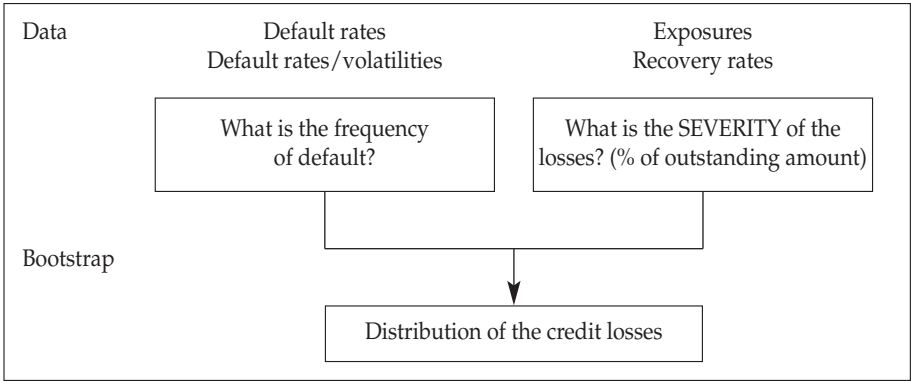
Figure 3: Loss distribution for the male segment (portfolio of 5,000 contracts)



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 4 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 4: Credit risk measurement framework



The objective is 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	0.09%	0.50%	0.25%
Minimum	0.00%	0.00%	0.00%
1st quartile	0.00%	0.09%	0.04%
Median	0.09%	0.18%	0.09%
3th quartile	0.12%	0.43%	0.21%
Maximum	0.38%	4.21%	2.82%
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

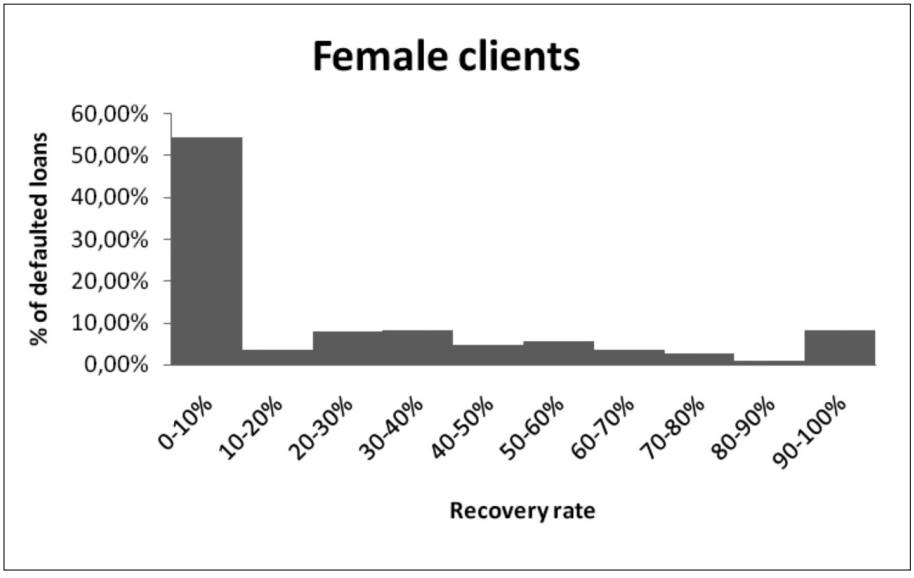
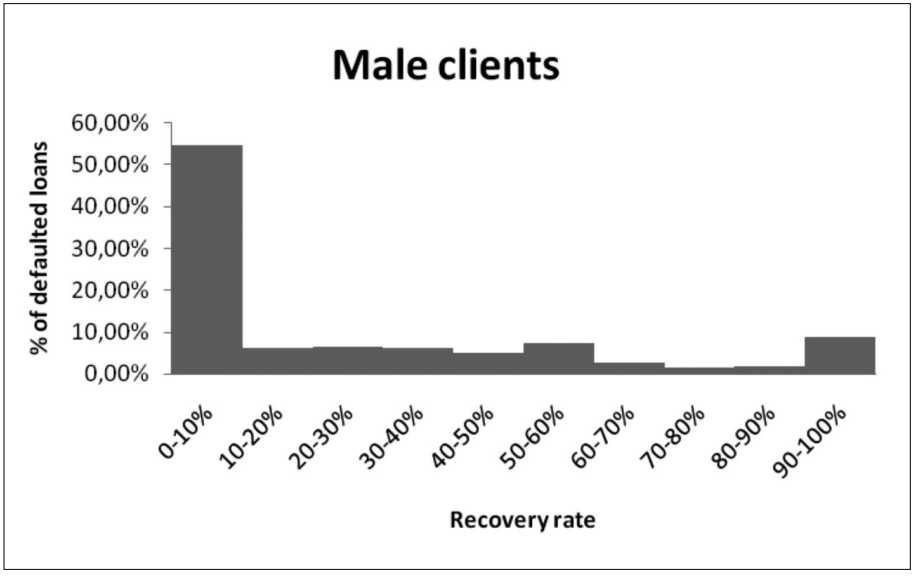


Figure 6: Recovery rate distribution for the male segment



4.4 The impact of loan amount on credit risk VaR

Table 6 shows the loss rates at the 99.9th percentile for the various portfolio segments in respect to loan amount and gender. When the size of the loan increases, the 99.9th percentile loss rate increases from 0.16 percent to 0.59 percent for women. This worsening trend can be observed in both the PD and LGD. When analyzing the credit risk in respect to loan amount for men, the conclusion is surprisingly different i.e. the total loss rates shown at the 99.9th percentile report do not increase with growing loan amounts. For instance, for larger loans (between 5,000 and 30,000 dirhams), the 99.9th percentile loss rate lies with 0.63 percent at approximately twice the average loss while for the loans between 3,000 and 4,500 dirhams the 99.9th percentile loss rate is 5.12 percent representing approximately 23 times the average loss. This allows us to suppose that the systematic risk varies greatly according to the segments and impacts much more the male rather than female clients.

Table 6: Summary statistics on loss rate distributions in respect to loan amount

	Women			Men		
Dirhams	PD	LGD	VAR (99.9%)	PD	LGD	VAR (99.9%)
490-2,000	0.06%	71.37%	0.16%	0.21%	83.52%	2.65%
2,000-3,000	0.11%	77.66%	0.26%	0.25%	69.86%	1.41%
3,000-4,500	0.15%	76.36%	0.21%	0.23%	74.06%	2.65%
4,500-5,000	0.20%	73.88%	0.26%	0.27%	82.70%	5.12%
5,000-30,000	0.26%	90.54%	0.59%	0.38%	89.18%	0.63%

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, the 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 the 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 sector 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 5,000 contracts, a bad period is identified 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 7 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 7: 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	5,000	0.04%	0.15%	0.30%	0.38%	0.42%
Bad period: 1st quarter 2004-1st quarter 2006	5,000	0.09%	0.24%	0.37%	0.41%	0.47%
Worst case: 1st quarter 2006	5,000	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	5,000	0.20%	0.95%	1.22%	1.38%	1.48%
Bad period: 3th quarter 1997-1st quarter 1999	5,000	0.74%	1.17%	1.38%	1.38%	1.48%
Worst case: 3th quarter 1997	5,000	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 8. Nevertheless, increasing portfolio 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-thirds. 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 8: Summary statistics on loss rate distributions for increasing portfolio sizes (50,000 iterations)

Female clients	Simulated portfolio loss rates				
Number of contracts in the portfolio		At loss distribution percentiles:			
	Mean	95	99.5	99.9	99.99
500	0.04%	0.20%	0.58%	0.85%	1.26%
1,000	0.04%	0.17%	0.44%	0.62%	1.07%
5,000	0.04%	0.15%	0.30%	0.38%	0.42%
7,500	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				
Number of contracts in the portfolio		At loss distribution percentiles:			
	Mean	95	99.5	99.9	99.99
500	0.20%	1.04%	1.55%	1.79%	1.92%
1,000	0.20%	0.99%	1.37%	1.66%	1.82%
5,000	0.20%	0.95%	1.22%	1.38%	1.48%
7,500	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 loss distributions of microfinance group loans based on simulated portfolios are analyzed. 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 get access to bigger loan size or individual loan, 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 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 the analysis we also consider a loan to a client as one contract. This means that the 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 it does not take the group effect into consideration. Nevertheless, given the size of the sample, omission of the group effect will not have impacted our outcomes greatly.

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[9] in June 2004 and revised in 2006 with a view to establishing a revised capital adequacy framework. The aim is to provide a number of

[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.

[9] Basel Committee on Banking Supervision, 2006, "International Convergence of Capital Measurement and Capital Standards: A revised framework", pages 12 to 79.

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 standardized 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.

The Internal Rating Based (IRB) approaches are based on a measure of the total losses[10] at a 99.9% confidence level. However, the risk-weighted function yields capital requirement for unexpected losses only; expected losses are treated separately. For retail exposure, the capital requirement K (per euro of each 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%[11]
- 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%:

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

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

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

[11] 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 9. One can appreciate that the capital requirements obtained through loss distribution simulations are far below the percentages required by banking regulation, especially for female clients that would be more penalized in respect to their risks if the Basel II accord or similar rules are applicable.

Table 9: Comparison of capital requirements: Internal model vs. Basel Committee's proposals

	PD inputs	LGD inputs	Capital requirements at 99.9 confidence level		
			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.

Diversification effects are also investigated, 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 it appears 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. Indeed, the implementation of such Accords or similar local regulations would penalize more female clients than male clients in respect to their underlying risks.

A study of this kind can help microfinance institutions manage credit risk and calculate economic capital. This in turn supports the microfinance institutions in case of adverse economic conditions.

Further research can test the robustness of the results or add more insights to credit risk in the microfinance industry.

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Résumé

Cet article est le premier à analyser le risque crédit supporté par une institution de microfinance. L'étude est basée sur un portefeuille d'une institution de microcrédit leader en Afrique du Nord. Le portefeuille inclut 1.144.770 contrats émis entre 1997 et 2007. Nous avons estimé les fonctions de densité des pertes et la VaR pour des portefeuilles octroyés aux clients masculins d'une part et aux clients féminins d'autres part. L'article analyse les similarités et les différences en matière de risque crédit en fonction du genre du client et les implications sur les exigences en fonds propres.

Mots clés: Microfinance; Risque crédit; Etude de genre; Capital réglementaire; Afrique, Maroc.