Pricing Microfinance Loans and Loan Guarantees using Biased Loan Write-off Data*

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Abstract

We present a simple, easy to implement methodology for pricing microfinance loans and loan guarantees using publicly available data on loan write-offs by Micro Finance Institutions (MFIs). Our methodology takes into account the selection bias inherent in available data in that MFIs that do not report loan write-off data are less likely to be better performers. Our quantitative analysis is consistent with pricing seen in a recent securitization deal. Our analysis suggests how securitization and loan guarantees can greatly expand the supply of funds for microfinance loans.

Keywords: Microfinance, Loan Guarantees, Securitization, Selection Bias, South Asia, India

Introduction

One of the key considerations in pricing a loan is the probability that the borrower might default. Popular and anecdotal accounts of the microfinance revolution (Robinson, 2001) boast of repayment rates that are in almost all cases above 95 percent. Yet, amidst all the euphoria, there are those who urge caution by carefully documenting that reported default rates, even for the most illustrious and visible cases such as the Grameen Bank, are underestimated (Morduch, 1998).

Those who are in the microcredit business understand this well. For instance, on January 20, 2004, Grameen Foundation USA ("Grameen") announced a securitization deal between ICICI Bank, India's largest private sector commercial bank, and Society for Helping and Awakening Rural poor through Education ("SHARE") Microfin Ltd., an Indian Micro Finance Institution (MFI). In the transaction, ICICI paid \$4.3 million for a portfolio of 42,500 loans from SHARE. SHARE will continue to service the loans while interest payments and principal will go to ICICI. ICICI priced these assets by forecasting the assets' expected monthly cash flows and discounting them by 8.75%. In addition to this expected 8.75% return, ICICI required SHARE to make an 8.0% first loss default guarantee. Grameen, paid for most of this guarantee by providing \$325,000 in donor capital. SHARE also made a small contribution of approximately \$25,000 to arrive at the 8.0% required default guarantee (\$4.3m x 8% = \$344,000).[1] Clearly, ICICI understands that the default premium on these microfinance loans may not be as small as 5% or less!

In this paper we show how microloans could be priced using data on loan write-offs. Fortunately, in recent years the MIX (Microfinance Information eXchange) Market (www.mixmarket.org) has made important strides in addressing this issue by creating an online information exchange containing relevant write-off data for many MFIs. However, because this data is self-reported and many MFIs do not report complete information, there is a substantial selection bias in the MIX Market sample. It will be reasonable to assume

[1]The default guarantee acts like default insurance, as it provides ICICI with a "first loss" protection. This also explains why the 8.75% interest rate charged on the loan protfolio is substantially less than the usual 12-13% SHARE pays for commercial loans. Grameen was able to raise its capital from philanthropists by convincing them that their contributions could be leveraged at a ratio of 12.5 to one (12.5x = 100.0% / 8.0%). Under this securitization structure, every dollar of donor capital results in \$12.50 of capital to the MFI.

that the MFIs reporting in the MIX Market generally represent the better performers in the industry.

In this paper, we provide a simple methodology for estimating the true distribution of loan returns using only observations that are self-reported by MFIs by assuming that those MFIs who choose not to report the information are likely to have on average a higher loan default rate than those MFIs who report the information. Estimating the true loan return distribution not only allows pricing of loan contracts, but loan guarantees of the type described above in the deal involving ICICI, SHARE and Grameen can also be priced with our methodology.

I. The Methodology

Suppose that the natural log of the returns generated on loan portfolios for MFIs, denoted R, are drawn from a normal distribution with mean μ and variance σ^2. Formally,

$$ln(R) \sim N(\mu, \sigma^2).$$

Since $ln(R)$ is distributed normally, we can define a standardized variable

$$x \equiv \frac{ln(R) - \mu}{\sigma} \sim N(0,1),$$

i.e., x will have a standard normal distribution with mean 0 and variance equal to 1. Let ϕ_x denote the standard normal probability density function and Φ_x denote the standard normal cumulative density function.

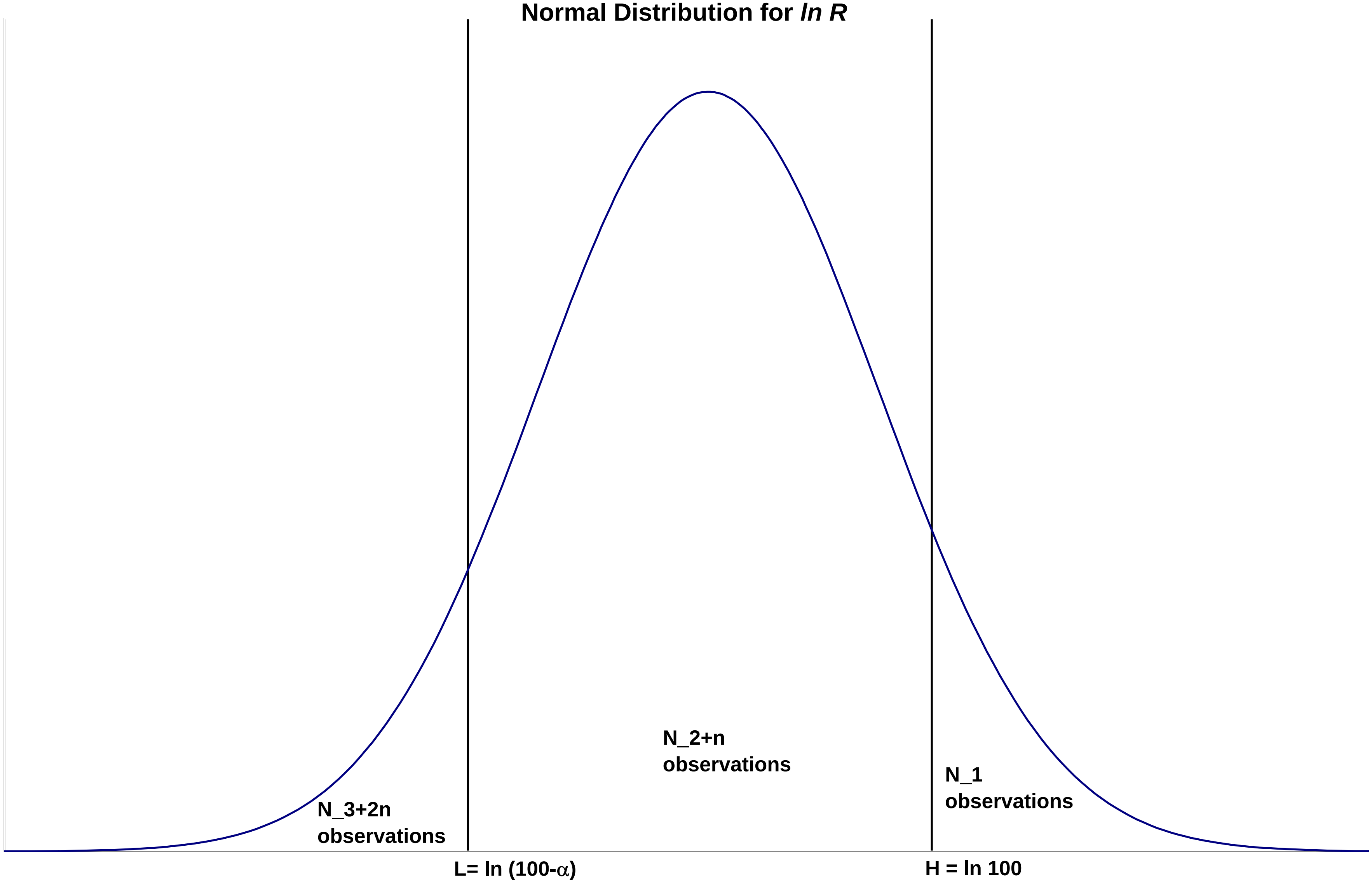
Let L and H denote two values of log returns such that $L < H$. We divide the loan write-off data into three buckets:

1. Bucket 1 ($R \geq 100$): MFIs that report zero percent loan write-offs (equivalent to a return of one hundred percent or more). We choose $H = ln(100)$.

2. Bucket 2 ($100 > R \geq 100 - \alpha$): MFIs with loan write-off rates between zero percent and another pre-specified cut-off rate (equivalent to some return that is less than one hundred percent, say $100 - \alpha$). We choose $L = ln(100 - \alpha)$.

3. Bucket 3 ($100 - \alpha > R$): MFIs with loan write-off rates greater than α (equivalent to returns smaller than $100 - \alpha$).

FIGURE 1
Normal Distribution for *ln R*



There are a number of MFIs that do not report any loan write-off numbers. The main insight that we will use in our pricing analysis is that these MFIs almost surely do not belong to Bucket 1 and are more likely to belong to Bucket 3 than Bucket 2. In particular, we will assume that MFIs with missing data are twice as likely to belong to Bucket 3 than to Bucket 2.[2]

Let N_1, N_2 and N_3 denote the number of MFIs that belong to Buckets 1, 2 and 3 respectively based on their self-reported loan write-off numbers. Let $3n$ denote the number of MFIs with missing loan write-off data. We will assume that n of these missing observations belong to Bucket 2 and the remaining $2n$ to Bucket 3. (See Figure 1).

The parameters of the distribution of log returns, μ and σ are determined, by setting:

$$\Pr[ln(R) > H] = \Pr[x > h] = 1 - \Phi_h = \frac{N_1}{N}, \tag{1}$$

$$\Pr[ln(R) < L] = \Pr[x < l] = \Phi_l = \frac{N_3 + 2n}{N} \tag{2}$$

where

$$N = N_1 + (N_2 + n) + (N_3 + 2n),$$
$$h \equiv \frac{H - \mu}{\sigma},$$
$$l \equiv \frac{L - \mu}{\sigma}.$$

It is easy to see that the probability of default is given by

$$\Pr[R < 100] = \Pr[x < h] = \Phi_h.$$

We now show how loans and loan guarantees can be priced. Once the parameters μ and σ are determined, the lognormal distribution of R is completely specified; let g denote the probability density function of R. The mean and variance of the lognormal distribution are:

$$\mathrm{E}[R] = \exp(\mu + \frac{1}{2}\sigma^2), \tag{3}$$

$$\mathrm{Var}[R] = \exp[2(\mu + \sigma^2)] - exp[2\mu + \sigma^2]. \tag{4}$$

The expected payoff of the lender with face value of the repayment of 100 is given by :

$$\int_0^\infty \mathrm{Min}\{100, z\} g(z) dz. \tag{5}$$

[2]It is easy to consider other partitions of MFIs with missing data into the two buckets as well.

The above expression reflects the fact that the lender never receives more than the full contractual value of 100 but will sometimes receive less if the borrower is unable to pay the entire amount.

If we were to price a loan guarantee[3] in which the lender is insured to receive its full payment of 100, the price of such a guarantee can be calculated as:

$$\int_0^\infty \text{Max}\{0, 100 - z\}g(z)dz. \tag{6}$$

The guarantor is obliged to pay the difference between 100 and what is collected from the borrower if that amount is less than 100.

Now, consider pricing the loan portfolio to ICICI in the type of securitization deal between SHARE, ICICI and Grameen described in the introduction. As long as the return is greater than 92, ICICI will get paid 100 because Grameen has guaranteed a loss of up to 8. If the return is less than 92, ICICI will receive that plus 8 from Grameen. Thus, ICICI's expected payoff is given by:

$$\int_0^\infty \text{Min}\{100, z + 8\}g(z)dz. \tag{7}$$

Similarly, Grameen's expected payment in such a deal can be calculated as:

$$\int_0^\infty \text{Min}\{8, 100 - z\}g(z)dz. \tag{8}$$

This represents Grameen's payment of 8 if the return is less than 92; if the return is between 92 and 100, Grameen only needs to make up the difference. Obviously if the return is greater than 100, Grameen doesn't need to pay anything.

II. Application to MIX Market Data

We downloaded the data (on March 26, 2005) - see the Appendix- on 420 MFIs from the website of Mix Market (www.mixmarket.org).[4] Of these MFIs, data on 63 were not reported on MIX Market site because microfinance represents less than 91% of their operations.

[3]For expositional simplicity, we are only considering risk-neutral pricing and have normalized the risk-free rate to equal zero.

[4]The data and the supporting analysis in this section are available in an excel spreadsheet from the authors upon request.

Financial analysis data were reported for 357 of these MFIs ($N = 357$). Of these, 78 MFIs reported a loan write-off ratio of 0%. These firms belong to our Bucket 1.

$$N_1 = 78.$$

We then ordered the remaining MFIs by their loan write-off ratios and chose $\alpha = 9.04\%$ as the lower cutoff for deciding the range for Bucket 2 because that provided a natural breakpoint.[5] That resulted in 160 MFIs with loan write-off ratios of between 0% and 9.04%. Thus,

$$N_2 = 160.$$

Seven MFIs reported write-off ratios of less than 9% and 112 MFIs had missing data. Thus,

$$N_3 = 7,$$

$$3n = 112.$$

We assume that 37 of the MFIs with missing data belong to Bucket 2 and the remaining 75 MFIs belong to Bucket 3. Thus,

$$1 - \Phi_h = \frac{78}{357},$$

$$\Phi_l = \frac{7 + 75}{357},$$

$$h = ln(100) = 4.60,$$

$$l = ln(100 - 9.04) = 4.51.$$

Solving (using the "solver" function in Excel), we obtain:

$$\mu = 4.56,$$

$$\sigma = 6.25\%.$$

Using these parameter values, we perform a reality check as follows. If we only consider observations that are between l and h (observations in Bucket 2), then these observations could be described as drawn from a truncated normal distribution with l as the lower truncation

[5] The choice of the lower cutoff point is somewhat arbitrary. It is sensible not to choose this cutoff too close to 100 because we would like the sizes of all three buckets to be reasonable so that we can approximate the probabilities by the relative frequency of observations in each of the three buckets.

level and h as the higher truncation level. The mean of the truncated distribution, μ_T, and the variance of the truncated distribution, σ_T^2, are given by (Johnson and Kotz, 1970):

$$\mu_T = \mathrm{E}[x \mid l < x < h] = \mu + \sigma \frac{\phi_l - \phi_h}{\Phi_h - \Phi_l},$$

$$\sigma_T^2 = \mathrm{Var}[x \mid l < x < h] = \sigma^2 \left[1 - \frac{h\phi_h - l\phi_l}{\Phi_h - \Phi_l} - \left\{ \frac{\phi_h - \phi_l}{\Phi_h - \Phi_l} \right\}^2 \right].$$

Using the parameter values, the truncated mean is calculated to be

$$\mu_T = 4.558$$

which is less than 4.588, the arithmetic average of the $N_2 = 160$ observations between l and h. This is reassuring because we have argued that MFIs that did not report any write-off data are likely to have smaller loan repayment rates. Thus, true truncated mean must be lower than the one calculated from biased observations. Similarly, truncated standard deviation is calculated to be

$$\sigma_T = 2.63\%$$

which is more than 1.98%, the estimated standard deviation of $N_2 = 160$ observations between l and h. Thus the estimated standard deviation is biased downwards compared to the true truncated standard deviation.

The mean and the standard deviation of lognormal distribution of return R, using (3) and (4) are calculated to be:

$$\mathrm{E}[R] = 95.45,$$

$$\mathrm{stdev}[R] = 5.97.$$

The pricing of loans and loan guarantees in expressions in (5) to (8) are calculated using numerical simulations using "Crystal Ball" in Excel. We obtain the following results:

The expected payoff of a lender with face value of the repayment of 100, using (5), is 94.59. In other words, a lender without any guarantees expects to lose over 5%. Lenders anticipating this will gross up the interest rate charged. However, if the lender's payoff is guaranteed, using for example the guarantee provided by Grameen and SHARE to ICICI, the expected payoff to ICICI, using (7), is calculated to be 98.97. In other words, with the guarantee ICICI expects to lose only about 1%, and therefore it doesn't need to gross up the interest rate charged as much. This is roughly consistent with ICICI charging only 8.75% to SHARE, whereas SHARE usually paid nearly 13% on loans without the guarantee.

Let us now calculate the expected cost to Grameen for providing the guarantee. This, using (8), is calculated to be 3.58. This makes sense as Grameen loses all of its 8% collateral only in some cases.

Finally, we calculate the expected cost of providing a complete guarantee to a lender or insuring the lender completely against default. Using (6), this is calculated to be 5.41. In other words, an insurer with deep pockets will only charge 5.41 per 100 to make the loans risk-less to lenders.

III. Concluding Remarks

We presented a simple, easy to implement methodology for pricing microfinance loans and loan guarantees using publicly available data on loan write-offs by Micro Finance Institutions (MFIs). Our methodology takes into account the selection bias inherent in available data in that MFIs that do not report loan write-off data are less likely to be better performers. In our analysis, we assumed, for simplicity of exposition, that returns for all MFIs are drawn from an identical lognormal distribution. The analysis can easily be adapted to cases in which more specific information about a particular MFI is readily available. Furthermore, we assumed that the self-reported loan write-off numbers are accurate. If the self-reported numbers are also biased, as suggested by Morduch (1998), those also need to be adjusted. Our goal here was to illustrate our approach rather than provide precise quantitative answers for a particular case.

Our quantitative analysis suggests securitizations in which the upper tranches can be made completely safe need not be prohibitively expensive. The riskier tranches could be held by informed intermediaries (who are likely to be better equipped to deal with adverse selection and moral hazard issues), philanthropic donors, and socially responsible investors (who may be more willing to accept losses), while the safer tranches could be marketed to tap commercial investors at large who demand competitive returns on their investments.[6] This can expand the supply of funds available for microfinance loans multiple-fold making

[6]See Demarzo and Duffie (1999) and Ohashi (2002).

it easier to meet the Millennium Development Goals set by the United Nations.

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Appendix

Loan Write-off Data, downloaded on March 26, 2005 from www.mixmarket.com

		2003
1	ACAD	-
2	ACTUAR Famiempresas - Antioquia	-
3	ADMIC	-
4	ADOPEM	-
5	AgroCapital	-
6	AKMA	-
7	Al Karama	-
8	Al Tadamun	-
9	AMK	-
10	Apoyo Integral	-
11	ARDCI	-
12	ASDEB	-
13	AssEF	-
14	AVFS	-
15	Banco ADEMI	-
16	Banco Los Andes ProCredit	-
17	BES	-
18	BPR EAAB	-
19	BPR Kali	-
20	BPR PKT	-
21	CADEFINANCE	-
22	Caisse de Sion	-
23	CAPAB	-
24	CAPEC Dahra	-
25	Caribbean Microfinance - GRD	-
26	Caribbean Microfinance - LCA	-
27	CCODER	-
28	CEAPE - PE	-
29	CMAC - Maynas	-
30	Confianza	-
31	Coopec Kalundu	-
32	Covelo	-
33	Crear - Arequipa	-
34	Crear - Tacna	-
35	CREDIAMIGO	-
36	CSS	-
37	DEC	-
38	DRC	-
39	Eco Futuro	-
40	EMPREENDA!	-
41	Emprendamos Juntos	-
42	Eshet	-
43	FADES	-
44	FADU	-
45	FCC	-
46	FED	-
47	FINCA - GTM	-
48	FINCA - HTI	-
49	Finca - MEX	-

50	FINCOMUN	-
51	FIS	-
52	FMDR	-
53	FONDECO	-
54	FONDESA	-
55	FORA	-
56	FUDEMI	-
57	Gasha	-
58	Génesis Empresarial	-
59	ICC - BLUSOL	-
60	IDESI La Libertad	-
61	IF	-
62	IMED	-
63	Independencia	-
64	Integra	-
65	KADET	-
66	Kagisano	-
67	KSCS	-
68	LAPO	-
69	Letlepu	-
70	MBT	-
71	MDB	-
72	Meklit	-
73	Metemamen	-
74	MICROFUND	-
75	Mikrofond	-
76	MMDCT	-
77	Nations Trust	-
78	NERUDO	-
79	NLCL	-
80	Novo Banco	-
81	OCSSC	-
82	OPIC-TOGO	-
83	Orangi	-
84	PEACE	-
85	PRIDE - TAN	-
86	PRIDE - UGA	-
87	PRODEM	-
88	PROSHIKA	-
89	PSHM	-
90	RCPB	-
91	RFPK	-
92	RUSCA	-
93	SAMBALI	-
94	SBDF	-
95	SEEDS	-
96	SFPI	-
97	Sidama	-
98	Sodeistviye	-
99	SOGESOL	-
100	Solución	-
101	Swayamkrushi	-

102	Tbiluniversalbank	-
103	The Enterprise Fund Ltd	-
104	Tiisha	-
105	TSKI	-
106	TSPI	-
107	Urwego	-
108	VMCA	-
109	Wasasa	-
110	World Relief - HND	-
111	Zakoura	-
112	Zambuko Trust	-
113	WC-Georgia	29.61%
114	SPBD	26.07%
115	MEDF	17.92%
116	PHL	17.72%
117	CODES	14.78%
118	Otiv Sambava	14.42%
119	2CM	11.66%
120	FENACOOPEC-CI	9.04%
121	Finca - MWI	9.03%
122	NWTF	7.27%
123	CREDIT	6.95%
124	Wisdom	6.75%
125	MEC ADEFAP	6.51%
126	BZMF	6.05%
127	UGF PAME	5.85%
128	Otiv Alaotra	5.81%
129	FONDESURCO	5.77%
130	EDYFICAR	5.76%
131	FINCORP	5.39%
132	Piyeli	5.12%
133	FIE	4.87%
134	GEC Grand Dakar	4.79%
135	Al Majmoua	4.74%
136	PRESTANIC	4.73%
137	Beehive EDC	4.72%
138	ACME	4.71%
139	Aurora	4.32%
140	Siyakhula	3.98%
141	FODEM	3.63%
142	EBS	3.48%
143	SCMPC	3.41%
144	BASIX	3.35%
145	IMCEC - Thies	3.35%
146	HKL	3.33%
147	MiBanco	3.28%
148	PROEMPRESA	3.27%
149	BTFF	3.02%
150	FECECAM	2.96%
151	MEC Ouakam	2.92%
152	CMF	2.91%
153	MMPC	2.84%

154	Edpyme Crear Trujillo	2.66%
155	BRAC	2.59%
156	FUCEC Togo	2.59%
157	CMAC - Sullana	2.56%
158	BURO Tangail	2.54%
159	Kafo	2.48%
160	SEF-SA	2.43%
161	RBV	2.38%
162	SOCREMO	2.36%
163	BancoSol	2.22%
164	CMAC - Arequipa	2.21%
165	GV	2.04%
166	PAPME	2.04%
167	PAMECAS	2.00%
168	TPC	1.86%
169	Fundación Paraguaya	1.75%
170	Finance Salone	1.74%
171	IMCEC - Dakar	1.73%
172	FAMA	1.71%
173	CREDIMUJER	1.66%
174	VFCF	1.65%
175	Sunrise	1.63%
176	CMS	1.54%
177	ACEP	1.49%
178	Otiv Toamasina	1.49%
179	BCS	1.45%
180	FUNDESER	1.45%
181	WWB - Medellín	1.44%
182	TEBA	1.42%
183	HOPE	1.38%
184	PRIZMA	1.38%
185	Banco Solidario	1.33%
186	ADEFI	1.23%
187	FINCA - GEO	1.20%
188	ACLEDA	1.16%
189	BESA	1.16%
190	ACTUAR - Tolima	1.13%
191	ProMujer - Nicaragua	1.11%
192	CMM - Bogotá	1.09%
193	Finamerica	1.09%
194	KC	1.05%
195	Soro Yiriwaso	1.04%
196	COAC Sac Aiet	1.02%
197	CRENDA	0.96%
198	Fundación ESPOIR	0.94%
199	Constanta	0.93%
200	AFK	0.91%
201	KAFC	0.89%
202	ACODEP	0.88%
203	Miselini	0.86%
204	PCCC	0.86%
205	FINDESA	0.84%

206	MI-BOSPO	0.83%
207	RBST	0.80%
208	BRI	0.79%
209	FINCA - KGZ	0.78%
210	CAPPED	0.75%
211	CEP-CECREV	0.75%
212	KAMURJ	0.75%
213	AMSSF/MC	0.74%
214	WWB - Cali	0.70%
215	FINCA - ARM	0.69%
216	ADIM	0.67%
217	Faulu - UGA	0.67%
218	Kondo Jigima	0.65%
219	Caja Nor - PER	0.64%
220	PRIDE - MAL	0.63%
221	FINADEV	0.62%
222	GGLS Save the Children	0.59%
223	Faulu - KEN	0.58%
224	KMBI	0.58%
225	Nyesigiso	0.56%
226	RCMEC	0.56%
227	Seawatch	0.53%
228	FDL	0.50%
229	Tchuma	0.50%
230	CERUDEB	0.48%
231	MECBAS	0.48%
232	BPR AK	0.44%
233	Nirdhan	0.44%
234	WAGES	0.43%
235	PADME	0.42%
236	UWFT	0.41%
237	FJN	0.37%
238	FMM - Bucaramanga	0.37%
239	SFE	0.35%
240	UMU	0.34%
241	CMMB	0.33%
242	MIKRA	0.32%
243	Compartamos	0.31%
244	EKI	0.30%
245	FMM - Popayán	0.30%
246	MUCREFAB	0.28%
247	Acción Rural	0.27%
248	BAI	0.27%
249	KLF	0.27%
250	CRYSTAL FUND	0.24%
251	Partner	0.24%
252	SKS	0.24%
253	CRECER	0.23%
254	COAC Maquita Cushunchic	0.22%
255	JMCC	0.20%
256	CCCP	0.19%
257	XacBank	0.19%

258	CEP	0.17%
259	AgroInvest	0.15%
260	BPR BMMS	0.14%
261	VF	0.14%
262	K-Rep	0.13%
263	Pharma-crédit	0.12%
264	PTF	0.10%
265	ABA	0.09%
266	MFW	0.09%
267	AMRET	0.08%
268	ASA	0.08%
269	MUCREFBO	0.08%
270	Al Amana	0.07%
271	Daulet	0.05%
272	Fonkoze	0.04%
273	KEP	0.03%
274	MIKROFIN	0.03%
275	Ameen	0.02%
276	PEDF	0.02%
277	ACEP - CM	0.01%
278	RBKV	0.01%
279	VFC	0.01%
280	ACF	0.00%
281	ACSI	0.00%
282	Adelante	0.00%
283	ADRI	0.00%
284	AREGAK	0.00%
285	ASEI	0.00%
286	BBK	0.00%
287	CARD Bank	0.00%
288	CARD NGO	0.00%
289	CBDIBA	0.00%
290	CCA	0.00%
291	CMEDFI	0.00%
292	COAC Jardín Azuayo	0.00%
293	COAC La Merced	0.00%
294	COAC San José	0.00%
295	CODESARROLLO	0.00%
296	COOPEC CAMEC MN	0.00%
297	Credi Fe	0.00%
298	CRG	0.00%
299	CVECA Mouhoun	0.00%
300	CZWSDA	0.00%
301	DBACD	0.00%
302	DECSI	0.00%
303	D-miro	0.00%
304	ECLOF - ECU	0.00%
305	ECLOF - MAL	0.00%
306	Ekukhanyeni	0.00%
307	ESED	0.00%
308	FAM	0.00%
309	FATEN	0.00%

310	FINCA - AZE	0.00%
311	Finca - TAN	0.00%
312	Finca - UGA	0.00%
313	FinDev	0.00%
314	FMFB	0.00%
315	FOCCAS	0.00%
316	FONDEP	0.00%
317	GEC Parcelles	0.00%
318	GECEFIC	0.00%
319	GK	0.00%
320	IAMD	0.00%
321	IDECE	0.00%
322	IDF	0.00%
323	ISSIA	0.00%
324	Kashf	0.00%
325	KPSCA	0.00%
326	KSF	0.00%
327	KVT	0.00%
328	MAYA	0.00%
329	MC²	0.00%
330	MEC Bosangani	0.00%
331	MECZOP	0.00%
332	MFSC	0.00%
333	MIFED	0.00%
334	MRFC	0.00%
335	MUFFA	0.00%
336	Mushuc Runa	0.00%
337	OIS	0.00%
338	Otiv Diana	0.00%
339	Otiv Tana	0.00%
340	PRASAC	0.00%
341	PRIDE - ZAM	0.00%
342	ProMujer - Peru	0.00%
343	REMECU	0.00%
344	SABR	0.00%
345	SCSCS	0.00%
346	SEAP	0.00%
347	SEF-TZ	0.00%
348	SFSBS	0.00%
349	SHARE	0.00%
350	SIPEM	0.00%
351	SMEP	0.00%
352	Spandana	0.00%
353	Sunlink	0.00%
354	TIAVO	0.00%
355	Tlholo	0.00%
356	UNICECAM	0.00%
357	USPD	0.00%