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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 ($\$4.3\text{m} \times 8\% = \$344,000$).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

¹The 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 portfolio 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 ($12.5 \times = 100.0\% / 8.0\%$). 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

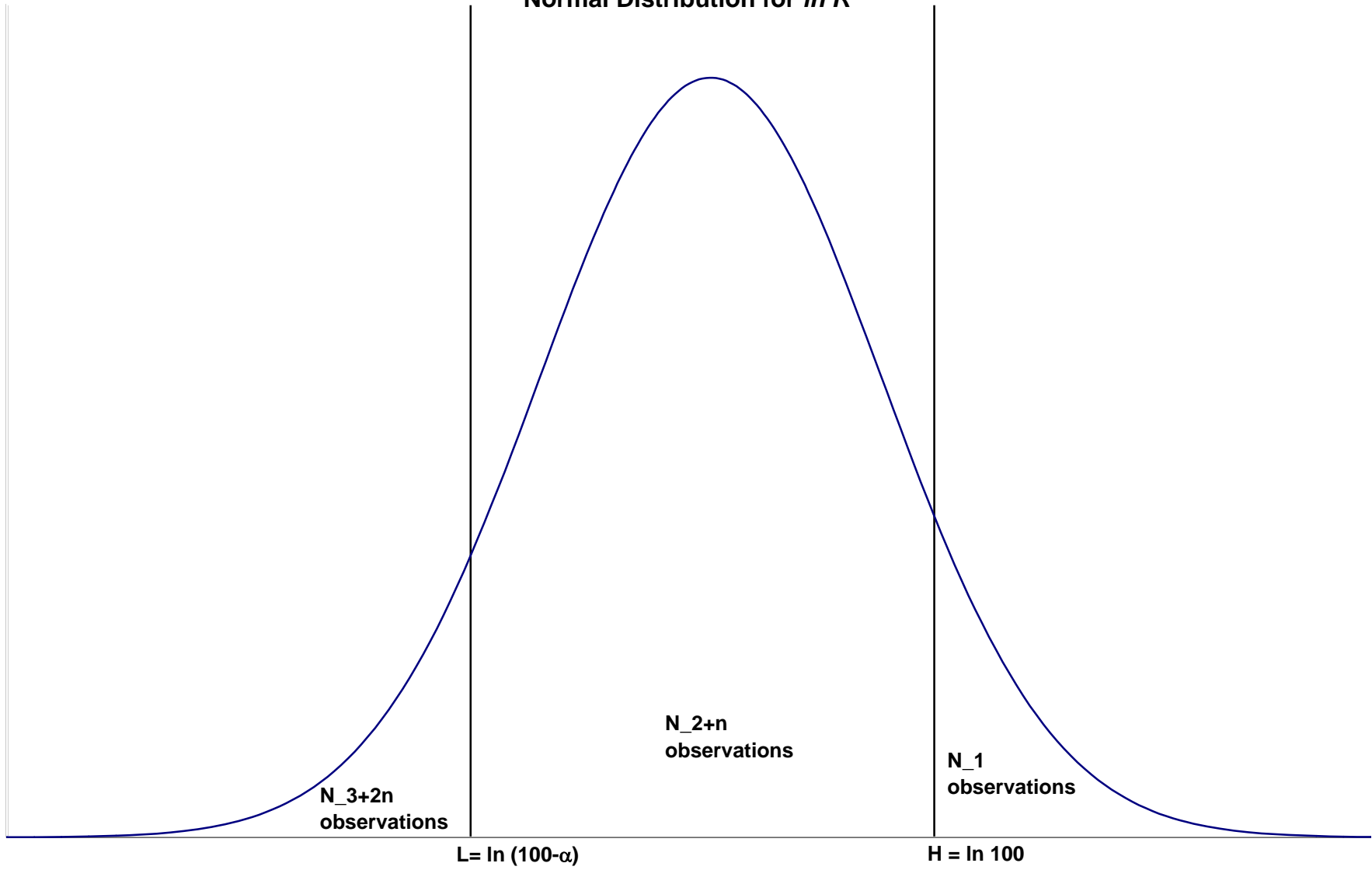
$$x \equiv \frac{\ln(R) - \mu}{\sigma} \sim N(0, 1),$$

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:

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

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

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:

$$\mathbb{E}[R] = \exp\left(\mu + \frac{1}{2}\sigma^2\right), \quad (3)$$

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

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

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

²It 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 guarantee³ in which the lender is insured to receive its full payment of 100, the price of such a guarantee can be calculated as:

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

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:

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

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

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

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.

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

⁴The 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 break-point.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

⁵The 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):

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

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

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:

$$E[R] = 95.45,$$

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

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

⁶See 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%
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303 D-miro	0.00%
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305 ECLOF - MAL	0.00%
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307 ESED	0.00%
308 FAM	0.00%
309 FATEN	0.00%

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312 Finca - UGA	0.00%
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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 MC ²	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 Tiholo	0.00%
356 UNICECAM	0.00%
357 USPD	0.00%