Universidad de los Andes
Facultad de Ingeniería

Methodologies for Cut-Off Point Determination in Credit Scoring Models for Not-for-Profit Governmental Institutions

Credit Scoring and Credit Control XII conference

August 24-26 2011

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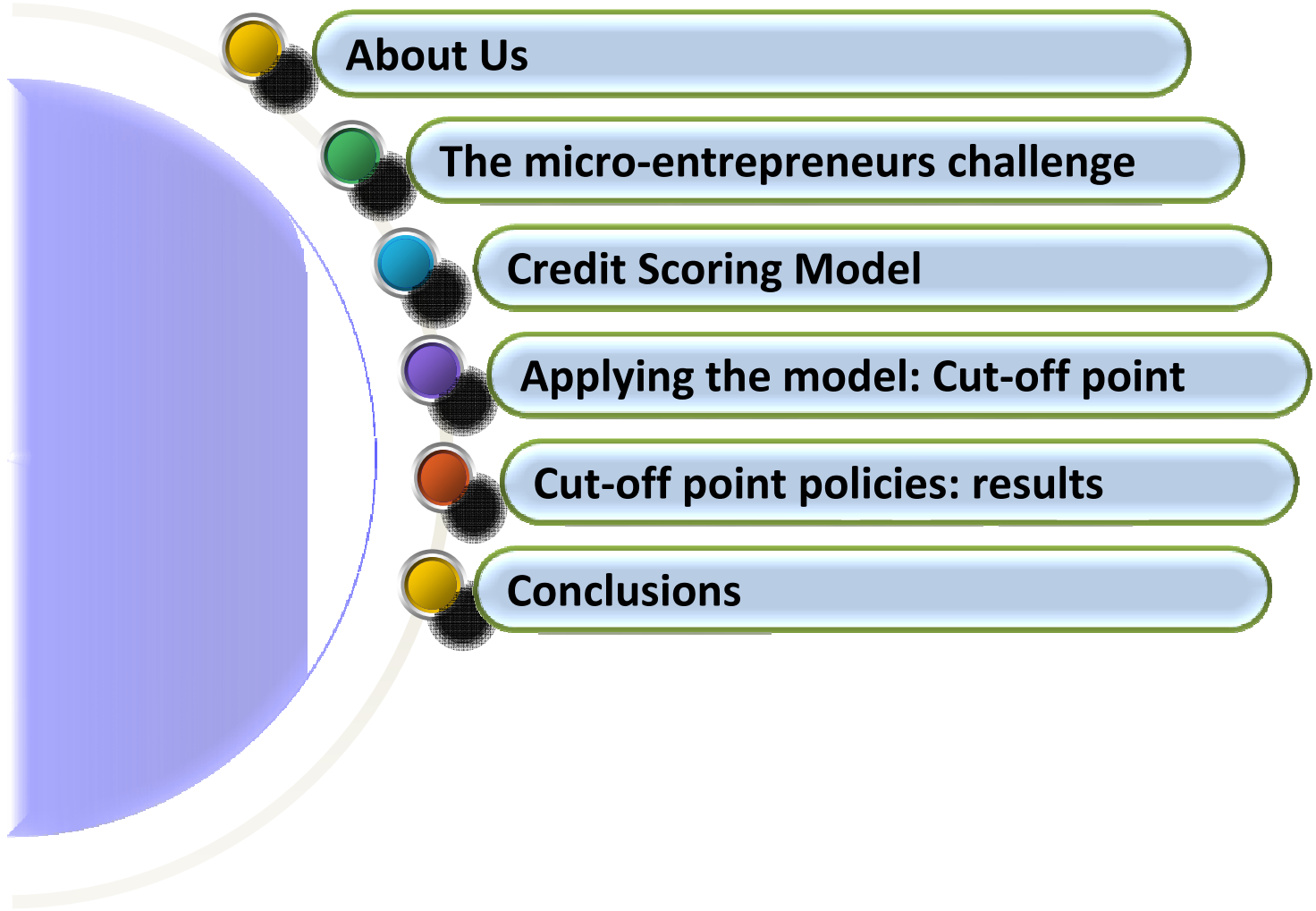
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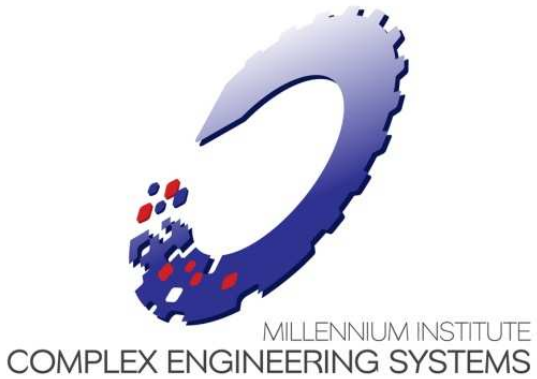
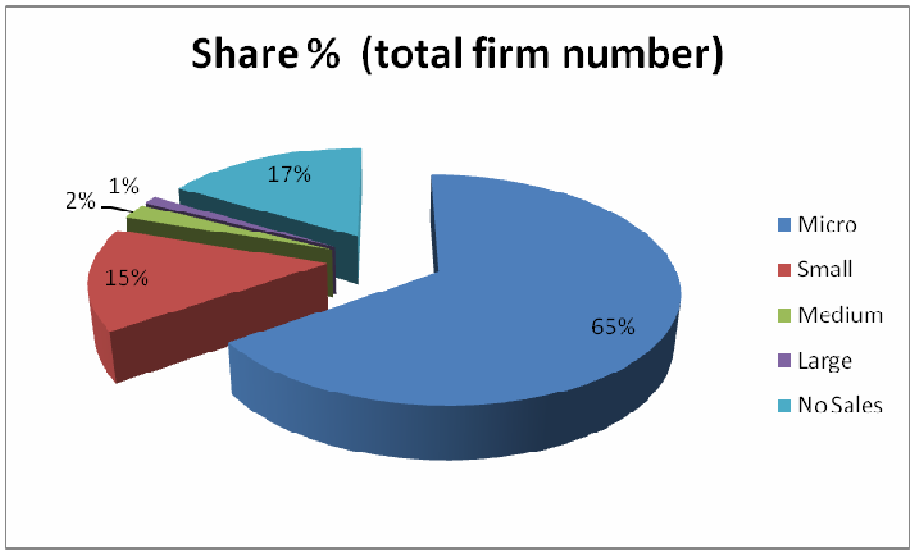
About Us

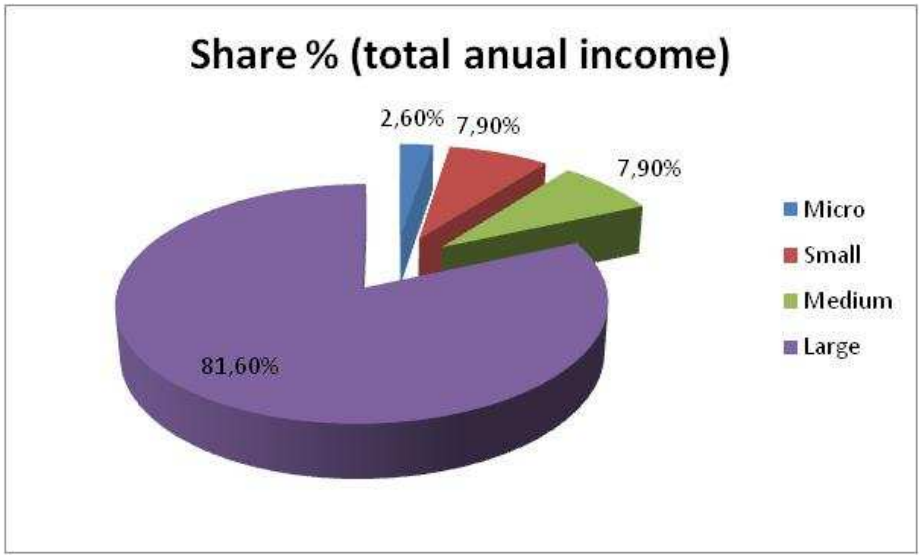
- *Data Mining Group, formed in year 2003*
- *Support from the Finance Center of the Department of Industrial Engineering (www.dii.uchile.cl/~cf) Millennium Science Institute on Complex Engineering Systems (www.sistemasdeingenieria.cl)*



The Micro-entrepreneurs challenge

➢*Micro entrepreneurs in Chile: (very) small firms with annual sales below US$113,000 (70.000 £).*

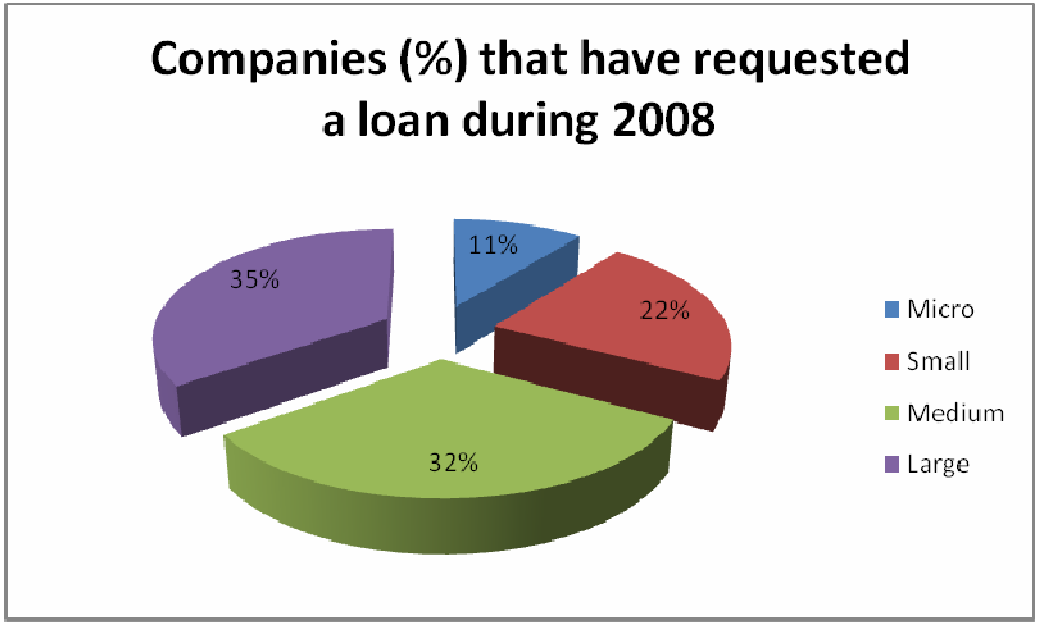




➢*They represent 21% of total Chilean workforce!*

The Micro-entrepreneurs challenge(2)

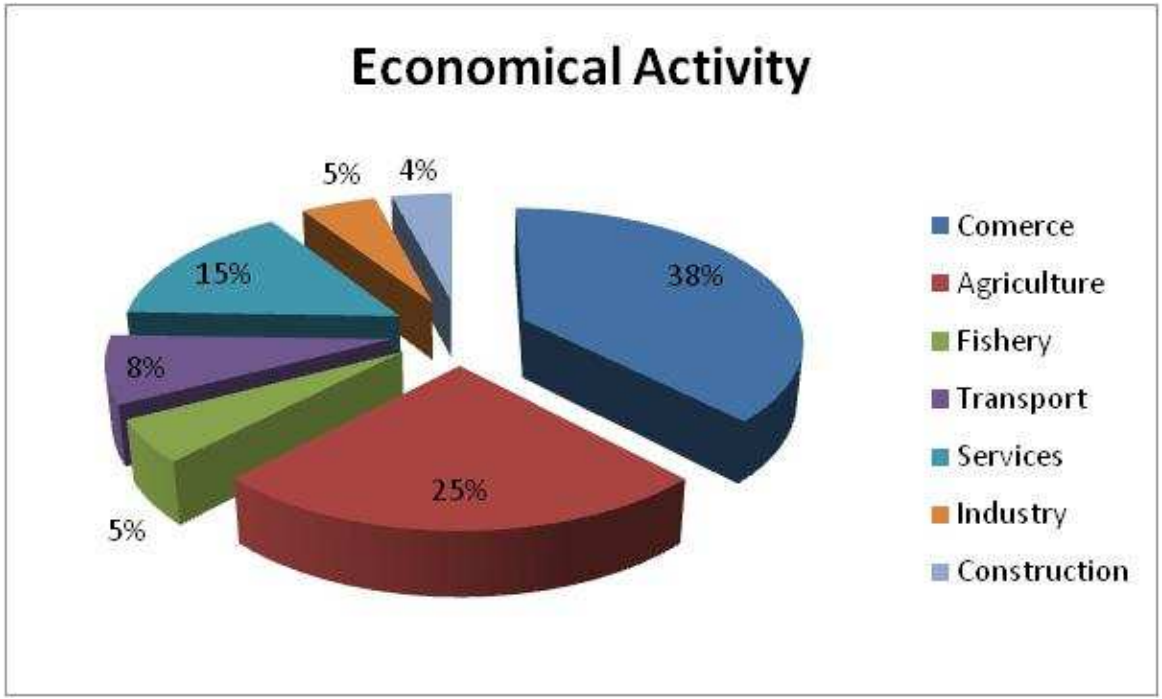
- *Little access to loans, due to low salaries and high risk.*
  - *Only 40% of the micro-entrepreneurs have access to loans.*
- *Micro-entrepreneurs with no access to loans tend to reduce their production, which translates in cost for society.*



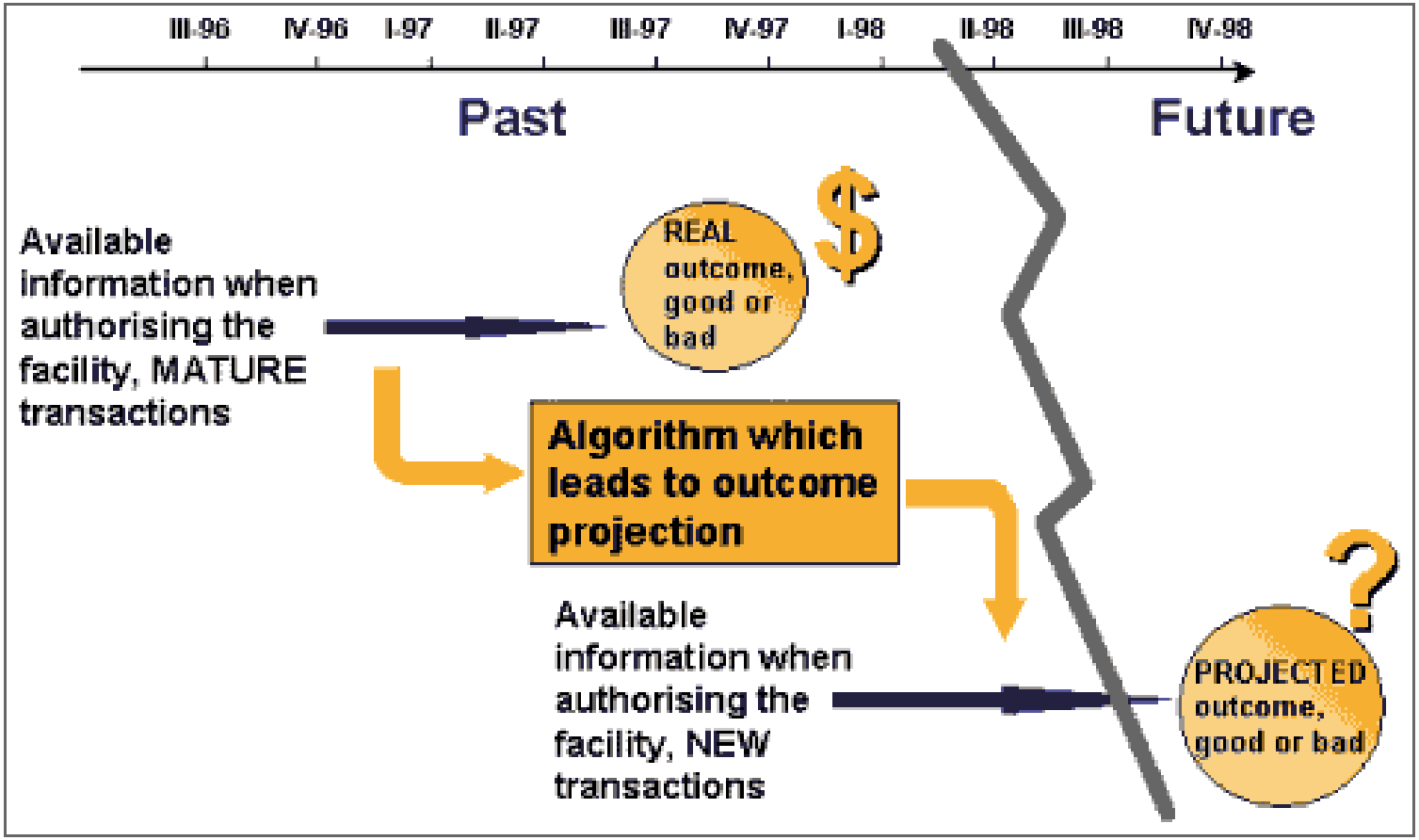
The Micro-entrepreneurs challenge(3)

➢*Agribusiness micro-entrepreneurs have support from the government, with subsidies and cheap loans.*

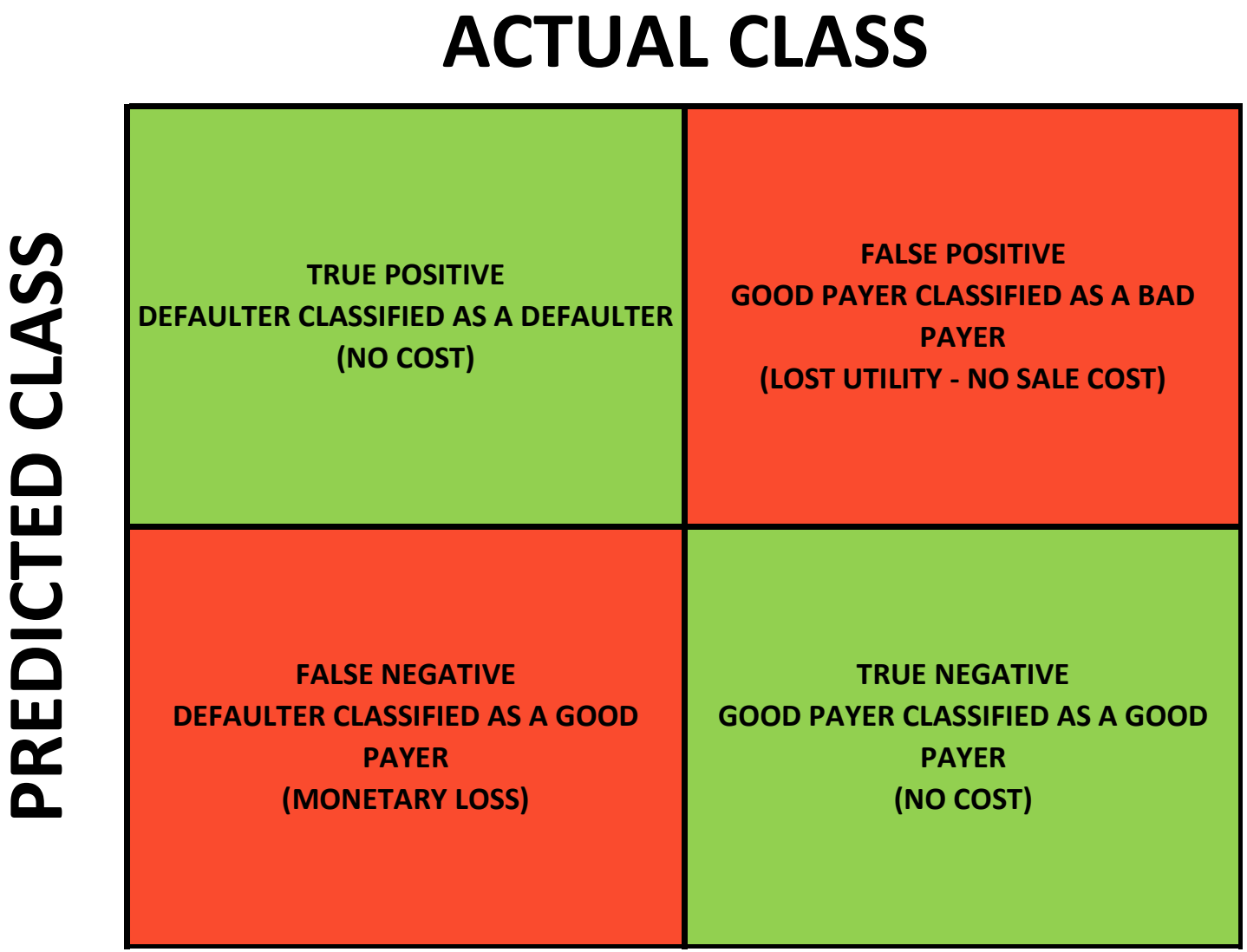
➢*Important economic sector for the micro-enterprise segment.*



Credit Scoring Model

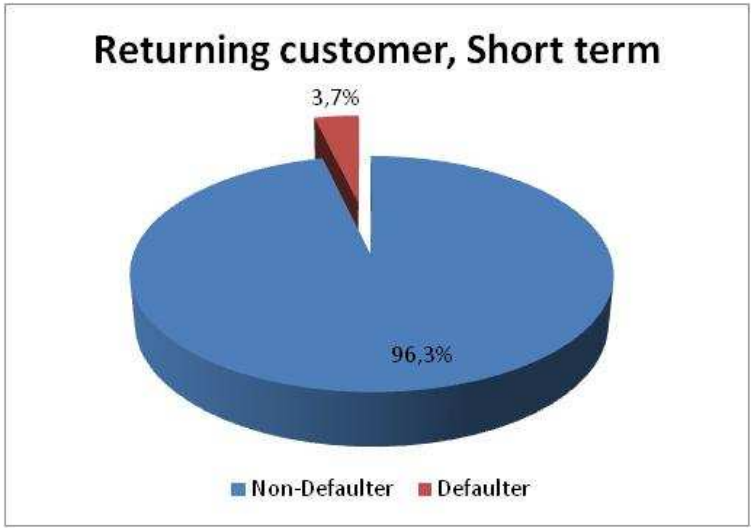


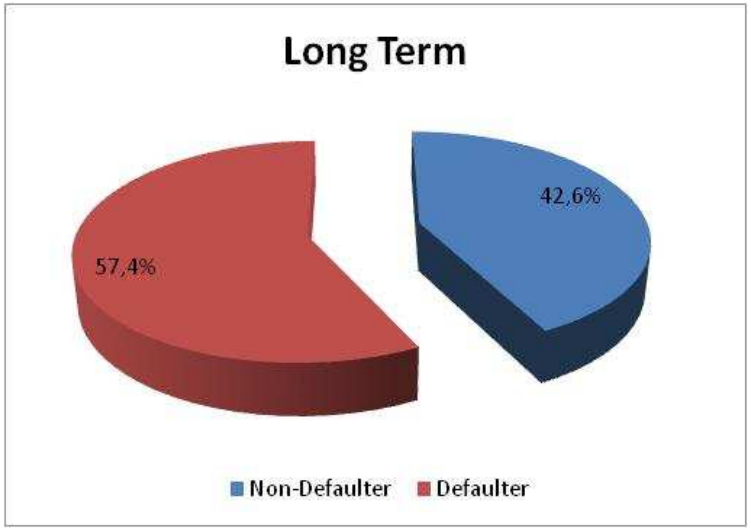
Credit Scoring Model(2)



Credit Scoring Model(3)

- *What we are facing..*
  - *Unbalanced and heterogeneous data set.*



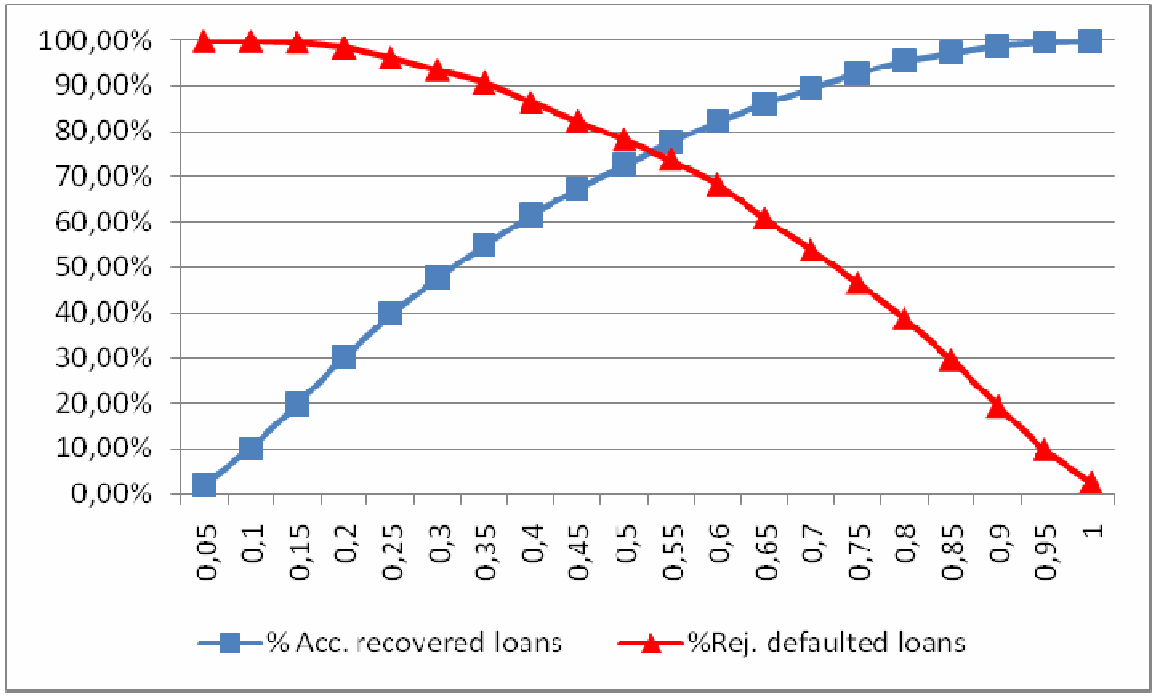


- *Costs of errors are unclear.*
- *State-owned financial institutions and traditional banks have different goals!*

Credit Scoring Model – Logistic Regression

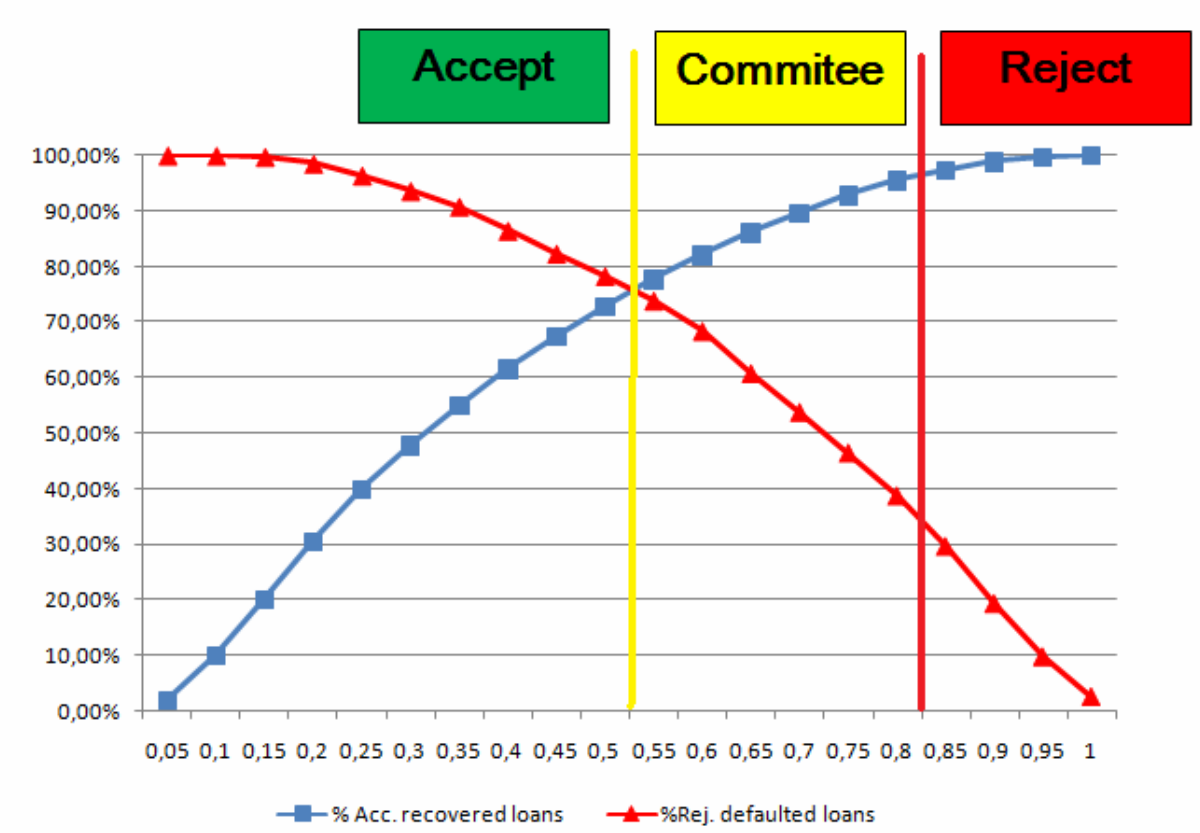
➢*Logistic regression constructs a function which determines the probability of default (PoD) for a particular customer.*

➢*With the PoD we construct classification tables and charts:*



Applying the Model – Cut-Off Policy

➢ *We propose a 3-zones cut-off point policy:*



Applying the Model – Cut-Off Policy(2)

- *Two cut-off points:*
  - *First Point: maximize effectiveness (equal cost of errors).*
  - *Second Point : minimize total cost*
    - *Cost of granting a credit to a 'bad' customer?*
    - *(Opportunity) cost of rejecting an application of a 'good' customer?*

Cut-Off Policy – Type I Error Cost

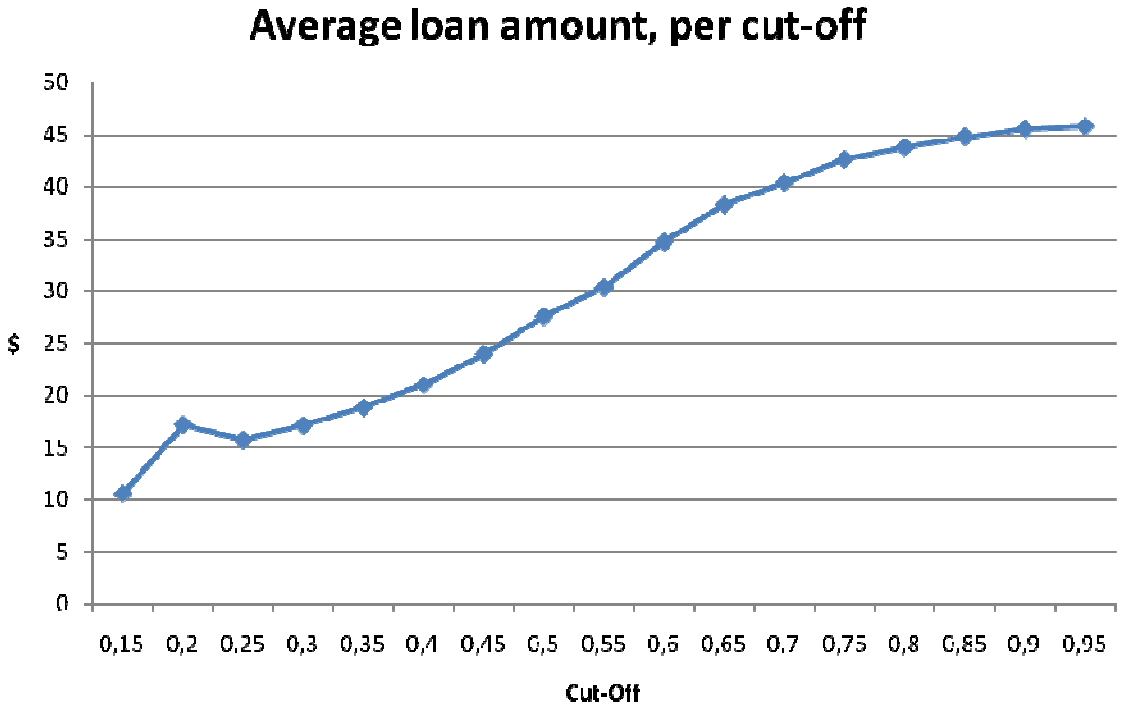
- *Use the expected Loss Given Default (or LGD).*

- *For micro-entrepreneurs, estimate the following:*
  - *The time until default occurs.*
  - *The indebted amount at that time.*

- *Since the idea is to estimate an average cut-off point, an additional step must be considered.*

Cut-Off Policy – Type I Error Cost(2)

➢*Since the greater the amount, the greater the risk, the number of defaults increases given the cut-off.*



➢*This way, the cost depends on the amount granted.*

Cut-Off Policy – Type II Error Cost

➢ *Traditionally, loss of interest income generated by a potentially 'good' customer.*

➢ *State owned corporation => no credit profit!*

➢ *Assumption: 'good' customers will improve their productivity if they receive a loan:*

Projected and declared annual income comparison (US$):

	access to loan	no access to loan	Difference/Average	Percentage
average annual income	$ 4,029.3	$ 2,964.1	$1,065.2	26.44%
expected loss of income have not granted credit	$ 1,032.9		$1,086.9	26.97%
expected additional income have granted credit		$ 1,140.9		

➢ *Social cost: loss of expected productivity, given by the 26,44% of the average amount of the granted loans.*

Cut-Off Policy – Results

➢ *Cut-off points and associated costs (USD, in thousands):*

Cut-Off	Default			Average	Average Rej.	Cost	Cost	Total
	0	1	Total	Amount	Cost	Good Payers	Defaulters	Cost
0.05	12	0	12	6.9	3.8	53296.1	0.0	53296.1
0.1	199	2	201	10.3	3.5	52754.5	7.1	52761.5
0.15	461	22	483	11.2	3.8	51391.1	91.8	51482.9
0.2	620	35	655	12.5	4.4	49349.3	260.3	49609.6
0.25	726	59	785	13.9	4.7	46687.9	558.4	47246.3
0.3	801	91	892	13.5	5.1	43831.1	1062.4	44893.6
0.35	939	138	1077	14.1	5.4	40342.2	1861.5	42203.7
0.4	1089	132	1221	16.0	5.7	35727.5	2740.0	38467.5
0.45	1134	188	1322	15.4	6.2	31119.4	4155.5	35274.9
0.5	1268	244	1512	19.6	6.7	24532.9	6103.8	30636.7
0.55	1095	285	1380	19.9	7.2	18763.4	8614.8	27378.2
0.6	935	288	1223	22.3	7.6	13244.4	11232.1	24476.4
0.65	657	289	946	25.1	7.9	8876.4	14059.1	22935.4
0.7	458	285	743	30.3	8.3	5205.4	17068.1	22273.5
0.75	336	263	599	29.1	8.5	2616.6	19807.7	22424.4
0.8	223	209	432	25.6	8.7	1106.3	22114.0	23220.4
0.85	123	204	327	23.4	8.9	346.7	24256.7	24603.4
0.9	50	85	135	22.2	8.9	52.8	25139.7	25192.5
0.95	8	12	20	25.0	8.9	0.0	25247.7	25247.7

Conclusions

- *Granting efficiently credits to the right micro-entrepreneur could generate a huge benefit for society.*

- *The proposed methodology quantifies the lost benefit for society when not granting a credit to a potentially good customer.*

- *Our numerical experiments underline the potential impact such a methodology might produce.*