Gender-Intentional Credit Scoring

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Speakers

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Agenda

- **Part 1:**
  - Gender-intentional techniques and implementation strategies for credit scoring
  - Q&A
- **Part 2:**
  - Walk-through of how to implement the analyses using Excel, R, and Python
  - Q&A

Saiyna Bashir, C4D 2021

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Key messages

- Evidence shows that **women tend to have, on average, better loan repayment rates** than men
- Under certain conditions, a **gender disaggregated data analysis** can identify ways to increase credit or **improve conditions for women** without increasing provider risk
- A gender-intentional approach can help lenders **more accurately measure portfolio risk**
- Gender lens analysis **can improve awareness of gender gaps** in finance
- **Lenders using credit scoring models can easily apply gender-intentional strategies—**such as setting different decision threshold policies for women and men
- Gender-intentional credit scoring strategies can **lead to a larger total portfolio and a larger number of loans given to women** for a given portfolio risk target

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Gender lens analysis of lending outcomes looks at how men and women differ in terms of data availability and credit risk and determine if there are opportunities to serve women better.

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Gender Lens Analysis

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Basic gender-lens analysis

TABLE 4. **Gender-lens analysis summary**

Gender-lens metric	Women	Men	Total
Share of applications	55%	45%	100%
Approval rate[a]	73%	67%	70%
Share of issued loans	60%	40%	100%
"Bad" rate	5%	10%	7%

Data Requirements:

- Borrower's gender
- Application outcome: Accepted or rejected.
- If accepted, a loan's "good" or "bad" status
- [Credit score or rating (if a model is used)]

Gender-lens analysis indicates:

1. What share of loans are issued to women and men
2. Loan approval rates for women and men
3. The rate of repayment for women and men

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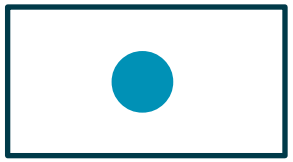
Gender-blind vs. Gender-lens



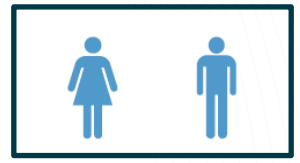


FIGURE 1. **7% "bad" rate**

Source: Authors.

- 7 of 100 borrowers pay late

FIGURE 2. **Gender analysis of "bad" rate for loans**

Source: Authors.

- 5 of 100 women pay late
- 10 of 100 men pay late

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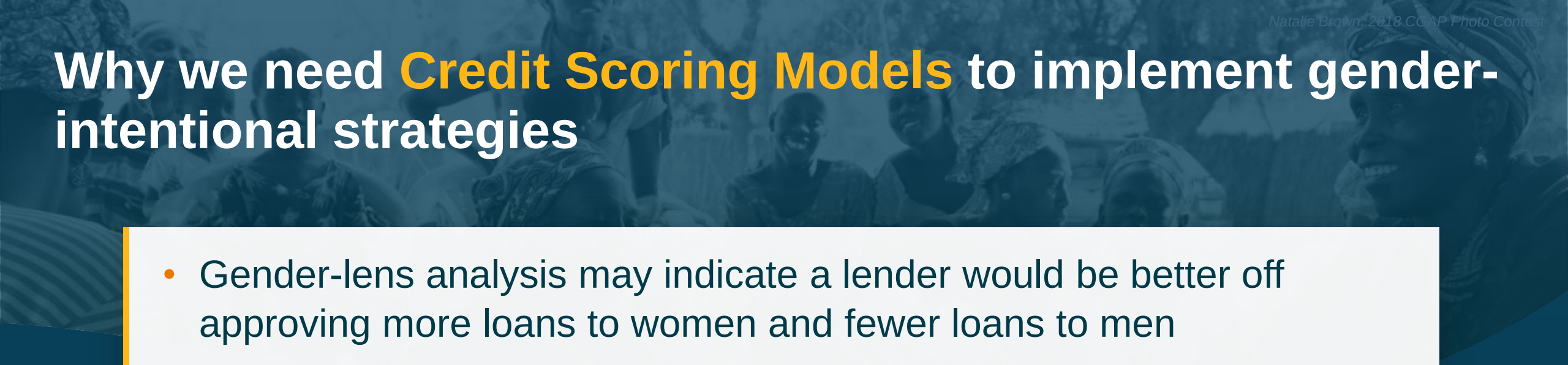
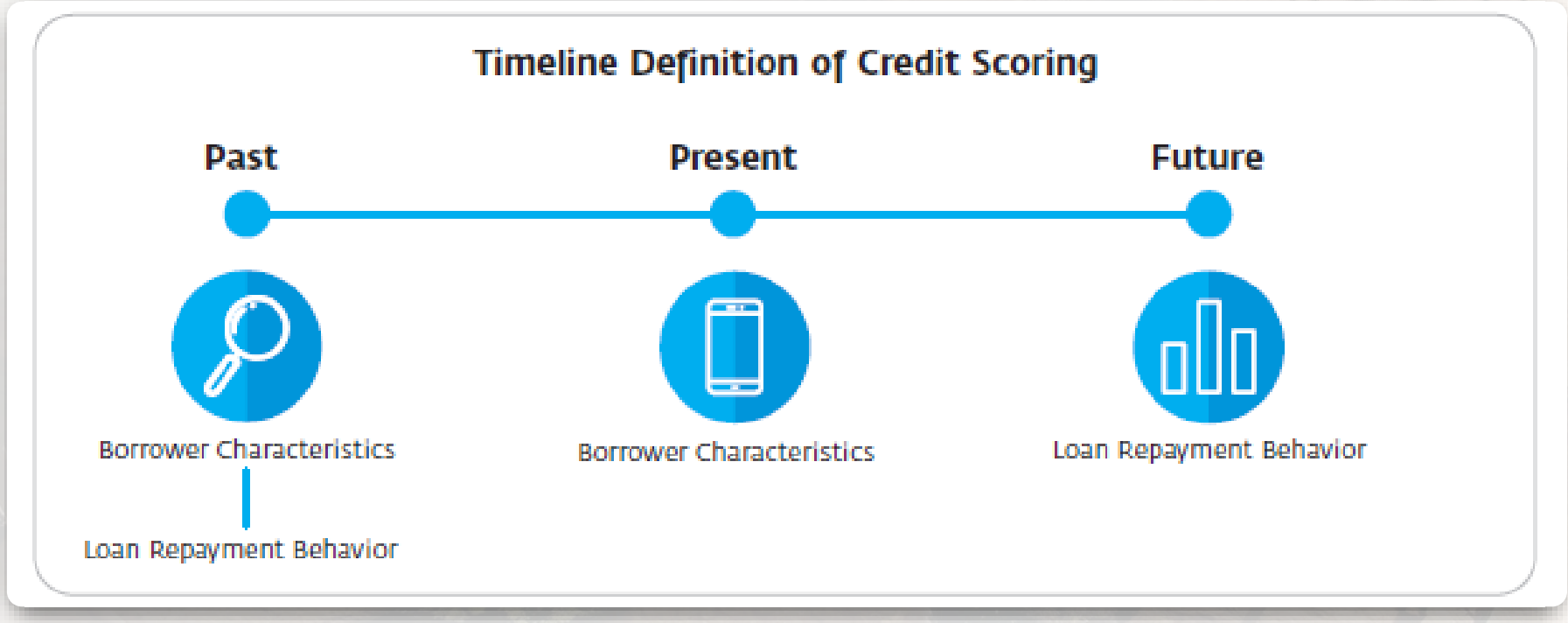


Why we need Credit Scoring Models to implement gender-intentional strategies

- Gender-lens analysis may indicate a lender would be better off approving more loans to women and fewer loans to men
- A credit scoring model is needed to determine the optimal number or share of loans that the lender should make to women
- Credit scoring or rating models help lenders make quantifiable and explicit adjustments to lending policy in a way that can be consistently implemented through the organization

Credit Scoring: study the past to predict the future



- Credit scoring is the study of past loan repayment in terms of borrower characteristics to predict future expected loan repayment
- Credit scores quantify and combine the relationships between past borrower characteristics and repayment
- More points are assigned to characteristics associated with better repayment

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Source: Data Analytics and Financial Services

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Cross-Tabulation analysis

Example: TymeBank

Loan repayment status	Female	Male	Row total
Goods	9,589	4,495	14,084
Bads	658	396	1,054
Bad Rate	6.4%	8.1%	7%
Column Total	10,247	4,891	15,138
% of Total Loans	67.7%	32.3%	100%

Source: Authors based on data shared by Tymebank

Cross-tabulation shows counts of "good" and "bad" loans for a particular borrower characteristic, in this case gender

"Good" and "bad" loans and "bad rates"

In credit scoring, the terms "good" and "bad" are used to label loan accounts based on their past performance

The definition of a "bad" loan varies by product and provider, buy one common "bad" loan definition is "90 days past due"

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Example - Credit Scoring: study the past to predict the future

Past

Present

Future

Gender	Bad %	Points
Male	14.5	0
Female	4.1	10.4

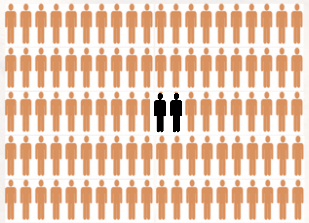
Age	Bad %	Points
< 21	16.4	0
22 - 35	12.0	4.4
36 - 50	8.6	7.8
> 50	2.9	13.5

Years in Business	Bad %	Points
< 1	22.1	0
1 up to 3	12.1	10
3 up to 7	7.9	14.2
7 to 12	3.9	18.2
> 12	1.5	20.6

Factor	Value	Score
Gender	Female	10.4
Age	41	7.8
Years in Business	8	18.2
Total		**36.4**

Credit Score	>=	<=	Goods	Bads	Total	Bad rate
Low Risk	33	44.5	2309	49	2358	2.1%
Average Risk	18	32	4591	492	5083	9.7%
High Risk	0	17	2100	459	2559	17.9%
Total			**9000**	**1000**	**10000**	**10%**

100 Applicants



2 will be ‘bad’ (and we don’t know which 2)

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Credit Scoring models and risk appetite

TABLE 5a. **Cross table scores by repayment: women**

A	B	C	D	E	F	G
Score band	"Good"	"Bad"	"Bad" %	Total	Cumulative "Bad" %	% Population
91-100	11	0	0%	11	0%	2%
81-90	40	1	2%	41	2%	9%
71-80	57	1	2%	58	2%	18%
61-70	68	2	3%	70	2%	30%
51-60	108	3	3%	111	2%	49%
41-50	108	6	5%	114	3%	68%
31-40	68	4	6%	72	4%	80%
21-30	57	5	8%	62	4%	90%
11-20	40	7	15%	47	5%	98%
0-10	11	3	21%	14	5%	100%
Total	568	32	5%	600		
% of Total	95%	5%	5%	1		

Source: Authors.

Cumulative "Bad" rates (column F) show expected bad rate for each cut-off score (column A)"

- For a 3% delinquency risk target, accept all loans scoring above 40
- For a 4% delinquency risk target, accept all loans scoring above 20

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Gender-Intentional Credit Scoring

Nicolas Réméné, 2020 C4D

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Gender intentional strategies

- In this section we will apply different strategies to **reduce bad loans from 7% to 5%** and compare the impact in terms of total portfolio size and loans given to women
- We will compare 4 options:

1. **Gender-blind approach** – No use of gender data in the modelling or the approval cut-off
2. **Gender-blind model with gender intentional cut-off** - No use of gender data in the modelling but approval cut-off score is selected separately by gender
3. **Gender variable included in model** – A gender variable is included in the model, no gender adjustment of approval cut-offs
4. **Separate scoring models** – A different scoring model is developed for each gender and cut-offs are selected separately for each gender

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Score cut-off strategies

1- Gender-blind: one cut-off score, higher than the original, that brings the past "bad" rate down to 5%

2- Gender-intentional: subset data by gender and determine separate cut-off scores for women and men to bring past "bad" rates for each group down to 5%

Loan repayment status	Female	Male	Row total
Goods	9,589	4,495	14,084
Bads	658	396	1,054
Bad Rate	6.4%	8.1%	7%
Column Total	10,247	4,891	15,138
% of Total Loans	67.7%	32.3%	100%

Source: Authors based on data shared by Tymebank

Metric	Strategy	
	Gender-blind: single cut-off	Gender-intentional: cut-offs by gender
% Women approved	78.6%	88.5%
"Bad" % women	4.3%	5%
% Men approved	78.9%	68.7%
"Bad" % men	6.4%	5%
Total "bad" %	5%	5%

Setting separate scoring decision thresholds by gender is an easy and straightforward way of accurately aligning scorecards with risk appetite and ensuring the maximum number of women borrowers are reached for any given risk target

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How to select the cut-off score?

TABLE 8. **Cut-off selection**

Row	Score	"Bad"	Cumulative "bad"	Cumulative "bad" rate
93	48	1	7	6.7%
94	48	0	7	6.7%
95	49	1	6	5.9%
96	49	0	6	5.8%
97	50	1	5	5%
98	52	0	4	4%
99	53	0	4	4.1%
100	53	0	4	4%
101	54	1	4	4.2%
102	54	0	4	4.1%
103	55	0	3	3.2%
104	55	0	3	3.2%
105	56	0	3	3.2%

Source: Authors.

1. Extract data on scores and "bad" loan status
2. Order loans from lowest to highest score
3. Add the total number of "bads" up to the current row (cumulative bads)
4. Divide the number of cumulative bads by the row number and find the row with the target risk rate of 5

The risk target of 5% is reached at a score of 50 points in this example

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Strategies: TymeBank South Africa data example

- CGAP analyzed a **data set of over 15,000 approved BNPL** loans
- These models were created **for research purposes only**

Using "gender" as a scorecard characteristic

Metric	Strategy	
	Gender-blind model: single cut-off	**Gender-intentional model: single cut off**
% Women approved	78.6%	84.6%
Late repayment % women	4.3%	4.7%
% Men approved	78.9%	75.4%
Late repayment % men	6.4%	5.6%

Building separate scorecards for women and men

Metric	Strategy	
	Gender-blind single cut-off	**Separate models for women and men**
% Women approved	78.6%	89.6%
"Bad" % women	4.3%	5%
% Men approved	78.9%	69.7%
"Bad" % men	6.4%	5%

To illustrate and quantify the simulation of a gender-intentional strategy, we assume the BNPL lender wants to lower its overall portfolio "bad" rate from 7% to 5%.

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Example: AB Bank Zambia: adding "gender" as a scorecard characteristic

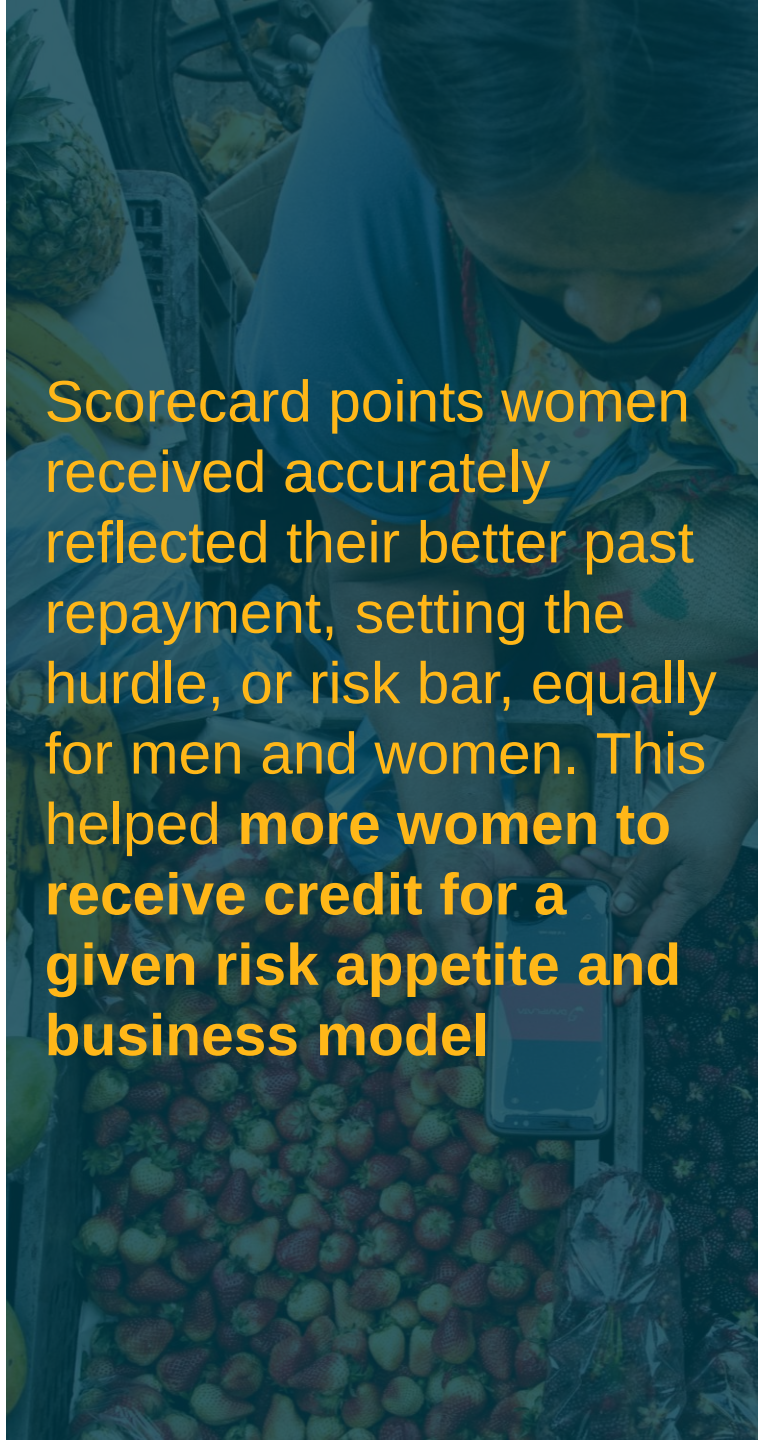
Adding a gender characteristic to ABZ's micro loan scorecard resulted in increasing the share of scored loans issued to women and evening the bad rates for men and women.

Over the period of 2012-2019 :

- **57% of micro loans were issued to women**
- **5% of loans to women were bad vs. 7% for men**

In 2019, ABZ started using a scorecard for micro loans and included a "gender" characteristic – women received points. Between 2020 and 2023:

- **60% of scorecard loans were disbursed to women**
- **Bad rates for both women** and men **decreased to 3.5%**



Scorecard points women received accurately reflected their better past repayment, setting the hurdle, or risk bar, equally for men and women. This helped **more women to receive credit for a given risk appetite and business model**

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Strategies and Results: TymeBank South Africa data example

Gender intentional approaches result in more loans to women and a larger portfolio for a given level of risk

Results of using strategy to reduce Bad loans from 7% to 5%

Per 1000 customers

Strategy	% Women approved	"Bad" % Women	% Men approved	"Bad" % Men	Women approved	Men approved	Total
1: Gender-blind single cut-off	79.6%	4.3%	79.8%	6.4%	534	252	786
2: Gender-blind with separate cut-offs by gender	84.6%	5.0%	75.4%	5.0%	597	222	819
3: Gender variable in scoring model, single cut-off	88.5%	4.7%	68.7%	5.6%	599	229	828
4: Separate scoring models by gender	89.6%	5%	69.7%	5.0%	607	232	839

The approaches presented not only result in better outcomes for women, but more accurate ways to predict risk and create business value for providers

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Other gender-intentional strategies: risk-based pricing

Can offer more affordable interest rates to women borrowers, making loan payments more affordable and possibly enabling more women to take loans that previously were too expensive for them

TABLE 13b. **Cross table scores by repayment with risk-pricing framework: gender-intentional for women**

A	B	C	D	E	F	G	H	I	J	K	L
Score band	"Good"	"Bad"	"Bad" %	Total	Cumulative "bad" %	% Population	Rate	Interest Income	Charge Off	Total Gross Margin	Gross Margin
91-100	11	0	0%	11	0%	2%	3%	330	0	330	3%
81-90	40	1	2%	41	2%	9%	5.5%	2,200	1,000	1,200	3%
71-80	57	1	2%	58	2%	18%	5%	2,850	1,000	1,850	3%
61-70	68	2	3%	70	2%	30%	6%	4,080	2,000	2,080	3%
51-60	108	3	3%	111	2%	49%	6%	6,480	3,000	3,480	3%
41-50	108	6	5%	114	3%	68%	9%	9,720	6,000	3,720	3%
31-40	68	4	6%	72	4%	80%	9%	6,120	4,000	2,120	3%
21-30	57	5	8%	62	4%	90%	12%	6,840	5,000	1,840	3%
11-20	40	7	15%	47	5%	98%	21%	8,400	7,000	1,400	3%
0-10	11	3	21%	14	5%	100%	31%	3,410	3,000	410	3%
TOTAL	568	32	5%	600				50,430	32,000	18,430	
% of Total	95%	5%	5%	1							

Source: Authors.

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Thank you

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