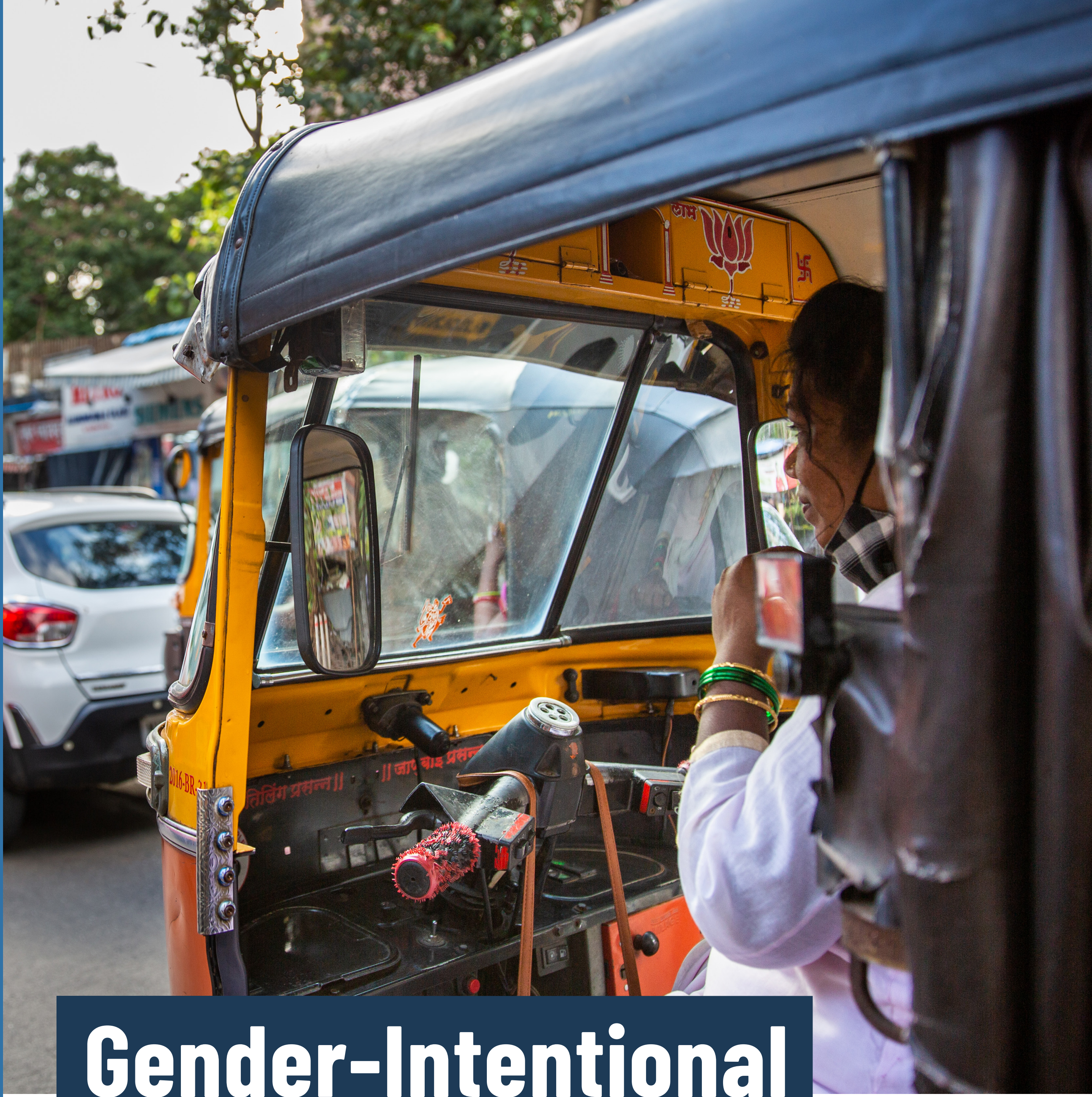
TECHNICAL GUIDE



Gender-Intentional Credit Scoring

March 2024 • **Dean Caire and Maria Fernandez Vidal**

CGAP

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Executive Summary

EVIDENCE SHOWS THAT WOMEN TEND TO have, on average, better loan repayment rates than men. The fact that the women receiving loans are, on average, lower risk than the men implies that women are being subjected to a comparatively higher bar for loan approval than men. These conditions present an opportunity to adjust lending models to more accurately assess risk and, as a result, increase financing to women.

This guide shows that a disaggregated gender analysis of a loan portfolio can unveil potential gender-intentional strategies to grow both the total loan book and the share of women borrowers without increasing the portfolio's credit risk. Because a gender-intentional approach can help lenders more accurately measure portfolio risk, such approaches not only can reduce the gender gap in access to credit, but they can make good business sense, by allowing providers to increase their portfolios or reduce their losses.

This guide presents a gender-lens analytical framework that lenders can use to determine whether lending decisions and outcomes in their portfolios differ by gender and, if so, how. For lenders using credit scoring models, the guide presents different gender-intentional techniques for adjusting their credit scoring models. It also presents implementation strategies—such as setting different decision threshold policies for women and men.

Finally, the guide uses actual loan application and repayment data from two banks to demonstrate how gender-intentional scorecard development and implementation strategies can work in practice:

- AB Bank Zambia (ABZ) incorporated gender into its microloan scorecard, resulting in more women receiving credit within the bank's existing risk appetite and business model.
- A Buy Now Pay Later (BNPL) product offered by digital TymeBank in South Africa is used to illustrate how gender-intentional model development and decisioning strategies could be used to increase both the total number of loans and the share of loans to women for a given portfolio risk level. It also shows how the model could be used for risk-based pricing, to lower interest rates for women borrowers.

These examples show that a gender-intentional approach can result in a larger total portfolio and a larger number of loans given to women for a given portfolio risk target. Even the simplest strategies result in significant improvement over a gender-blind approach. More sophisticated approaches, like developing separate credit scoring models, are likely to have the greatest impact in terms of increasing both total lending and lending to women.

INTRODUCTION

Why is a gender-lens analysis useful?

A GENDER LENS CAN BE APPLIED BY financial services providers (FSPs) in many ways to support women's financial inclusion. This paper focuses exclusively on the application of a gender lens to risk measurement in the context of lending. It does not attempt to fully cover the potential of applying a gender lens in the financial sector. Analysing lending outcomes through a gender lens could help lenders understand how men and women differ in terms of data availability and credit risk and determine whether there are opportunities to serve women better. This guide provides a simple gender-lens analysis framework as well as more detailed gender-intentional strategies for lenders using credit scoring models. While the guide focuses on gender and on women as the underserved group, this type of analysis could be applied to any underserved segment for which sufficient data is available.

While some FSPs, especially in the microfinance space, focus on serving women, the majority do not have a gender-differentiated approach to credit. While lenders may perceive a gender-blind approach as fair, we argue that women often face additional challenges when being evaluated by a system developed primarily for men. Not considering those challenges in decisions related to lending can be detrimental to women's financial inclusion.

Existing evidence, including practical experience working with lenders in 'developing' markets,[1] suggests that women tend to have better on-time loan repayment rates than men. If, at the time of a loan application evaluation, women and men's risk is assessed with the same accuracy, the women and men that are approved by the process should have the same risk level. However, evidence shows that women who receive loans, on average, repay better than men. This implies that, on average, they are lower risk. In a discretionary loan-officer-driven assessment process, this could be the result of bias or discrimination[2]. While a data-driven approach reduces the possibility of this, a difference can still exist as a result of insufficient data available for women and the use of data sources and models that do not fully account for gender differences.

Such conditions may present an opportunity to adjust lending models to more accurately assess risk and, as a result, increase financing to women. While our

1 The authors have worked with more than one hundred lenders in developing markets and encountered very few cases where men had higher on-time repayment rates than women. Similar assertions can be found in literature. See: "Loan repayment rates equal or exceed those of men," Mayoux, L. (2000). Micro-finance and the Empowerment of Women: A Review of the Key Issues. *ILO Working Papers*, (993441343402676), https://www.ilo.org/public/libdoc/ilo/2000/100B09_285_engl.pdf, accessed February 2, 2024; and "The business case for focusing on female clients is substantial, as women clients register higher repayment rates," https://www.ilo.org/wcmsp5/groups/public/---dgreports/---gender/documents/meetingdocument/wcms_091581.pdf, page 2, accessed February 2, 2024

2 Montoya et al. (2020) in "Bad Taste: Gender Discrimination in the Consumer Credit Market," found in a simulated experiment that the approval rate of loan requests submitted by female borrowers was 18.3% lower compared to the approval rate of otherwise identical loan requests submitted by male counterparts.

analysis does not look to uncover the root cause of different outcomes by gender, it does show that some types of data used in a scoring model or lending process have different importance for men and women. For example, in a variety of contexts, women are less likely than men to have assets such as land, houses or cars registered in their name. As a result, formal asset ownership may be a more important risk indicator for men, while a women's access to assets may be better reflected through informal family channels. In this example, considering formal asset ownership in the same way for women and men may result in lower scores for women, while not necessarily reflecting their repayment capacity.

This guide shows that, under certain conditions, a disaggregated gender analysis of a loan portfolio can unveil potential gender-intentional strategies to grow both the total loan book and the share of women borrowers, without increasing the portfolio's credit risk. Where possible, such approaches not only make good business sense, but also can help reduce the gender gap in access to credit.

The gender-lens analysis presented in this guide can improve a lender's understanding of the effectiveness of its underwriting models in assessing the credit risk of women and men borrowers. It might confirm pre-existing beliefs, identify hidden biases, or uncover unintended consequences of certain practices. The majority of developing markets are not limited by legislation such as the Equal Opportunity Credit Act (USA) or the National Credit Act (South Africa), which prohibit or strongly discourage the use of gender in credit underwriting[3]. Therefore, where no regulatory restrictions prevent it, this analysis can also lay the groundwork for the design and implementation of gender-intentional strategies that can improve lending outcomes for women.

How to use this guide?

This guide is intended to be a "how-to" resource for lenders, accessible to readers with a wide range of skills and experience. No specific prior knowledge or use of credit scoring should be necessary to understand and benefit from the key elements in this guide. Its content is likely to be most relevant and actionable for lenders and their stakeholders, particularly those already using credit scorecards. Nevertheless, its broader approach and ideas may be used with other types of data-driven analytical models and key performance metrics in organizations with a gender-inclusive objective.

The guide starts with the simplest content and incrementally progresses through levels of increasing intervention – from analysis, to changes in policy, to changes in credit scoring models.

Section one of this guide presents an analytical framework to examine if lending decisions and outcomes differ by gender and, if so, how. Understanding the current situation is a necessary first step in determining what opportunities may exist to improve the gender-responsiveness of lending models. Such analysis would be of interest to all lenders, including those who do not currently use credit scoring models. The second section presents gender-intentional techniques for adjusting the usage of existing credit scoring models to achieve gender-responsive targets. These techniques require no prior knowledge of credit scorecard development in order to apply them. The third section discusses two gender-intentional scorecard development techniques that can improve the gender-responsiveness of a credit scoring model, namely: 1) using gender as a variable in scorecard construction; and 2) building separate scorecards for women and men. The last section examines how gender-intentional strategies can be applied to offer risk-adjusted interest rates to borrowers.

3 A 2019 study published by the US Federal Reserve, Geng Li (2018), notes in regards to the Equal Opportunity Credit Act: as a result, information on credit histories and demographic characteristics has rarely been collected in the same data source, making evaluation of gender-related differences in the credit market challenging, accessed July 27, 2023.

Table 1 summarizes the requirements for applying the different analyses presented in the guide.

TABLE 1. **Using this guide**

Section:	Target Audience:	Data Requirements:	Skills Needed:
Gender-lens analysis	All lenders	• Gender • Loan outcomes	• Basic data analysis
Gender-intentional scorecard usage	Lenders using scoring or rating models	• Gender • Scores • Loan outcomes	• Basic data analysis • Credit risk management
Gender-intentional scorecard development	Lenders that develop their own credit scoring-rating models	• Gender • Granular borrower data • Loan outcomes	• Scorecard development • Credit risk management
Appendix: Analyst's toolbox	Credit analysts and/or data scientists developing models	• Gender • Granular borrower data • Loan outcomes	• Using statistical software

Source: Authors.

SECTION 1

Gender-lens analysis

IN ITS SIMPLEST FORM, A GENDER-LENS analysis of lending models requires compiling a table of data on past loans with the following information:

1. Borrower's gender
2. Loan outcome
    a. Accepted or rejected.
    b. If accepted, a loan's "good" or "bad" status from a business standpoint. In credit risk management, "bad" commonly indicates a level of delayed or incomplete repayment that renders a loan unprofitable. (Box 1).
3. Credit score or rating (if a risk-ranking model is used).

With this "loan-level" data,[4] it is possible to calculate:

- The share of women and men borrowers
- The approval rate for women and men
- The "bad" rate for loans to women and men (see Box 1 above).

A gender-lens analysis with these three pieces of information 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

BOX 1. **"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. Traditionally, credit scorecards are produced using logistic regression models that predict the likelihood of a loan having a "bad" outcome, and loans are segregated or grouped according to their likelihood of repayment. The definition of a "bad" loan varies depending on the intended use, the product characteristics and each FSP's economics. A common "bad" loan definition, used in some cases also for provisioning, is "90 days past due".

The share of "bad" loans for a given score or score range is called the "bad rate".

Looking for More Information? The popular book *Credit Risk Scorecards* has a comprehensive discussion about "bad" loan definitions: Siddiqi, N. (2012). *Credit risk scorecards: developing and implementing intelligent credit scoring (Vol. 3)*. John Wiley & Sons.

The gender-lens snapshot informs which, if any, types of gender-intentional strategies discussed in sections one and three, have the potential to improve women's lending outcomes. By contrast, **the analysis does not tell us why** men or women are being approved or repaying at a given rate. To try and understand that, a lender would need to take a deeper look at its organizational culture, entire lending process, and other social norms that may influence lending outcomes.

4 Loan-level refers to a data table where each row in the table represents one loan, such that one client could have several loans and therefore several rows of data in the table.

Table 2 is an example of a cross tabulation[5] of gender and the "good" or "bad" loan status for 100 loans. The columns contain data on the number of loans to women (B), loans to men (C), and total loans (D), and these are further separated into "good" loans (row 1), "bad" loans (row 2), and total loans (row 4).

Credit risk analysis of cross tabulations focuses on:

- Row 3: the share of women and men repaying late (red font)
- Row 5: the share of women and men borrowers (blue font)

TABLE 2. **Cross tabulation of gender and loan repayment**

	A	B	C	D
	Loan repayment status	**Women**	**Men**	**Row total**
1	Goods	57	36	93
2	Bads	3	4	7
3	**Bad Rate**	**5%**	**10%**	**7%**
4	Column Total	60	40	100
5	**% of Total Loans**	**60%**	**40%**	**100%**

Source: Authors.

In this example, women make up the majority of borrowers (60%) and have repaid notably better than men ("bad" rate of 5% versus 10% for men). Table 3 is a cross tabulation of loan approval status (accept or reject) and gender.

Rows 3 and 5 summarize women's slightly lower rejection rate (27% versus 33% for men) and larger share of applications (55% versus 45 for men%).

Table 4 summarizes the gender-lens analysis for presentation and discussion.

TABLE 3. **Cross tabulation of gender and loan application approval**

	A	B	C	D
	Loan approval status	**Women**	**Men**	**Row total**
1	Accept	40	30	70
2	Reject	15	15	30
3	**Rejection Rate**	**27%**	**33%**	**30%**
4	Column Total	55	45	100
5	**% of Total Loans**	**55%**	**45%**	**100%**

Source: Authors.

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%

a The approval rate is 1 minus the rejection rate shown in Table 3.

Source: Authors.

This simple analysis indicates that more women than men apply for and are approved for loans. It also shows that women have been significantly better at repaying their loans. The lower "bad" rate for women indicates that there could be an opportunity to leverage gender-intentional strategies to increase the total number and share of loans going to women.

Extending gender-lens analysis to a credit scorecard

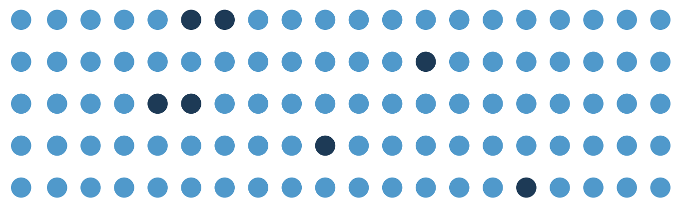
The gender-lens analysis up to this point has not involved any credit scorecard. While such general

5 A cross tabulation compares a loan's "good" or "bad" status with another borrower characteristic (or behavior) in order to understand the relationship of that characteristic to loan repayment. The "Analyst's Toolkit" appendix details how to create cross tabulations in Microsoft Excel and the popular open-source data analytics software packages R and Python.

analysis is useful for understanding the relative share of loans to women and their loan repayment (or "bad" rate), a credit scorecard, or other similar tools that differentiate clients, such as rating or segmentation models, will be needed to develop and implement gender-intentional credit risk management strategies.

Consider a lender with no scoring or rating models. It is most likely unable to assign each borrower a quantitative likelihood of repaying late and rank borrowers in order of low to high risk. The lender instead may reasonably expect that lending only to new borrowers that fully satisfy its underwriting criteria will allow it to maintain its loan portfolio risk level (that is its "bad" rate and/or "portfolio-at-risk" (PAR) amount[6]) at about the same level as in the recent past. In other words, new borrowers who look, behave, and meet the same screening terms and conditions as past borrowers are likely to also repay like past borrowers. In the gender-lens analysis example from section one, 7% of loans were "bad". The lender might thus assume that each future loan to a borrower who meets its lending criteria will have a 7% chance of being "bad". This means that for every 100 loans it approves, it expects seven of them will be "bad" but does not know with any certainty which seven these will be (see figure 1).

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



Source: Authors.

If this same lender looked at the gender-lens analysis, it would see that only five out of 100 loans to women were "bad", but 10 out of 100 loans to men (or twice as many) were "bad". The average "bad" rate across the portfolio (with no gender distinction) is 7% (see figure 2).

The gender-lens analysis indicates that the lender would be better off approving more loans to women and fewer loans to men. But it cannot clearly determine the optimal number or share of loans that the lender should make to women. In the absence of a scorecard or segmentation model, a lender can only use a "test and learn" approach, making gradual adjustments to its lending criteria to approve more women over time. However, to determine the optimal approach, a credit scoring model is needed. 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. The basics of credit scorecards and their usage are discussed in the next section.

BOX 2. **Start simple and build**

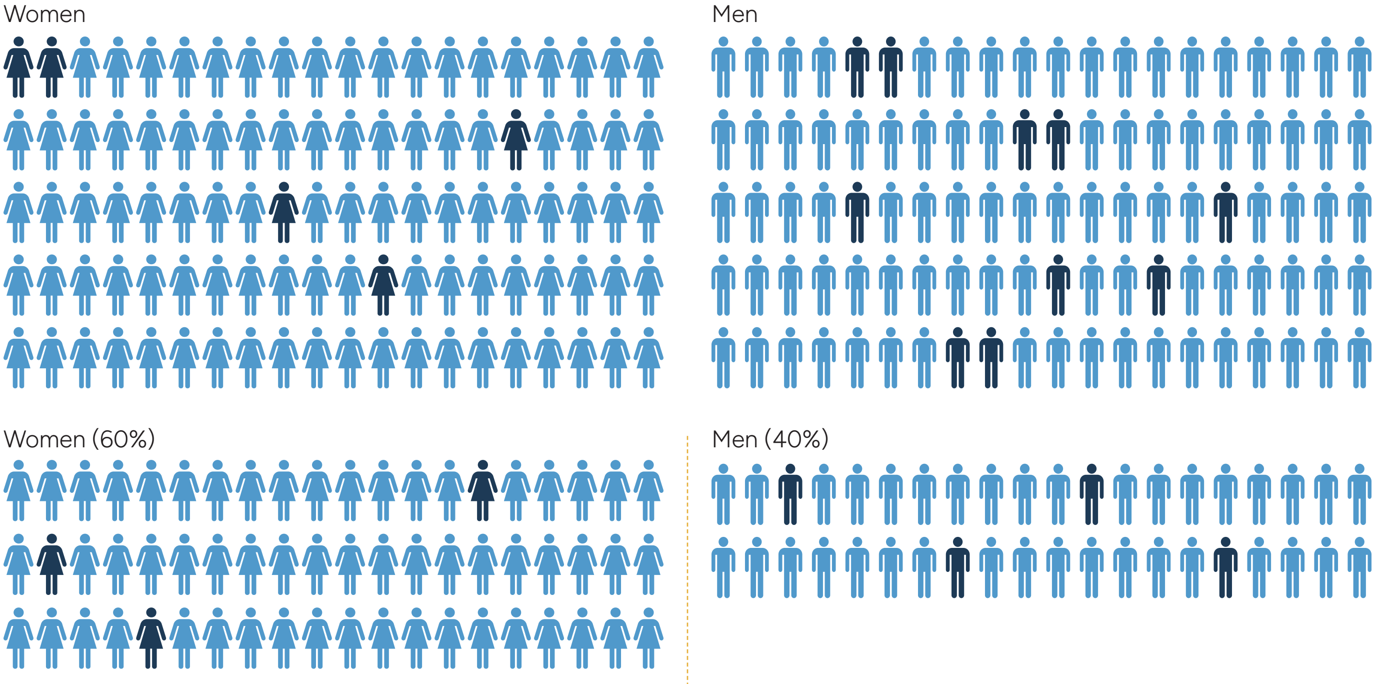
The gender lens analysis presented in this section was kept simple to illustrate how to analyze two key performance metrics, loan approval and repayment rates, by gender. Analysis can be extended to any number of other lending outcomes, such as:

- Financing amounts (average, median, maximum)
- Loan terms and conditions (collateral and guarantee requirements)
- Accuracy of past scorecard probability of default estimates

The key in all analyses is to consider not only the raw numbers, but to keep in mind the context in which they were generated, including the role of subjective judgment in the lending process, social norms, and terms and conditions of the products offered.

6 The "Portfolio at Risk" rate is most generally defined as the sum of outstanding principal amounts of loans with one or more overdue payments, divided by total amount of loan principal outstanding.

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



Source: Authors.

Calculating credit scores

Studying past loan repayment in terms of borrower characteristics to predict future expected loan repayment[7] is the foundation of "credit scoring". Various conventions and techniques[8] can be used to quantify and combine the relationships between past borrower characteristics and repayment. These are then turned into "credit scores", where more points are assigned to characteristics associated with better repayment and higher credit scores indicate lower repayment risk.

To extend the gender-lens analysis example from section one, assume the lender used a credit scorecard with a point scale of 0 (highest risk) to 100 (lowest risk) and it has issued 1,000 loans[9]. Table 5a and 5b are cross-tabulations similar to Table 2, but rotated so that each row is a 'scoring bucket'[10] and the columns B, C and E present counts of "good", "bad" and total loans, respectively, with the "bad" rate in column D. Additionally, the tables include the shaded columns:

- F: The "bad" rate at any cut-off score (going from high to low)
- G: The share of loans approved at any given cut-off score (from high to low)

Table 5a shows that the scorecard ranks risk appropriately for loans to women—because the "bad"

7 An adaptation of: "The study of past borrower behavior and characteristics to predict future behavior of new and existing borrowers," from Schreiner, 'Credit scoring for microfinance: Can it work?', *Journal of Microfinance/ESR Review*, Vol. 2.2 (2009): 105-118.

8 A simplified derivation of scorecard points based on "bad rate differences" is presented on page 83 of Caire, D. E., Camiciotti, L., Heitmann, S., Lonie, S., Racca, C., Ramji, M., and Xu, Q. (2017). Data analytics and digital financial services: handbook.

9 Credit scorecard evaluation requires studying an adequately large pool of loan data with hundreds of delinquent loans. The numeric example was expanded to 1,000 loans to reflect that scorecard development necessarily works with larger data sets.

10 Score ranges for this example are based on equally divided buckets each containing 10 points (for example 0-10, 11-20, etc).

rate in column D steadily increases as scores decrease—from a low of 0% for loans scoring 91 to 100 points up to a high of 21% for loans scoring between 0 and 10 points.

Table 5b shows that the scorecard also rank-orders loans to men by “bad” rate (from a low of 0% for scores over 90% to a high of 42% for scores of 10 or less).

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.

TABLE 5b. **Cross table scores by repayment: men**

A	B	C	D	E	F	G
Score band	**“Good”**	**“Bad”**	**“Bad” %**	**Total**	**Cumulative “Bad” %**	**% Population**
91-100	7	0	0%	7	0%	2%
81-90	25	1	4%	26	3%	8%
71-80	25	1	4%	26	3%	15%
61-70	45	2	4%	47	4%	27%
51-60	44	3	6%	47	5%	38%
41-50	66	5	7%	71	5%	56%
31-40	58	5	8%	63	6%	72%
21-30	57	8	12%	65	7%	88%
11-20	25	11	31%	36	9%	97%
0-10	7	5	42%	12	10%	100%
Total	359	41	10%	400		
% of Total	90%	10%	10%	1		

Source: Authors.

With credit score information, a lender can make more precise choices in its approval process. For example, let's assume the lender wants to lower risk and approve only applicants with a 4% or lower expected risk of default or "bad rate". If the lender managed its loans to women and loans to men as two separate portfolios, it would look at column F in Table 5a and 5b, and find that it could approve women with a score above 20 and men with a score above 60 (the lowest score bands in which the cumulative bad rate is 4%). The example highlights the particular and fairly common situation where women have lower average "bad" rates, where gender-intentional scorecard usage strategies can potentially increase lending to women without changing portfolio risk. This can lead to a "win-win" of both increased lending to women and greater gross revenue.

The next section uses data shared by two banks working with CGAP, to demonstrate how to apply gender-intentional scorecard development and usage strategies to potentially increase financing to women.

SECTION 2

Gender-intentional scorecard usage

TO ILLUSTRATE THE PRACTICAL application of gender-intentional strategies, we will move from section one's stylized data examples, to a case study developed using actual loan application and repayment data shared by TymeBank in South Africa (Box 3). The data covers a two-year period over which it used a "gender-blind" application scorecard to decide on "buy-now-pay-later" (BNPL) retail loans. A gender-lens snapshot of its BNPL scored loan portfolio is shown in Table 6.

Women make up a two-thirds majority of the bank's BNPL borrowers. Women also have a "bad" rate[11] that is nearly two percentage points lower than the rate for men (6.4% versus 8.1% respectively), resulting in a portfolio average "bad" rate of 7%.

TABLE 6. **TymeBank gender-lens analysis**

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

BOX 3. **A note on testing gender-intentional strategies with actual data**

TymeBank in South Africa did not share its proprietary scorecard with CGAP, but instead shared its model scores, loan repayment performance and the granular data it collects to assess borrowers. TymeBank's actual credit scoring model is "gender-blind", meaning that no information about an applicant's gender is used when calculating the scores or in setting approval and credit limit policies. This modelling choice is driven by South Africa's regulatory environment and National Credit Act.

For this guide, CGAP analyzed a data set of over 15,000 approved BNPL loans to build both gender-blind and gender-intentional models and to investigate expected lending outcomes for women based on gender-intentional scorecard development and strategies. These models were created for research purposes only.

Table 7 dives deeper into this data by segregating the bank's actual gender-blind application scores[12] into "risk bands" (ranges of scores). Column E shows in red font, that the "bad" rate for women across different risk bands is about 1 to 2 percentage points lower than the rate for men, with the exception of the lowest risk band 1.

11 Based on a "bad" loan definition used for this exercise which may differ from actual measures of delinquency used by TymeBank for its own credit risk management purposes.

12 Based on the scores shared with CGAP as probability estimates, but without insight on the scoring algorithm itself.

TABLE 7. **Gender-lens analysis of TymeBank's application scorecard for BNPL products**

A	B	C	D	E (C-D)
	Bad rate			
Risk band	Overall	Women	Men	**Women difference**
1	2.3%	2.5%	1.9%	0.6%
2	3.8%	3.3%	5.1%	**-1.8%**
3	7.3%	6.7%	8.5%	**-1.8%**
4	9.6%	9.3%	10.2%	**-0.9%**
5	12.3%	11.9%	13%	**-1.1%**
Total	7%	6.4%	8.1%	**-1.7%**

Source: Authors based on data shared by Tymebank

Overall, this gender-lens analysis suggests that there could be potential to further increase lending to women through a gender-intentional approach. Such a "scorecard strategy" based approach, focused on "bad" rates rather than loan amounts[13], could involve approving more women and/or approving fewer men, or differentiating pricing or other loan terms and conditions based on risk.

Gender-lens analysis should be looked at carefully and critically before acting — not least because "bad" rates by gender or other criteria, can also differ due to chance and the window of time under study. Using large data samples and conducting regular gender-lens analysis can help raise awareness of any differences in the average borrower risk profiles of men and women — which can inform other thinking around loan products. These may include product design, marketing, terms and conditions, risk assessment models, and lending procedures.

Implementation Strategies

Women's better loan repayment per score range or "risk level," as assessed by a credit scorecard, creates opportunities for gender-intentional strategies to potentially expand lending to women within a given risk appetite or business model.

For example, assume that the bank with a BNPL product is no longer TymeBank in South Africa, but a lender not constrained by regulatory concerns around the use of gender information. Assume also that this bank has a specific goal to reach as many women as possible within its 7% risk appetite. Such a bank could look for ways to approve more BNPL loans to women until its women's average "bad" rate reached or exceeded 7%. This is a potential "win-win" for the bank and for women. The downside is that to maintain the overall portfolio "bad" rate at 7%, the rate for men also needs to be reduced from 8% to 7%. Without any other changes or levers (or all else equal), this would require restricting lending to the highest risk, or lowest scoring for men.

In order to illustrate and quantify the simulation of a gender-intentional strategy, we will assume this BNPL lender wants to lower its portfolio "bad" rate from 7% to 5%. We examine the effects of using a gender-intentional versus a gender-blind approach to establish the "cut-off" scores to achieve this. In practice, lenders can use this strategy to increase lending at their existing risk level.[14]

With no changes to the credit scoring model itself, the lender could apply a new loan approval strategy that is either:

13 Scorecard strategies are often set around target delinquency rates, rather than "portfolio at risk" (PAR) rates that depend upon loan amounts.

14 While the most proactive gender-intentional strategies would involve increasing the number of total loans issued to women, we are unable to illustrate such a strategy with historical data, since we cannot know the repayment outcome of loans that were not issued. To increase the portfolio "bad" rate for women to 7%, the lender would need to approve loans for women that it previously rejected. While that can be implemented in practice, it cannot be quantified on historical data since these loans were not generated.

- **Gender-blind:** one cut-off score, higher than the original, that brings the past "bad" rate down to 5%.
- **Gender-intentional:** separate cut-off scores for women and men to bring past "bad" rates for each group down to 5%.

The exact cut-off score to achieve a 5% target cannot be determined precisely from a cross-table such as Table 7, where scores are grouped in ranges. Instead, finding the cut-off score requires more granular data as per the example[15] in Table 8, which depicts rows 93 to 105 of a larger sample. Customers are ordered from lowest to highest score, shown in the second column. The third column shows whether the loan was "good" or "bad" ("bad" =1). The fourth column adds up the total number of "bads" up to that row. The last column shows the cumulative "bad" rate, which is column 4 divided by column 1. In this example, customers with a score of 50 and above would be approved and others rejected to achieve a portfolio level "bad" rate of 5%.

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.

Table 9 compares the impact of gender-intentional versus gender-blind cut-off scores for the BNPL portfolio, in terms of outreach to women with a target of a 5% "bad" rate.

TABLE 9. **Women approved under gender-blind and gender-intentional strategies**

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%
Approvals per 1,000 borrowers		
Number women	534	599
Number men	252	229
Total	786	828

Source: Authors.

A "gender-blind" cut-off score would equally approve close to 79% of past men and women borrowers. Applying a gender-intentional strategy to a gender-blind scorecard approves 88% of past women borrowers, but only 69% of past men borrowers. This results in a higher total approval, 83% versus 79%, allowing for a larger loan portfolio for a given level of risk. While it may seem fair to use the same score cut-off for everyone, in practice, having a single cut-off means that the bar set for women in terms of risk and in this example, is higher than it is for men. In the gender-blind case, a group of women who are rejected will

15 For simplicity, we used a stylized example to show the methodology. For a 15,000 sample, a very large number of decimals would need to be included to show the difference between one score and the next.

have a lower “bad” rate than the lowest scoring men who were approved.

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. It is important to note that in conditions where the past “bad” rate on loans to women is higher than on loans to men, the separate thresholds strategy will not help to increase lending to women. In these cases, different gender-intentional interventions such as changes to product design or the management of sales and collections channels could be considered.

The next section looks at gender-intentional scorecard development techniques and the potential benefits they may have in improving lending outcomes for women.

SECTION 3

Gender-intentional scorecard development

GENDER DATA CAN ALSO BE explicitly considered when building scorecards either by:

1. Using "gender" as a scorecard characteristic
2. Building separate scorecards for women and men

These methods require credit scorecard development capabilities, but are no more complex than developing a gender-blind scorecard. They require the intentional use of gender data in model construction (option 1) and/or the development of separate scorecards for men and for women—using either the same set of variables for both groups. Or, possibly, finding different sources of data that may help paint a more accurate picture of a man or woman's creditworthiness (option 2). In the presence of a rich dataset, the latter provides a better opportunity to identify different risk factors. But the former may yield for more reliable results when samples for either gender are not large enough to build reliable models on their own.

Using gender as a scorecard characteristic

If we revisit the gender-lens example from section one, Table 4c shows how points might be derived for a scorecard characteristics "gender" using "bad rate differences," or subtracting each "bad" rate from the highest "bad" rate of 10% for men.[16] Women would receive 5 points and men would receive 0 (zero) points.

If we use this simple "bad rate differences" method to derive points for each characteristic in a scorecard and *assume gender is not correlated with other borrower characteristics*, the 5 points added to women's credit scores will directly reflect their lower past "bad" rate of 5 percentage points relative to

TABLE 4c. **Deriving scorecard points from late-repayment rate differences**

Gender-lens metric	Women	Men	Total
"Bad" rate	5%	10%	7%
Point calculation	10-5 =5	10-10 =0	

Source: Authors.

16 A simplified derivation of scorecard points based on "bad rate differences" is presented on page 83 of Caire, D. E., Camiciotti, L., Heitmann, S., Lonie, S., Racca, C., Ramji, M., & Xu, Q. (2017). Data analytics and digital financial services: handbook.

men. In practice, however, scorecard characteristics are correlated with one another to some degree. For this reason, "traditional" scorecard development most commonly uses logistic regression to combine, and simultaneously derive, the scorecard points for all model characteristics[17]. Regardless of specific machine learning-based algorithms or chosen conventions for presenting scorecards, the use of a gender characteristic in the scorecard should result in overall scores that reflect women's better past repayment rate relative to men.

AB Bank Zambia (ABZ) example

Women make up the majority of ABZ's micro loan borrowers. Over the period of 2012-2019, 57% of micro loans were issued to women and 43% were issued to men. Over that same period, women had a "bad" rate 2% points lower than men (or 5% versus 7% for men).

When ABZ developed its first micro loan scorecard in 2019, gender was included as a scorecard characteristic. Women received additional points in their credit score, and men received none. Gender was one of the scorecard's 14 characteristics and its points accounted for around 5% of the maximum possible score.

Unlike the example of gender-intentional strategy results "simulated" for this research using TymeBank data, ABZ implemented its scorecard that gave higher scores to women. Analysis of data on over 16,500 micro loans issued using the scorecard in three years between 2020 and 2023 shows evidence of an increase in the share of loans issued to women within the scoring process. Women received 60% of loans versus 40% for men, which was a 3% increase over the 57% share of past micro loans to women. More importantly, women and men over the period also had the same lower "bad' rate of 3.5%[18]. This means that the additional points women borrowers received at the scoring stage accurately reflected their better past repayment, helping to "correct" the gender-blind score and set the hurdle, or risk bar, equally for men and women. In summary, including gender in the scorecard helped ABZ achieve its gender-intentional strategy, and the desired effect: for more women to receive credit for a given risk appetite and business model.

TymeBank South Africa example

Including a gender characteristic in a gender-intentional scorecard using TymeBank's BNPL data, resulted in women scoring points that represent a past "bad" rate nearly 2% points lower than the "bad" rate on loans to men[19].

Applying a single approval cut-off score to this gender-intentional scorecard, where women receive points, resulted in a 6% point increase in women receiving loans from 79% to 85%, and a 4% point reduction in loans issued to men from 79% to 75%, as shown in Table 10. The difference in the "bad" rate for men and women was reduced to 1% point (or the difference between 5.6% for men minus 4.7% for women). from an earlier difference of 2.1% (6.4% for men minus 4.3% for women).

Adding a gender characteristic to a scorecard is a transparent and simple way to directly reflect differences in the past late repayment rates of women and men in credit scores. In both of the examples using data from CGAP partners, including gender in

17 Scorecard points are usually transformations of logistic regression coefficients. For more information on logistic regression, please see pages 23-24 of Fernandez Vidal, M.., & Barbon, F. (2019). Credit Scoring in Financial Inclusion. *Technical Guide; CGAP: Washington, DC, USA.*

18 With the introduction of the data driven scoring process, riskier clients rejected by the scoring model often passed a longer, traditional underwriting process. That portfolio of loans approved "traditionally" had a significantly higher average "bad" rate than the scorecard loan portfolio, explaining the general decrease in risk (for women and men) in the scorecard loan portfolio.

19 This gender-intentional scorecard developed for research purposes only was developed with logistic regression and the point conversion and scorecard presentation method used by the author resulted in women scoring 4 points and men scoring zero. If instead the scorecard points were assigned based on the simple 'bad rate differences' methodology presented in Table 4c in the text, women would receive 2 scorecard points.

TABLE 10. **BNLP scorecard with a gender variable versus a gender-blind model**

Metric	Strategy		At past "bad" rate of 7%
	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%	6.4%
% Men approved	78.9%	75.4%	
Late repayment % men	6.4%	5.6%	8.1%
Approvals per 1,000 borrowers			
Number women	534	597	677
Number men	252	222	323
Total	786	819	1,000

Source: Authors based on data shared by Tymebank

the model increased the number of women receiving loans and reduced the difference between "bad" rates by gender in the scorecard loan portfolio. In the BNPL case, adding gender to the model is able to correct some, but not all, of the difference in "bad" rates by gender from 2.1% to 0.9%. This difference in "bad" rates by gender could potentially be reduced further by also creating interactions between gender and the relevant variables in the model, or by developing separate scorecards for women and men.

Building separate scorecard models for women and men

The last gender-intentional strategy that this guide explores is the development of separate scorecard models for women and for men. Such an approach has the potential to predict better for each group, particularly if certain borrower characteristics are more strongly related to "bad" loans and/or mainly relevant only for women or men. Particularly, the wider development community continues to invest in finding new sources of alternative digital data that can proxy for the traditional forms of credit assessment data that is less likely to be available for women in some societies—most notably asset ownership and formal credit history.

For the following example using TymeBank BNPL data, gender-specific scorecards were developed for women and men using the same source data from the credit bureau. Table 10 shows that developing separate models by gender, which also have separate approval thresholds, resulted in a 9% increase in loans issued to women from 79% to 88% women approved, with a commensurate 9% reduction in loans issued to men from 79% to 70%. Importantly, the gender-specific scorecards led to 30 additional loans per 1,000 borrowers, an almost 4% increase on previous loan numbers, which should boost revenues and profits. However, the additional value of developing separate models depends on the availability of data and is likely to deliver a bigger upside when a greater variety of data points is available.

TABLE 11. **BNPL gender-specific scorecard versus gender blind model**

Metric	Strategy		At past "bad" rate of 7%
	Gender-blind single cut-off	**Separate models for women and men**	
% Women approved	78.6%	89.6%	
"Bad" % women	4.3%	5%	6.4%
% Men approved	78.9%	69.7%	
"Bad" % men	6.4%	5%	8.1%
Approvals per 1,000 borrowers			
Number women	534	607	677
Number men	252	232	323
Total	786	839	1,000

Source: Authors based on data shared by Tymebank

Summary of gender-intentional scorecard interventions

Table 12 summarizes the results of gender-intentional scorecard usage (2) and scorecard development strategies (3 and 4) in comparison with the gender-blind model and strategy (1) for the TymeBank BNPL data.

At a 5% acceptable risk target (expected "bad" rate), each of the gender-intentional strategies enables lending to a larger number of borrowers, and, particularly, a larger number or share of women, than using a gender-blind strategy. The best result could potentially be obtained from developing separate models for each gender where different data sources may be available and/or more predictive for men or women . While we expect all the techniques to increase both total lending and lending to women, how effective each technique is will depend on the specific dataset, with more complex approaches more likely to produce better results on larger datasets with more variables and bigger samples.

One solution does not fit all

Remember that gender-lens analysis may not always lead to obvious gender-intentional strategies for scorecard use and development. Nevertheless, the exercise will raise institutional awareness of the current situation and also can help identify any elements of existing scorecards or their usage policies that have unintended consequences, working to the detriment of women or men.

TABLE 12. **Comparison of gender-blind and gender-intentional models and strategies**

					Per population of 1,000		
					667	333	1000
A	B	C	D	E	F	G	H
Strategy	**% Women Approved**	**"Bad" % Women**	**% Men Approved**	**"Bad" % Men**	**Number Women**	**Number Men**	**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%	75.4%	5%	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%	607	232	839

Source: Authors.

SECTION 4

Other gender-intentional strategies

THE GUIDE HAS THUS FAR LOOKED AT gender-lens analysis of loan approvals based on historical repayment data and some gender-intentional strategies to increase lending to women. However, gender-lens analysis has many other potential uses.

For example, women's lending outcomes could potentially be improved through gender-intentional risk-based pricing strategies linked to credit scores. In the situations we have considered so far —where women have lower "bad" rates— such strategies could 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.

We once again use the TymeBank South Africa data to illustrate (for research purposes only) one example of how such a strategy can be simulated and prepared for testing and/or implementation.

Tables 13a and 13b expand on tables 5a and 5b from the gender-lens analysis presented in section one, to include a framework for estimating expected gross margin by credit score band. The table assumes an average loan size of $1,000 and a required gross margin target of 3%, or $3 earned for every $100 lent. In addition to the columns found in Tables 5a and 5b, these "risk-pricing framework" tables add the following columns, where references to other columns in the table are denoted with brackets.

H: Interest Rate equal to the past "bad" rate of the score band [A] plus the target gross margin (3% points in this example) [L].

I: Interest Income equal to the number of total loans [E] in the score band multiplied by the average loan amount of $1,000.

J: Charge Off equal to the number of "bad" loans [C] multiplied by the average loan amount of $1,000

K: Total Gross Margin equal to the interest income [I] minus charge-off [J]

In the interest of simplicity, this framework assumes that all "good" loans earn the full charged interest rate and all "bad" loans result in a loss equal to the loan's full principal.

The framework illustrates that risk-based pricing can help ensure that interest income offsets losses expected per score band based on past lending experience. Table 13a presents a gender-blind risk-based pricing framework applied to all borrowers.

Table 13b presents a gender-intentional risk-pricing strategy for women. Because women have lower past "bad" rates than men, the fee required to earn the 3% target gross margin (column H) is lower than it is when accounting for the higher "bad" rate for men.

Table 14 shows the interest rate reduction for women across credit score bands ranges from 0.5 to 2% for 90%

TABLE 13a. **Cross table of scores by repayment for all borrowers: gender-blind risk pricing framework**

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	18	0	0%	18	0%	2%	3%	540	**0**	540	3%
81-90	65	2	3%	67	2%	9%	6%	3,900	**2,000**	1,900	3%
71-80	82	2	2%	84	2%	17%	6%	4,510	**2,000**	2,510	3%
61-70	113	4	3%	117	3%	29%	7%	7,910	**4,000**	3,910	3%
51-60	152	6	4%	158	3%	44%	7%	10,640	**6,000**	4,640	3%
41-50	174	11	6%	185	4%	63%	9%	15,660	**11,000**	4,660	3%
31-40	126	9	7%	135	4%	76%	10%	12,600	**9,000**	3,600	3%
21-30	114	13	10%	127	5%	89%	15%	17,100	**13,000**	4,100	3%
11-20	65	18	22%	83	7%	97%	31%	20,150	**18,000**	2,150	3%
0-10	18	8	31%	26	7%	100%	49%	8,820	**8,000**	820	3%
Total	927	73	7%	1000				101,830	**73,000**	28,830	

Source: Authors.

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.

of women borrowers, with even larger rate reductions for the lowest scoring, or highest risk, borrowers[20].

When looking at implementing risk-based pricing strategies, there are of course many other areas to consider including:

- Market perception of interest rate differences and reputational risk, particularly in highly connected rural communities served by microfinance programs. This approach could be easier to implement in the micro, small and medium enterprises (MSME) context, where it is more standard for different businesses to have different costs of capital.
- Regulatory interest rate caps and the competitiveness of interest rates in the market.
- "Selection bias": if high risk borrowers are still approved, this could lead to an adverse selection problem, where only the worst borrowers agree to high prices, leading to "bad" rates that are significantly higher than expected in the riskiest scoring bands. However, the opposite effect may be observed for the best (highest scoring) borrowers when lenders compete to offer the best rates. The ability to offer lower interest rates can attract a larger group of the "best" borrowers away from lenders offering only "standard" rates.

Like all of the other gender-lens analysis and gender-intentional strategies presented in this guide, looking at various aspects of lending through a gender lens can help lenders to better understand how men and women borrowers differ and examine ways to improve lending outcomes for women.

TABLE 14. **Summary of interest rates and differences for women under gender-blind and gender-intentional strategies**

Gender-blind	Gender Intentional	Difference	% Population
3%	**3%**	0%	2%
6%	**5.5%**	-0.5%	9%
5.5%	**5%**	-0.5%	18%
7%	**6%**	-1%	30%
7%	**6%**	-1%	49%
9%	**9%**	0%	68%
10%	**9%**	-1%	80%
14%	**12%**	-2%	90%
31%	**21%**	-10%	98%
49%	**31%**	-18%	100%

Source: Authors.

20 Risk-based pricing may also lead to lowering cut-off scores when the analysis makes it clear that past losses require setting risk-adjusted interest rates that are too expensive based on market competition, regulations on maximum charges, etc.

SECTION 5

Conclusions

THIS GUIDE HAS PROVIDED AN overview of how gender-lens analysis can help lenders better understand how men and women differ in terms of data availability and credit risk and whether there are opportunities to better serve women as a result of this. Our examples illustrate how a lender can implement the analysis and, where possible, turn its findings into adjustments to scorecard models and their usage policies.

Using CGAP partner data from the field, we both back-tested strategies that promised the possibility of improving credit conditions for women and shared ABZ's achievement of increasing data-driven lending to women in line with its overall risk appetite. A gender-intentional approach to credit scoring models can help providers more accurately measure and price risk, with the potential to increase lending and reduce interest rates for women.

The approaches presented in this guide not only result in better outcomes for women, but also demonstrate that there are more accurate ways to predict risk that create business value for providers.

This is a relatively new field and CGAP and its partners are continuing to explore ways to use data to improve outreach to women and other underserved groups. Particular areas for further research and innovation include harnessing digital data sources and tracing digital "footprints" that may give us a better understanding of women borrowers, who may not be well represented in more traditional data sources.

APPENDIX

Analyst's toolbox

THE DATA PACK ACCOMPANYING THIS guide (downloadable at the link: https://www.cgap.org/sites/default/files/2024-02/Final%20Analysts%20Toolkit_Data_Pack.zip) provides instructions and detailed examples showing how to perform gender-lens analysis and set gender-intentional scoring strategies using Excel, R-Studio and Python. It also shows how to implement the analytical methods presented and discussed in the Technical Guide. Its contents are:

1. **Example_loan_data.xlsx:** a synthesized data set of 7,500 loan applications and 5,000 issued loans with properties like the real examples discussed in the guide.
2. **Analysts_Toolkit_Excel_Templates.xlsx:** this file contains example loan data and templates to create each type of table presented in the guide. The table numbers in the Excel file correspond to those used in the guide. Text boxes provide additional clarifications on how the analyst can load new data in the same format and adapt the templates as needed to perform gender-lens analysis of any number of scorecards.
3. **Gender_Intentional_Credit_Scoring_Analysts_Toolkit_R.R**: this file contains coding examples of how to create each type of table presented in the guide using R software. The code is annotated and the numbering of analytical tables corresponds to the numbering in the guide. This code can be adapted or used with any data set by using the same header (column) names for the five required data fields and making minor adjustments to technical details such as the point scale for a given scorecard.
4. **Gender_Intentional_Scoring_Toolkit.ipynb:** this file contains coding examples of how to create each type of table presented in the guide using Python software. The code in the jyptr notebook can be adapted or used with any data set by using the same header (column) names for the five required data fields and making minor adjustments to technical details such as the point scale for a given scorecard.

Please direct any questions on use of this toolbox to dcaire@ifc.org.

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African Development Bank / African Development Fund

AFD

Bill & Melinda Gates foundation

British International Investment

Udenrigsministeriet
Ministry of Foreign Affairs of Denmark

European Investment Bank

Federal Ministry for Economic Cooperation and Development

giz

Global Affairs Canada

IDB | LAB

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IFC International Finance Corporation

IFAD
Investing in rural people

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JOA
JERSEY OVERSEAS AID

KFW

KOICA Korea International Cooperation Agency

THE GOVERNMENT OF THE GRAND DUCHY OF LUXEMBOURG

center for inclusive growth

mastercard foundation

MetLife Foundation

Ministry of Foreign Affairs and International Cooperation

Ministry of Foreign Affairs of the Netherlands

FMO
Entrepreneurial Development Bank

PROPARCO
GROUPE AFD

Sida

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