We are IntechOpen, the world's leading publisher of Open Access books
Built by scientists, for scientists

6,100
Open access books available

149,000
International authors and editors

185M
Downloads

154
Countries delivered to

Our authors are among the

TOP 1%
most cited scientists

12.2%
Contributors from top 500 universities

BOOK CITATION INDEX

CLARIVATE ANALYTICS INDEXED

WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com

Chapter

Risk Management Tools to Improve the Efficiency of Lending to Retail Segments

Mikhail Pomazanov

Abstract

This chapter discusses the issue of assessing the quality of risk management for a wide segment of retail lending (from consumer loans to loans for self-employed persons and SMEs). The quality of risk management is assessed using the generally recognized approach of the ROC analysis methodology and assessment of the optimal level of discrimination, taking into account risk-return. The chapter substantiates a marginal formula for assessing the economic benefits of improving the discriminatory power of the scoring models on which risk management is based. Based on the presented approach, it is possible to economically justify the costs of investment resources aimed at improving models and their technical implementation in credit business processes. An assessment of the quality of risk management in the mass lending segment reveals problems in lending strategies caused by the inefficiency of return in relation to risk in individual segments. This provides evidence-based grounds for adjusting strategies. The review of perspective modern directions of development and improvement of scoring models is presented.

Keywords: probability of default, gini index, profit, efficiency, validation, risk-management, credit, retail

1. Introduction

Modern recommendations of banking supervision reflect the requirements for the organization of the use of internal rating models and their quality, allowing the bank to bring the regulatory requirements of reserves and capital closer to economically justified, i.e., risk-sensitive [1]. The requirements of the National Banking Regulator are complex, concerning the preparation of high-quality and validated data for the development of models, the requirements for the development itself, the administrative independence of developers from the interests of business, regular validation of models on current data, systematic refinement of risk assessment models, etc. When deficiencies in discriminatory ability or stability are identified, the requirements define mandatory regular reporting to the Bank's Management and the Regulator on the results of quality analysis of the applied internal rating models. The requirements for the risk and capital management system of the banking group through the implementation of internal procedures for assessing capital adequacy reflect the requirements [2] to establish the procedure and frequency for assessing the effectiveness of risk assessment methods. It is required to update the documents that establish risk assessment methods and the procedure for validating quantitative models. Obviously, the implementation of these requirements is costly for the bank, including the participation of highly qualified specialists, and the improvement of IT infrastructure and business processes. Therefore, the question arises of the adequacy of costs in relation to the credit institution's own economic effect with an increase in the level of efficiency of risk assessment methods, as well as a management decision-making system based on these methods.

Improving the quality of risk assessment modeling brings financial and nonfinancial benefits in terms of the following points:

1. savings on losses associated with credit risk in terms of reducing potential losses by more carefully separating “bad” and “good” borrowers;

2. improving the transparency of the lending business, stimulating the improvement and optimization of the lending business process, and taking into account the risks;

3. improving the image of the credit institution in terms of audit, rating agencies, and investors;

4. meeting the requirements of the National banking regulator in ensuring risk management standards and loss provisions.

The introduction of credit scoring in the banking sector has privileges which have been summarised by Al Amari [3] as follows: more efficient processing time, and subsequent support for the decision-making process; minimization of credit process costs and effort; fewer errors made; provision of estimations to be compared in post audits; inclusion of variables supported through objective analysis to assess the credit risk; modeling based on real data; interrelation between variables are considered; fewer customer-information needs for credit decisions; the cut-off score can be changed according to environmental factors affecting the banking sector.

The direct financial benefit of the first bullet is determined by the discriminatory power of the borrower's analytics based on scoring risk assessment models. This is especially true for mass banking products.

Credit scoring has been considered a major scoring tool for the past several decades and has been widely studied in various fields, including finance and accounting. Various scoring methods are used in the fields of classification and forecasting, where statistical methods are commonly used. The literature explores both complex and traditional techniques, as well as criteria for evaluating effectiveness. In [4], it provides a comprehensive review of 214 articles/books/abstracts that relate to the applications of credit scoring in various fields in general, but primarily in finance and banking. This paper provides a broad overview of various statistical methods and performance evaluation criteria. This review [4] showed that there is no best statistical method to use when building scoring models.

To increase the power of credit scoring, in the presence of the Big Data of individuals, various methods are used, including those based on artificial intelligence methods. As shown in [5], organizations by applying deep learning and machine learning techniques can tap individuals who are not being serviced by traditional financial institutions. If systems can be designed to accommodate more pragmatic analysis conditions, then this can help improve the conditions of the client profile analysis process. At the same time, process models should be developed for comprehensive analysis and then they can become a sustainable solution for managing the loan system.

The significant dependence of the profit of lending and investing in debt instruments on the quality of risk management has been substantiated by many studies. In [6], the authors developed a model for evaluating the profit that the improvement of rating systems brings. Results of a numerical analysis indicate that improving a rating system with low accuracy to medium accuracy can increase the annual rate of return on a portfolio by 30–40 bp. Therefore, compared to the estimated implementation costs, banks could have a strong incentive to invest in their rating systems. In [7], it is shown that the simple cut-off approach can be extended to a more complete pricing approach, which is more flexible and more profitable. Demonstrated that, in general, more powerful models are more beneficial than weaker ones, provides an example of modeling, and demonstrates the benefit in absolute terms. Later work [8] also examines the economic benefits of using credit scoring models, linking the discriminatory power of the credit scoring model to the optimal credit decision.

The main idea of the presented approach is based on the fundamental analogy of risk management activities with a certain generalized rating/scoring system, which also makes decisions in the retail lending segment. Risk management can be matched to the ROC/CAP-curve, and its power of discrimination can be assessed [9]. Then, determine how optimally such a rating system makes decisions, considering its own power and exogenous risk-return factors.

Approaches to assessing economic efficiency using the ROC-curve methodology were proposed earlier, but they were not directly related to risk management in lending. In [10], the authors' study indicates that banks have incentives to voluntarily participate in a positive credit information exchange mechanism. Because even a small difference in discriminatory power arising from an information gap can lead to a significant drop in profitability since the distribution of change in borrower quality is endogenous due to adverse selection problems. A paper [11] presents a methodology for assessing the economic value of adding additional data to predictive modeling applications. The methodology is based on the representation of the ROC curve and begins with an assessment of the impact of additional data on the performance of the model in terms of overall classification scores. This effect is then translated into economic units, which give the expected economic value that the firm would receive from acquiring a particular information asset. With this valuation, the firm can then set a data acquisition price that targets a specific return on investment. In the work presented in Section 2, we will answer the question of assessing the effectiveness of risk management in making credit decisions and give a methodology for validation. Section 3 proves the formula for marginal profit when the scoring model is improved in units of the Gini index. Section 4 specifies the area in the Gini coordinates and the ratio of profit to risk, where the marginal economic effect, defined by the presented formula, takes place. Section 5 discusses practical cases that are resolved using the marginal formula and typical causes of risk management inefficiency, as well as an overview of current trends in the development of scoring modeling.

2. Method for evaluating effectiveness indicators of risk management in retail lending business

Let's simulate the situation, assuming that a fixed number of applicants applied for a loan to the bank $\boldsymbol{B}$. At the same time, a number $\boldsymbol{A}$ of them passed the procedure of credit risk management and received a loan. We also know the number $\boldsymbol{D}$ of defaults among those who received the loan. Let's also assume that we can evaluate the situation in the credit market and know which share $\boldsymbol{DR}$ would have defaulted if it had not gone through our credit risk management procedure but would have received a loan as soon as it asked for it.

The entire population of applications can be presented in the form of **Table 1**, in which all values are given to the results of the bank's risk management procedures. The values in the lighter cells are the result of the calculation, while the values in the remaining cells are objective data.

From **Table 1**, you can see the classification errors (Type I errors, Type II errors [12]):

- Type I errors—applications were rejected, but the servicing of similar loans on the market by "refuseniks" was not accompanied by a default: $\boldsymbol{B} \times (\mathbf{1}–\boldsymbol{DR})–\boldsymbol{A} + \boldsymbol{D}$;

- Type II errors—a positive decision was made, but servicing the loan was accompanied by the realization of the target variable, i.e., default $\boldsymbol{D}$.

Parameters $\boldsymbol{A}$ end $\boldsymbol{D}$ are known exactly after the choice of the period for which the effectiveness of risk management is assessed. However, the parameters $\boldsymbol{B}$ end $\boldsymbol{DR}$ require additional calculation. In [13], a method for estimating these parameters and substantiating the corresponding formulas. The parameter $\boldsymbol{B}$ (the number of applicants who applied to the bank) should be adjusted taking into account the number of borrowers who were approved, but for some reason did not take a loan. This parameter will be less than the number of personal applications that have been considered. The parameter $\boldsymbol{DR}$ is also not equivalent to the share of defaulted borrowers for the selected period, which can be obtained from the standardized credit history bureau bulletin for the lending segment of interest. Because if a client comes to the bank and is denied a loan application, then there is a probability not equal to one that this client will receive a loan from another bank. Therefore, the population of applicants coming to the bank is not equivalent to the population of borrowers receiving a loan in the market, which is monitored by the Credit Bureau, it is worse. To assess the scale of this phenomenon, a specialized report of the Credit Bureau helps to find out the share of such applicants among the "refuseniks" of the bank, as well as the quality of servicing the loans they received. This requires additional research, which is practiced, and it is quite legal.

The result of the risk management decision	Default	No default	Total
Refuse	B × DR – D	B × (1 – DR) – A + D	B – A
Loan issued	D	A – D	A
Total	B × DR	B × (1 – DR)	B

Table 1.
Segmentation of the applicant population in terms of risk management.

After evaluating the above parameters, **Table 1** will give the coordinates of the fat dot **Figure 1**.

Through this bold point, you can draw a CAP[1] curve, according to which you can evaluate the Gini index, which is a generally recognized measure of the discriminatory power of the rating system, equivalent to the work of the entire risk management (more precisely, the quasi-Gini index).

To restore the CAP curve, the well-known Van der Burgt model [14] is used, which has an independent variable k that is a solution to the equation:

$$CAP(x) = \frac{1 - e^{-kx}}{1 - e^{-k}}, \tag{1}$$

where k is a parameter showing the effectiveness (power) of risk management decisions.

The constructed curve includes a point known to us, the coordinates of which we know:

$$x = \frac{B–A}{\mathrm{B}}, CAP(x) = \frac{B \times \mathrm{DR}–D}{B \times \mathrm{DR}}$$

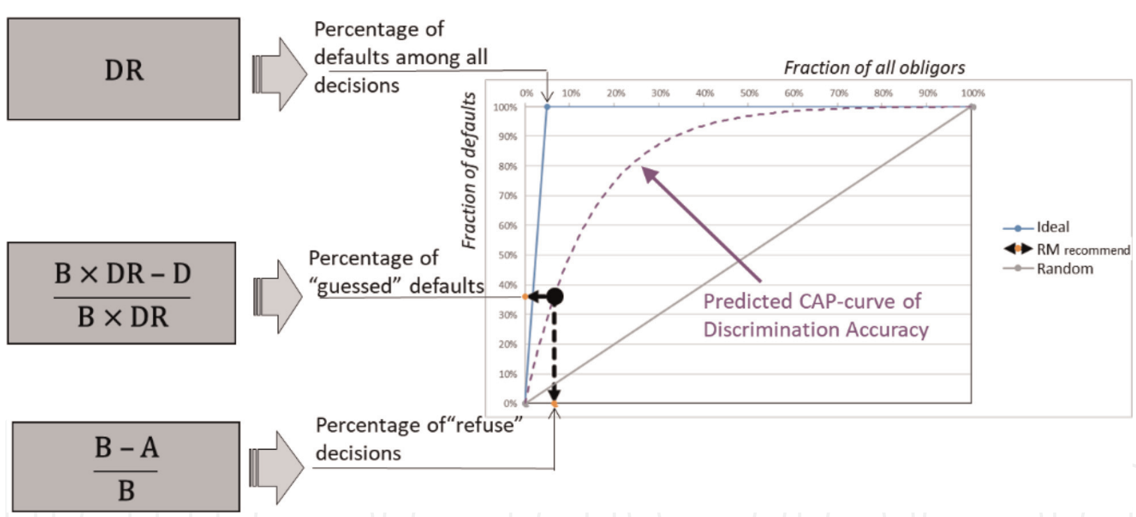

Figure 1.
Reconstruction of the CAP-curve of discriminatory accuracy of risk management procedures.

Model	**Gini ranges**		
	Red zone (%)	**Yellow zone (%)**	**Green zone (%)**
Behavioral	<40	40–60	>60
Applicative	<35	35–55	>55

Table 2.
Stereotypical recommendations of zonal assessments of the Gini metric.

[1] Cumulative Accuracy Profile.

The Gini curve index (1) is calculated by the formula:

$$Gini(k, DR) = \frac{2}{1 - DR} \times \left(\frac{1}{1 - e^{-k}} - \frac{1}{k} - \frac{1}{2}\right), \quad (2)$$

which sets an objective metric of the power of discriminatory risk management procedures.

Obviously, the requirements for this metric may or may not be very strict, but the widely used recommendations of zonal estimates can be offered as a baseline for retail lending banking practice (**Table 2**).

Each obtained value of the Gini index of all cumulative risk management procedures can be attributed to one or another zone. The concept of totality means that not one internal procedure, for example, a scoring model, is evaluated, but the whole set of rules and procedures is used by risk management to make a decision on a loan application. The complex uses, among other things, antifraud, manual underwriting tools, brake lights, etc.

The next tool for assessing the effectiveness of risk management should be the assessment of commercial effectiveness. To what extent is the point of "refusal" justified from the point of view of the economics of lending to the retail product under study in a bank? It is clear that the optimal discrimination point for “bad” and “good” borrowers should correspond to the level of losses EL(x) that do not exceed the marginal return (M) on the loan product.

The level of expected losses EL will be determined by the level of default of borrowers who have passed the approval procedure above the level of the quantile position x of the entire population of applicants

$$\mathrm{EL}(\mathrm{x}, \mathrm{Gini}) = \mathrm{DR} \times (1 - \mathrm{CAP}(\mathrm{x}, \ \mathrm{Gini})) \times \mathrm{LGD}. \quad (3)$$

This level is determined by Type II errors and the level of losses given default (LGD). Where CAP(x, Gini)) will be determined through the expressions (1) and (2), which are defined in the previous step of estimating the discriminating power.

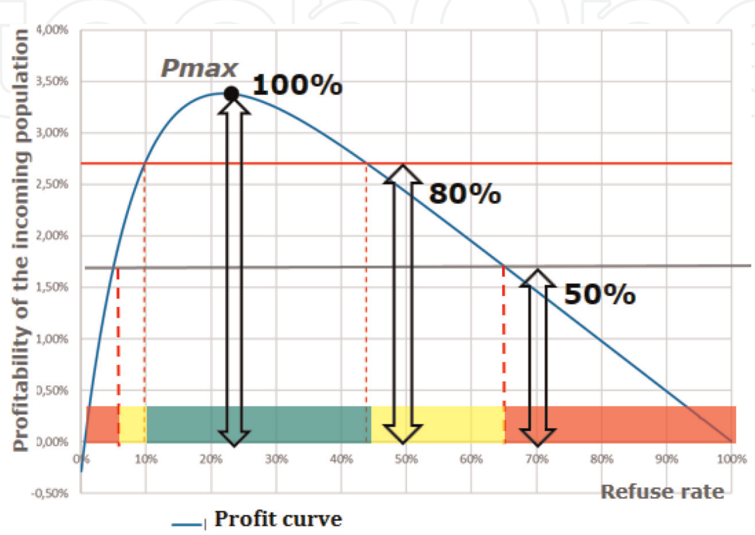

Figure 2.
Zonal representation of approval levels relative to the optimal profit level.

Assuming that the value M is given as NPV rate of the income of the credit product under study for the vintage period, taking into account all costs and terms of amortization of loans (credits), then we can propose a simple formula for the profit from a unit volume of all incoming applicants:

$$\mathrm{P(x, Gini) = M - x \times M - EL(x, Gini)} \tag{4}$$

Formula (4) simultaneously depends on Type I/II errors. Moreover, their balance is determined by external factors—the level of the market default rate and the profitability of the product. Gross profit (4) will have a maximum at a certain level of approval (optimal rejection rate) because with complete rejection, all applicants' $\mathrm{P(1, Gini) = 0}$ and vice versa, if you approve everyone, then you can have a loss if $\mathrm{DR} \times LGD > M$.

The question of determining the parameter regions where the maximum exists will be considered in the next section. But it can be argued that in the condition of equilibrium activity of the credit market (there is no excess profit and excessive demand, there is no global depression and catastrophic risks, etc.), such a maximum takes place. Therefore, it is logical to formulate the efficiency metric of commercial approval/rejection decisions in terms of the levels of deviation of these decisions from the maximum efficiency. And both in the direction of more approval, and less. **Figure 2** shows the profit curve.

Typical evaluation zones are indicated. Typical zonal levels are not the most stringent, but each bank can zone this metric for itself based on its own experience and goals.

The allowable level α of failure range $\left[X_\alpha^-, X_\alpha^+\right]$ is calculated quite simply:

- optimal failure point is calculated $\mathrm{X_{opt}} = \frac{1}{\mathrm{k}} \ln\left(\frac{\mathrm{DR \cdot LGD \cdot k}}{\mathrm{M \cdot (1 - e^{-k})}}\right)$;
- find the roots of the equation X_α^-, X_α^+: $(1-\alpha) \cdot \mathrm{P}\left(\mathrm{X_{opt}}, \mathrm{Gini(k)}\right) = \mathrm{P}\left(\mathrm{X_\alpha^\pm}, \mathrm{Gini(k)}\right)$, where $\mathrm{P(x, Gini(k))}$ follows from (2)-(4).

As a result, we get two tools for evaluating the effectiveness of risk management in a given segment of the retail lending business. The first is an assessment of the discriminating power of risk management, and the second is the economic efficiency of the credit policy, considering risks (the cut-off level).

3. Marginal economic effect improving of the discrimination power of bank borrowers

To assess the discriminating power of a rating system (model) in financial engineering, curves are traditionally used that determine its quality [15, 16], this analytics is borrowed from a well-developed theory of radio signal reception. Any rating (or scoring) system, if it confidently discriminates between "good" and "bad" borrowers, will spread the initial statistical distribution of customers by rating (scoring) score s. That is, two different distributions are obtained - default, with a density of $f_D(s)$, and nondefault, with a density of $f_N(s)$, which can be determined by the expiration of the term (usually one year) after the "measurement" of the rating s .

The probability distribution functions of getting into the rating below s for nondefault and default clients will be expressed by the corresponding integrals[2]

$$F_N(s) = \int_{-\infty}^{s} f_N(\xi)\mathrm{d}\xi, F_D(s) = \int_{-\infty}^{s} f_D(\xi)\mathrm{d}\xi, F_N(s) \in [0, 1], F_D(s) \in [0, 1].$$

ROC[3] end CAP curves are defined in the square of unit area on the plane (X, Y) in parametric form:

$$ROC(x) = F_D(s),\ x = F_N(s),$$
$$CAP(x) = F_D(s),\ x = (1-p)\cdot F_N(s) + p\cdot F_D(s),$$

where $p = DR$ (likewise (3)) is the share of defaults for the period under review.

From the CAP and ROC curves, the exact formula [17] can be used to express the default probability of the borrower, whose position in the rating is determined by the coordinate $x \in [0, 1]$ (local position in the distribution of all borrowers)[4]:

$$PD(x) = p \cdot CAP'(x), \tag{5}$$

or

$$PD(x) = \frac{p \cdot ROC'(x)}{p \cdot ROC'(x) + 1 - p}, \tag{6}$$

where x—quantile position of the borrower among nondefault one. The Gini index will be calculated using the well-known formula

$$AR = \frac{2 \cdot \int_0^1 CAP(x)dx - 1}{1-p}. \tag{7}$$

According to formulas (5) and (6), the dependence of the default probability on the rating will be largely determined by the behavior of the CAP (or ROC) curves of the rating model, as well as the distribution of borrowers (companies, clients) by rating score.

The average annual expected losses for the borrower EL are determined by the formula $\cdot LGD$, so the expected loss for a borrower with a quantile x coordinate will be determined as follows:

$$EL(x) = PD(x) \cdot LGD = p \cdot LGD \cdot CAP'(x) = EL \cdot CAP'(x), \tag{8}$$

where $EL = p \cdot LGD$ is the average market loss parameter, which is exogenous.

Suppose that the bank has an unlimited resource base and is potentially ready to lend to the entire flow of incoming applications, with a volume of "1", then it will receive a

---

2 If the rating score or rating is not continuous (i.e., has a limited number of positions), then the integral is replaced by the sum, and the distribution over the rating is discrete.

3 Receiver Operating Characteristic.

4 Here and below, the prime denotes the derivative, as in the conventional notation.

loss, with a volume of EL. However, the rating system (i.e., the entire risk management process) rejects x (%) of the incoming flow, generating a loss,[5] due to unrealized profit, determined by the credit margin M. In addition, there are credit losses among system-approved borrowers (3) $EL_x = EL \cdot (1 - CAP(x))$ (**Figure 3**).

The economic effect of improving the rating system has two fundamental components. The first is the reduction in risk EL_x among approved borrowers, which is obvious since the improved rating system will have a steeper profile of the $EL(x)$ schedule, which means that the level of losses will be lower. The second is a decrease in the level of deviation (cut-off), which implies an increase in the volume of the loan portfolio with a constant flow of applicants and constant lending rates.

We introduce the notation as $= {}^{\mathrm{EL}}\!/_{M}$.

Marginal income theorem from increasing the discriminatory power of scoring

Let the CAP curve CAP(x, AR) have a single root $\tilde{x}(\mathrm{AR}) \in (0, 1)$ of the equation$\frac{\partial^2}{\partial x \partial \mathrm{AR}}\mathrm{CAP}(x, \mathrm{AR}) = 0$. If the business is guided by the goal of maximizing profit in its decision on the cut-off level, then there is a region in the parameter space $\beta > 0$, $\mathrm{AR} \in (0, 1)$, in which the annual return P from a marginal increase in the Gini index by ΔAR will be estimated as follows:

$$P > \tilde{\pi} \cdot \Delta AR. \tag{9}$$

Where $\tilde{\pi} = \hat{E} \cdot \frac{EL}{2}$ this is a parameter for a loan portfolio with a constant amount $\hat{E}$.

In fact, this means that, given the amount of loans $\hat{E}$ (annual) and the level of expected average annual losses of applicants EL, for each percentage point of increase in

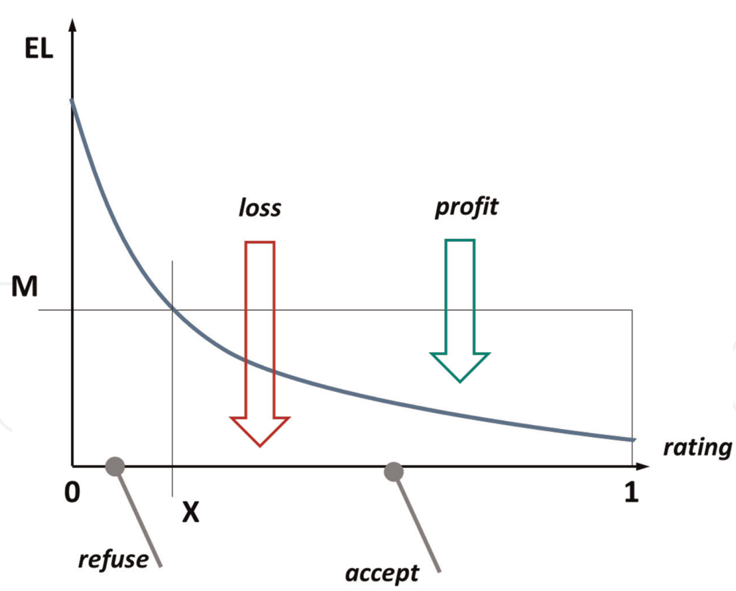

Figure 3.
The optimal point **X** *cut-off (cutting off "bad" from "good" borrowers) must correspond to the level of losses* EL(x) *that does not exceed the marginal return on the loan (margin* M*).*

[5] In addition to the lost profit, the loss from the deviation is assumed to be zero, although in practice this is not the case, since the "refuseniks" go through the process of internal underwriting, which is costly for the bank. These costs are a much smaller order of magnitude than credit losses, but in an accurate financial model, of course, should be taken into account.

the power of the rating system, there will be a guaranteed increase in profits of $\tilde{\pi} \cdot 0.01$ in the parameter space estimated in the next section. That is, given that provisions on placed loans (passed by risk management) may be less than the risks of the applicants, then for each percentage point increase in the risk management Gini index, the income level is estimated as half the volume of provisions multiplied by 0.01.

Proof

The total profit of the credit process will be determined by the formula (4):

$$\hat{\Pi} = M \cdot (1 - \hat{x} - \beta \cdot (1 - CAP(\hat{x},\ AR,\ p)), \tag{10}$$

where $\hat{x}$ – optimal cut-off point. Obviously, the point $\hat{x}$ will be calculated from the condition as follows:

$$\frac{\partial \Pi}{\partial x} = M \cdot (\beta \cdot CAP'_x(\hat{x},\ AR,\ p) - 1) = 0, \tag{11}$$

Which is equivalent to the identity$EL(\hat{x}) = M$ and corresponds **Figure 3**.

If the discrimination power AR is increased by a small amountΔAR , then the formula for marginal income should be obtained from the expression:

$\Delta\Pi = \frac{d\hat{\Pi}}{dAR} \cdot \Delta AR + o(\Delta AR)$. From (10) follows that

$$\pi = \frac{d\hat{\Pi}}{dAR} = M \cdot \left(-\frac{d\hat{x}}{dAR} + \beta \cdot CAP'_x \cdot \frac{d\hat{x}}{dAR}\right) + \mathrm{EL} \cdot CAP'_{AR}(\hat{x}, AR, p).$$

The first part of this expression is equal to zero due to the condition (11), means remains as:

$$\pi = \mathrm{EL} \cdot CAP'_{AR}(\hat{x}, AR, p).$$

Taking into account the volumes of placed funds $\hat{E}$, which are less than potential ones by $1 - \hat{x}$, the resulting formula will be rewritten in the form as shown below:

$$\pi = \frac{\hat{E}}{1 - \hat{x}} \cdot \mathrm{EL} \cdot CAP'_{AR}(\hat{x}, AR, p). \tag{12}$$

To estimate the guaranteed value of the desired marginal profit π, it is necessary to carry out more transformations (12). Namely, if formula (7) is rewritten taking into account all arguments, $AR = \frac{2 \cdot \int_0^1 CAP(x,\ AR,\ p)dx - 1}{1-p}$,

Then, after differentiation with respect to AR, we get the identity as:

$\frac{2}{1-p} \cdot \int_0^1 CAP'_{AR}(x, AR, p)dx = 1$. Which can be used in formula (12) and it will be rewritten in the following form:

$$\pi = \hat{E} \cdot \frac{\mathrm{EL}}{2} \cdot \frac{1-p}{1-\hat{x}} \cdot \frac{CAP'_{AR}(\hat{x}, AR, p)}{\int_0^1 CAP'_{AR}(x, AR, p)dx}. \tag{13}$$

Taking into account the mean value theorem (for example, [18], Theorem 5.19.), we can state that there are closed subsets $\hat{x}$ of the interval [0,1] on which the function of the right fractional part of the expression: (13)

$$\frac{CAP'_{AR}(\hat{x}, AR, p)}{\int_0^1 CAP'_{AR}(x, AR, p)dx} \geq 1 \tag{14}$$

.

If we require a fairly simple property of the CAP-curve, namely that there be a unique root $\tilde{x}(AR) \in (0, 1)$ of equations $\frac{\partial^2}{\partial x \partial AR} CAP(x, AR) = 0$, then these subsets are the only segment[6] $[x_1, x_2] \in [0, 1]$.

Then, if $\hat{x} \in [x_1, x_2]$, then we get a guaranteed estimate as:

$$\pi \geq \hat{E} \cdot \frac{EL}{2} \cdot \frac{1-p}{1-\hat{x}}.$$

The cut-off level x̂ exceeds the default probability level p. Indeed, the optimal cut-off for an ideal model (AR = 1) should be at a minimum level of x̂ = p, in this case, $(1-p)/(1-\hat{x}) = 1$. For a real model, if it has 0 < AR < 1, the cut-off level must be greater than for the ideal one equal to p, which means $(1-p)/(1-\hat{x}) > 1$. Therefore, it can be argued that the segment $[x_1, x_2]$ guaranteed level $\pi > \tilde{\pi}$ occurs when $\tilde{\pi} = \hat{E} \cdot \frac{EL}{2}$. ∎

4. The area of risk-return and the Gini index, in which the margin effect works

This section presents the result of modeling the marginal profit of a unit amount of placed funds $\hat{E}$ in relation to the marginal profit guaranteed by formula (9) using the Van der Burgt CAP-curve model (1).

We define the normalized marginal return from an increase in discriminatory power AR as the ratio $\pi/\tilde{\pi}$. The profitability level π is determined by formula (12), guaranteed by $\tilde{\pi}$ formula (9). In the Van der Burgt CAP-curve model, the function $k(AR, p)$ is implicitly defined (2). In addition, as it is easy to see, the condition of the Theorem on the existence of a unique root $\tilde{x}(AR) \in (0, 1)$ of equations $\frac{\partial^2}{\partial x \partial AR} CAP(x, AR) = 0$ is true. This means that there is a single segment belonging to the cut-off level of $[x_1, x_2] \in [0, 1]$, in which inequality (14) is satisfied and there is a connected domain of parameters in which the conservative estimate (9) is true. Let's show it.

The normalized marginal return will be calculated by the formula as shown below:

$$\pi/\tilde{\pi} = \frac{2 \cdot CAP'_k(\hat{x}, k, p)}{(1-\hat{x}) \cdot \frac{dAR}{dk}},$$

where $k(AR, p)$ is the solution of the transcendental equation (2). After simple transformations, the formula for the normalized marginal return for the model under consideration is obtained:

$$\pi/\tilde{\pi} = \frac{1-p}{1-\hat{x}} \cdot \frac{(\hat{x}-1) \cdot e^{-k(\hat{x}+1)} - \hat{x} \cdot e^{-k\hat{x}} + e^{-k}}{e^{-k} - \frac{(1-e^{-k})^2}{k^2}}.$$

---

[6] Obviously, the function $CAP'_{AR}(\hat{x}, AR, p)$ has zero values at the boundaries of the interval x̂ ∈ [0,1], as well as the function $CAP(\hat{x}, AR, p) - \hat{x}$. Therefore, it is sufficient to have a unique extremum x̂ of the function $CAP'_{AR}(\hat{x}, AR, p)$ for inequality (14) to give a unique segment $[x_1, x_2] \in [0, 1]$ as a solution.

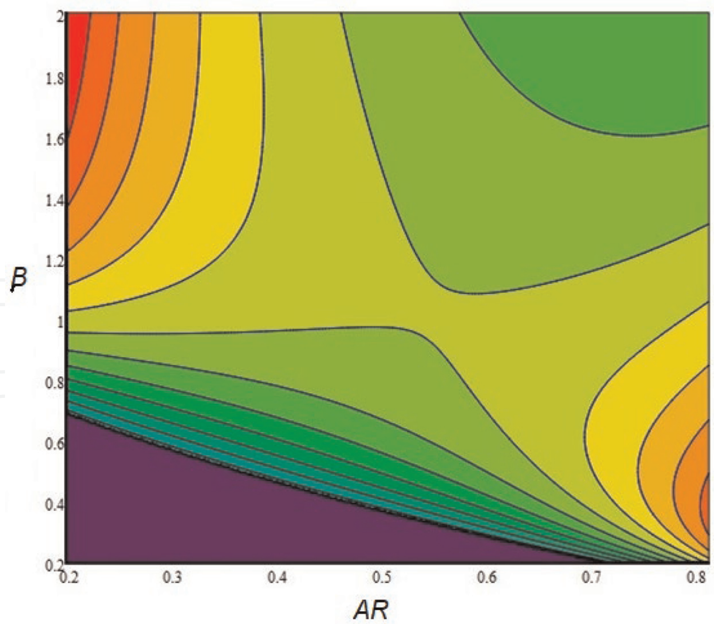

Figure 4.
Level lines of the normalized marginal return in the range of parameters $\in [0.2, 2]$, $\boldsymbol{AR} \in [0.2,\ 0.8]$. *In the blue area, the normalized marginal return does not reach unity (guaranteed return (9) is not achieved).*

Numerical study of the Van der Burgt CAP curve model for a realistic set of parameters $\frac{EL}{M} \in [0.2, 2]$, $AR \in [0.2, 0.8], p = 4\%$ (the influence of parameter p is small) presented in **Figure 4**.

Figure 4 shows the normalized marginal return level lines in a two-dimensional range of parameters. In the blue (close to triangular) area of low risk and the power of the rating system, the guaranteed marginal return is not achieved. In the upper part of the parameter area, the marginal return from improving the rating system already exceeds the guaranteed value by 2–3 times, especially in reddening zones.

The presented case shows the practical reliability of a conservative estimate of marginal return when the rating system is improved in the range of risk parameters that are most interesting for the use of rating models in decision making.

5. Results and discussion

Table 3 presents three common reasons for the weakness of discriminatory procedures in practice, for which hypotheses have been formed to improve their effectiveness. The formulation of these hypotheses, their development and increase in the effectiveness of risk management are the goals of its validation for the retail (including corporate) lending business.

The conservative marginal profit formula (9) gives the bank's management, without building complex financial business models, a conservative benchmark or tool that is the basis for making a decision to invest in their own risk management infrastructure to improve the efficiency of credit decision-making.[7] This also includes the decision to invest in the acquisition of third-party services that increase the effectiveness of risk management.

[7] By investment, here we mean the general regular and individual costs attributable to the cost of the business process.

Problem	Suggestions for solving the problem
Among the clients approved by the bank, a significant part leaves the offer unclaimed or goes to another bank. Those who use the offer turn out to be of lower quality than the average for approved ones. The result is a decrease in the Gini index.	Segment approved clients by credit quality, offering the best of them more favorable terms (Risk Based Pricing, RBP).
Reduced (increased) level of approval of applicants, decrease in the commercial effectiveness of the product due to the growth of type I or II errors.	Regular policy adjustments based on a request for market data (by market segment, by reference group) from the Credit Bureau. Adjusting the optimum failure rate to current rates.
Low discriminatory power of the lending process in certain segments. Result: zero Gini index, unreasonably high failure rate.	Refinement of scoring models, introduction of segment-oriented models, testing and validation of customized and (or) industry-specific scoring by the Credit Bureau.
Stagnation of the overall level of commercial efficiency of retail lending.	Regular validation of risk management procedures, scoring models, system of rules (stop factors), study of the behavior of "refuseniks". Implementation of motivational tools for risk managers and employees of lending departments to improve the efficiency of the lending process.

Table 3.
Typical reasons for risk management weakness.

Here are some simplified business cases:

- the bank intends to create a separate department that controls the quality of rating models, their validation, the quality of implementation and application in the business process. It is assumed that such a department will lead to an improvement in the discriminatory process by at least a 5% Gini index. Loan portfolio controlled by a discriminatory process based on rating modeling is $10 billion, estimate of expected losses based on IFRS 9 provisions for the first stage of impairment[8] is 2%. What budget of this business function will break even for the bank? Applying formula (9), we obtain only financial profit estimated at least $\$10$ billion $\cdot\ 2\%/2 \cdot 5\% = \$5$ million annual. Nonfinancial profit is expressed in bullets 2–4 of Section 1;

- the bank understands that the quality of internal ratings is at an average level and is inferior to the quality of ratings provided by the services of a professional rating agency. Moreover, it is inferior, according to agreed estimates, by at least 10% of the Gini index. The bank allows the involvement of an agency for a nonpublic rating of borrowers that are doubtful for the bank (legal aspects should be in the background and not discussed). The cut-off level of such applicants' projects is 50%, the expected losses, as in the first case, are 2%. The cost of the nonpublic rating service is $3 thousand. Starting from what credit limit does it become profitable to involve the services of a rating agency, provided that the services are paid at the expense of the bank? A simple calculation using (9), considering the doubling of the cost, including for "refuseniks", gives a

[8] These are credit loans for which there are no clear signs of deterioration in credit quality yet. As a rule, all applicants, after making a decision on a loan, belong to the first stage of impairment.

conservative result $\$6$ thousand $\cdot\, \mathbf{2/2\%/10\%} = \$\mathbf{6}$ million . That is, this is the limit, starting from which, it is advisable to attract a rating agency, and this limit can be proportionally reduced, taking into account lending for a period of more than one year, since the expected losses will increase proportionally (more precisely, almost proportionally).

In practice, decision-making problems are obviously more difficult. Since all related aspects must be considered, such as the incomplete “marketability” of proposed transactions, the quality of collateral and its assessment, data privacy factors, the target aspect of financing, control mechanisms, etc. However, this does not detract from the value of the fundamental profit assessment proposed by the developed approach.

Currently, there is a continuous improvement in scoring approaches to assess the applicant for loans. The methods use extended data, including nonfinancial data, which requires additional resources both to maintain significantly increased data volumes and to implement more complex algorithms and procedures. The payback of these resources for the credit business can be assessed by the above tools. According to the portfolio statistics of the decisions made, it is possible to objectively assess the current effectiveness of risk management. In [19], an overview of the areas of alternative credit scoring is presented. This field is emerging and gaining popularity due to the critical role of alternative data in accelerating access to financial services. Historically, a creditworthiness assessment has required the existence of past financial activity, such as repaying a loan. Such strict requirements made people with little or no financial history “credit invisible”. Advances in artificial intelligence and machine learning have enabled scoring algorithms to work with nonfinancial data, such as digital footprints from mobile devices and psychometric data, to calculate credit scores. Although most invisible loans are in developing countries, research in this area is predominantly conducted in developed countries, and most alternative credit scoring models are trained on data from developed countries.

The study [20] explores the use of psychometric tests developed by the Entrepreneurial Finance Laboratory (EFL) as a tool to identify high credit risk and potentially increase access to credit for small business owners in Peru. Administrative data is used to compare accrual and repayment behavior patterns among entrepreneurs who have been offered credit based on the traditional credit rating method and the EFL tool. It has been found that a psychometric test can reduce the risk of a loan portfolio if it is used as a secondary screening mechanism for entrepreneurs already working in a bank, i.e. those who have a credit history. For nonbank entrepreneurs who do not have a credit history, using the EFL tool can increase access to credit without increasing portfolio risk. Another pilot project [21] to study the effectiveness of scoring based on psychometric data was launched in 2017 in Spain as part of the business microcredit segment (i.e. social microcredit for self-employed clients who want to start a business and need help from social organizations to develop your business plan). Initial statistical tests say that the discriminatory power (as measured by the Gini index of the ROC curve) can be in the range of 70-80% (compared to the 30–40% Gini index offered by traditional models). This means that the use of psychometric scoring can significantly increase the discriminating power and give a financial profit (9), which for the reference population of loan applicants should exceed the costs of introducing new risk management tools.

Another example of improving scoring power by expanding data coverage is a study [22] showing that adding social media-derived variables to a scorecard increases the Gini index by 7–8%.

And, of course, improving the scoring schemes themselves, considering the dynamics of scoring variables, and approaches that go beyond regression also show their increased discriminatory effectiveness. Yibei et al. [23] proposes a Bayesian optimal filter to provide risk prediction for lenders, assuming that published credit ratings are estimated simply from structured financial data. A recursive Bayesian scoring is proposed to improve the accuracy of credit scoring by incorporating a dynamic customer interaction topology. Theoretically, it is shown that, in accordance with the proposed concept of evolution, the developed scoring system has higher accuracy than any effective estimate, and the standard errors are strictly less than the lower Cramer-Rao bound in a certain range of scoring points. In [24], the approach of logistic regression is improved by introducing a new class of covariant categorization methods in regression models for binary response variables. Application to real data and Monte Carlo simulation study suggests that one of the methods of this class has better predictive performance and lower computational cost than other methods available in the literature.

6. Conclusion

This chapter presents a set of original tools that can be used in practice to improve the quality and efficiency of risk management for mass lending products (retail, microfinance, SME, and others). The first tool that is successfully used in the banking practice of the largest banks in Russia is the assessment of the effectiveness of credit decision-making in terms of discrimination of applicants for a loan. It relies on the generally accepted approach of ROC analysis. Measurement indicators are:

- assessment of the quasi-Gini indicator of the overall lending process, based on the decisions to reject and approve applicants;

- assessment of the scale of nonoptimality of the cut-off level of candidates, taking into account the current market risk-return of the segment of the population of candidates for bank clients.

Based on the results of measuring the effectiveness of risk management, it seems possible to give reasonable hypotheses for improving the business process in a given segment or proposals for restructuring or closing the direction.

The second tool is the rigorously proven Marginal income theorem (9) underscoring power amplification. Which gives a simple formula for the lower estimate of such income. The application of this formula can serve as a fundamental economic justification for the issue of allocating resources to improve scoring models, procedures, and the quality of risk management in general, depending on the current risk-return and discriminatory power. It is shown that the formula works in the most interesting areas for decision-making. Namely, when the risk/return of incoming candidates is greater than one and when the risk management in its decisions has a discriminating power that is much higher than random. Examples of consequences, hypotheses, and business cases are proposed. Also, a targeted overview of modern promising areas for improving the efficiency of risk management in terms of improving the accuracy of scoring models underlying credit business processes is given.

IntechOpen

IntechOpen

Author details

Mikhail Pomazanov
National Research University Higher School of Economics, Moscow,
Russian Federation

*Address all correspondence to: mhubble@yandex.ru

IntechOpen

© 2022 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/3.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

References

[1] Basel III. A Global Regulatory Framework for More Resilient Banks and Banking Systems. Basel Committee on Banking Supervision; 2011. pp. 1-77 . Available from: https://www.bis.org/publ/bcbs189.pdf [Accessed: August 01, 2022]

[2] ECB Guide to the internal capital adequacy assessment process (ICAAP). European Central Bank: Banking Supervision. 2018. pp. 1-45. Available from: https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.icaap_guide_201811.en.pdf [Accessed: August 01, 2022]

[3] Al Amari A. The credit evaluation process and the role of credit scoring: A case study of Qatar [Ph.D. thesis]. University College Dublin; 2002. pp. 1-387. Available from: https://books.google.ru/books?id=mXPjSAAACAAJ [Accessed: August 01, 2022]

[4] Abdou H, Pointon J. Credit scoring, statistical techniques and evaluation criteria: A review of the literature. Intelligent Systems in Accounting, Finance & Management. 2011;**18**(2–3): 59-88. DOI: 10.1002/isaf.325

[5] Rudra Kumar M, Kumar GV. Review of machine learning models for credit scoring analysis. Revista Ingeniería Solidaria. 2020;**16**(1):1-16. Available from: https://revistas.ucc.edu.co/index.php/in/article/view/3087. DOI: 10.16925/2357-6014.2020.01.11

[6] Jankowitsch R, Pichler S, Schwaiger Walter SA. Modelling the economic value of credit rating systems. Journal of Banking & Finance. 2007;**31-1**:181-198. DOI: 10.1016/j.jbankfin.2006.01.003

[7] Stein RM. The relationship between default prediction and lending profits: Integrating ROC analysis and loan pricing. Journal of Banking and Finance. 2005;**29**:1213-1236. DOI: 10.1016/j.jbankfin.2004.04.008

[8] Blöchlinger A, Leippold M. Economic benefit of powerful credit scoring. Journal of Banking and Finance. 2006; **30**:851-873. DOI: 10.1016/j.jbankfin.2005.07.014

[9] Engelmann B, Hayden E, Tasche D. Measuring the Discriminative Power of Rating Systems. Bundesbank Series 2 Discussion Paper2003. DOI: 10.2139/ssrn.2793951

[10] Joon-Ho H, Sangche L. Economic effects of positive credit information sharing: The case of Korea. Applied Economics. 2011;**43**:4879-4890. DOI: 10.1080/00036846.2010.498364

[11] Brian D, Claudia P, Troy R. Bigger is better, but at what cost? Estimating the economic value of incremental data assets. Big Data. 2014;**2**:87-96. DOI: 10.1089/big.2014.0010

[12] Chen Y, Chen S, Chen Y. Decision quality by the loss cost of type I and type II errors. The TQM Journal. 2013;**25**(2): 202-220. DOI: 10.1108/17542731311299627

[13] Pomazanov MV. Validation of the effectiveness of the bank retail portfolio risk management procedure. Procedia Computer Science. 2022;**199**:798-805. DOI: 10.1016/j.procs.2022.01.099

[14] van der Burgt M. Calibrating low-default portfolios, using the cumulative accuracy profile. The Journal of Risk Model Validation. 2008;**1**:17-33. DOI: 10.21314/JRMV.2008.016

[15] Birdsall TG. The Theory of Signal Detectability: ROC Curves and their Character. In: Cooley Electronics

Laboratory. Ann Arbor, Michigan: Department of Electrical and Computer Engineering, The University of Michigan; 1966. p. 451. Available from: https://hdl.handle.net/2027.42/3618 [Accessed: August 01, 2022]

[16] Hanley JA. Receiver operating characteristic (ROC) methodology: The state of the art. Critical Reviews in Diagnostic Imaging. 1989;**29**(3):307-335

[17] Tasche D. Estimating Discriminatory Power and PD Curves When the Number of Defaults Is Small. Working Paper. Lloyds Banking Group; 2009. Available from: https://arxiv.org/abs/0905.3928 [Accessed: August 01, 2022]

[18] Rudin W. Principles of Mathematical Analysis. 3rd ed. New York: McGraw-Hill; 1976. p. 113. ISBN 978-0-07-054235-8

[19] Njuguna R, Sowon K. Poster: A scoping review of alternative credit scoring literature. In: ACM SIGCAS Conference on Computing and Sustainable Societies (COMPASS '21). New York, USA: Association for Computing Machinery; 2021. pp. 437-444. DOI: 10.1145/3460112.3471972

[20] Arráiz I, Bruhn M, Stucchi R. Psychometrics as a Tool to Improve Screening and Access to Credit Policy Research Working Paper. Washington, DC: World Bank; 2015. Available from: https://openknowledge.worldbank.org/handle/10986/23471 [Accessed: August 01, 2022]

[21] Microbank's pilot on psychometric scoring. European Microfinance Network (EMN). 2018. Available from: https://www.european-microfinance.org/publication/microbanks-pilot-psychometric-scoring [Accessed: August 01, 2022]

[22] Masyutin AA. Credit scoring based on social network data. Business Informatics. 2015;**3**(33):15-23. Available from: http://cyberleninka.ru/article/n/credit-scoring-based-on-social-network-data [Accessed: August 01, 2022]

[23] Yibei L, Ximei W, Boualem D, Xiaoming H. Credit scoring by incorporating dynamic networked information. European Journal of Operational Research. 2020;**286**(3):1103-1112. DOI: 10.1016/j.ejor.2020.03.078

[24] Silva D, Pereira G, Magalhães T. A class of categorization methods for credit scoring models. European Journal of Operational Research. 2022;**296-1**:323-331. DOI: 10.1016/j.ejor.2021.04.029