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Procedia Computer Science 199 (2022) 798–805

Procedia Computer Science

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The 8th International Conference on Information Technology and Quantitative Management (ITQM 2020 & 2021)

Validation of the effectiveness of the bank retail portfolio risk management procedure

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Abstract

The article considers the issue of quantifying the quality of discrimination (approval) in the retail portfolio segments based on current statistical data on the level of refuse of customers who applied to the bank, the current level of defaults and market data (credit history bureaus). The analysis of the economic efficiency of the practiced level of approval/rejection of applications, taking into account the credit risk, is carried out. On the example of several cases, the typical reasons for the weakness of the quality assessments of discrimination of risk procedures are considered.

Keywords: validation; optimal solution; retail lending; Gini index; credit process; risk management procedure; rating; default

1. Problem statement

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 [1], 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 to 40 bp. So, compared to the estimated implementation costs banks could have a strong incentive to invest in their rating systems. In [2], 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. Demonstrates that, in general, more powerful models are more beneficial than weaker ones, provides an example of modeling, demonstrates the benefit in absolute terms. Later work [3] 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 paper [4] substantiates a universal and simple marginal formula for guaranteed profit from improving the rating-scoring model underlying credit decisions.

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10.1016/j.procs.2022.01.099

The main idea of the presented approach is based on the fundamental analogy of risk management activities with a certain generalized rating system, which itself 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 [5]. Then, determine how optimally such a rating system makes decisions, taking into account its own power and exogenous risk-return factors.

2. Segmentation of applicants' portfolio

The first step in the quantitative quality assessment procedure is to define a portfolio of applications for

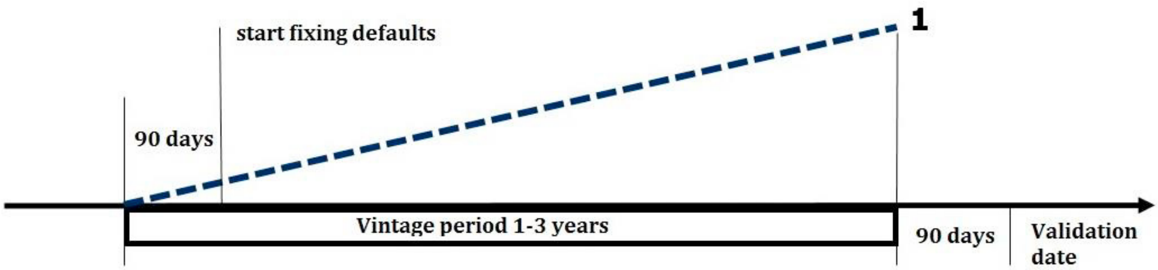

Fig. 1. Vintage portfolio model for validation

analysis and segment it. The selection is carried out according to the historical period (vintage) of loans issued, segmentation - according to the status of the loan application. When determining the historical period, it is important to achieve the exclusion of seasonal factors, that is, the period should be homogeneous in terms of their influence. Since the main control variable of discriminatory procedures in retail lending is overdue over a certain number of days (30+, 60+, 90+, etc.), the historical period continues to the left and right along the timeline for the number of days that defined in the business rules for this credit type. That is (Fig. 1): the studied segment of borrowers is selected; the vintage period is selected; uniformity of distributions is assumed.

Loan applications included in the analyzed portfolio are segmented by the status of issue (Tab. 1).

Table 1. Segmentation of applications by status of loan issuance and grouping for inclusion in validation statistics

Loan	Status	Packet	Fraction
Issued	Loan application approved	**A**	20%
Not issued	The application was approved, but the client refused to receive	**A’**	30%
Not issued	In the process of registration	**-**	5%
Not issued	Refusal for minimum requirements (errors, debt burden, age, etc.)	**-**	5%
Not issued	Refusal after underwriting	**C**	5%
Not issued	Refusal after checking for fraud	**C**	5%
Not issued	Refusal after checking credit history	**C**	20%
Not issued	Refusal after scoring analysis	**C**	10%
			100%

Where (Tab. 1):

• Packet **A** is included in validation statistics, gives default statistics;

• Packet **A’** is taken into account in validation statistics, does not give default statistics;

• Packet **C** is included in validation statistics, does not give default statistics;

• applications without a packet (-) are not included in the validation statistics, since for these applications the bank does not have the freedom to make an approval/refusal decision.

It is necessary to adjust the statistics of the effective number of applicants for the share of borrowers who have not taken out a loan. The adjustment leads to the results:

$$\mathrm{B} = \mathrm{A} + \mathrm{C} \times \frac{\mathrm{A}}{\mathrm{A}+\mathrm{A}'} \qquad (1)$$

The abstract example given in Tab. 1 give $\mathrm{B} = 36\%$.

3. Correction of market default rate to the share of "refuseniks" who received a loan from another bank

At the next stage, a hypothesis is formulated: applicants who have passed the mandatory formal stages of selection have market default indicators adjusted for the statistical share of those who enter the market after the bank's refusal. Indeed, if an applicant comes to a bank and receives a refusal on a loan application, then there is a possibility that this client will receive a loan from another bank and will enter the default rate market statistics. This means that the default rate of applicants who applied to the bank should be higher than the market default rate. Therefore, it is necessary to study the credit activity of “bank refuseniks” in the credit market after receiving a refusal from the bank.

The standardized report of the Bureau of Credit Histories (BCH) helps to assess the scale of this phenomenon, which allows you to find out the share of such clients, as well as the quality of services received by such “refuseniks” on the market. The formula for adjusting the default rate (DR) level of applicants who applied to the bank for the share of those who are credited by the market (reference group), but were refused by the bank, is as follows:

$$\mathrm{DR}=\mathrm{DR(M)} + \frac{\mathrm{A}}{\mathrm{B}} \times \left(\frac{1}{\mathrm{p}} - 1\right) \times \left(\mathrm{DR(M)} - \mathrm{DR(A)}\right) \qquad (2)$$

Where $\mathrm{DR(M)}$ – an estimate of the average market share of defaults for the vintage period of issuance according to the BCH data (in our example, we will further consider this figure to be 4.8%). The numerator of this indicator is calculated by simply summing up the number of all borrowers of the studied segment of BCH statistics that have reached the given delay barrier (for example, 90 +), on all reporting periods of the vintage period Fig. 1, denominator is the sum of all;

B – adjusted percentage of applicants applying to the bank (1);

$\mathrm{DR(A)}$ – percentage of defaults among borrowers credited by the bank (3%);

p – the average statistical percentage of abandoned applicants entering the credit market after a bank refusal (in our example, the indicator is taken equal to 70%).

Thus, after substitution of all values, the adjusted share of defaults will be 5.23%. The derivation of formula (2) is presented in the Appendix.

4. Validation of risk management procedures

The entire population of applications can be presented in the form of Tab. 2, in which all values are reduced to the results of the bank's risk management procedures. Values in lighter cells are calculated and values in dark cells represent objective data.

From Tab. 2 you can see the classification errors (Type I errors, Type II errors [6]):

— Type I errors — applications were rejected, but the servicing of similar loans on the market by “refuseniks” was not accompanied by a default: B × (1 – DR) – A + D;

— Type II errors — a positive decision was made, but the loan service was accompanied by the implementation of the target variable, i.e. default (D).

Table 2. Segmentation of the applicant population in terms of risk management

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

To assess the effectiveness of risk management, the Gini index method is used, which shows the power of discriminatory procedures. To do this, we need to construct a CAP curve based on the known solution point available to us.

To reconstruct the CAP curve, we use the well-known Van der Burgt model [7], which has an independent variable k, which is the solution of the equation:

$$\mathrm{CAP}(x) = \frac{1-e^{-kx}}{1-e^{-k}}, \tag{3}$$

where k – a parameter that shows the effectiveness (power) of risk management solutions.

The result of the reconstruction of the CAP-curve is shown in Fig. 2. The plotted curve includes a point known to us, the coordinates of which we obtained earlier: on the OX axis - the percentage of rejected applications (decisions to “refuse”) in the general population of borrowers; on the OY axis, the percentage of defaults in rejected applications, relative to all defaults.

The Gini index of the resulting curve (3) is calculated by the formula:

$$\mathrm{Gini}(k) = \frac{2}{1-\mathrm{DR}} \times \left(\frac{1}{1-e^{-k}} - \frac{1}{k} - \frac{1}{2}\right), \tag{4}$$

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

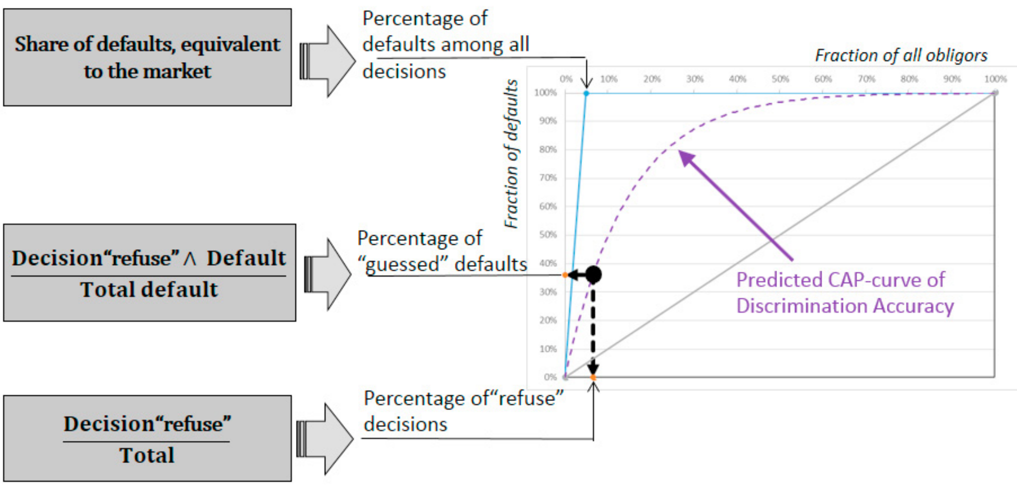

Fig. 2. Reconstruction of the CAP-curve of discriminatory accuracy of risk management procedures

Obviously, the requirements for this metric can be both very strict and not very strict, but, as a basic benchmark from the banking practice of retail lending, one can offer widely used recommendations of zonal estimates in Tab. 3.

Table 3. Stereotypical recommendations of zonal assessments of the Gini metric

Gini Ranges / Model	Red zone	Yellow zone	Green Zone
Behavioral	<40%	40%-60%	>60%
Applicative	<35%	35%-55%	>55%

Thus, each obtained value of the Gini index of all aggregate risk management procedures can be attributed to one or another zone. The aggregate means that not one internal procedure is assessed, for example, a scoring model, but the whole complex of rules and procedures used by risk management to make a decision on a loan application - “refusal” or “approval” (Tab. 1).

5. Metric of commercial efficiency of risk management solutions

The next step in the validation of risk management should be an assessment of the economic (commercial) efficiency: to what extent the “point of refuse” is justified from the point of view of the economics of lending for the retail product under study in the bank. It is clear that the optimal point of discrimination for "bad" and "good" borrowers should correspond to the level of EL(x) losses not exceeding the margin yield (M) on the credit 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

$$\mathrm{EL}(\mathrm{x},\mathrm{Gini}) = \mathrm{DR}\times\left(1-\mathrm{CAP}(\mathrm{x},\mathrm{Gini})\right)\times\mathrm{LGD}, \qquad (5)$$

this level is determined by Type II errors and the level of losses given default (LGD). Where, $\mathrm{CAP}(\mathrm{x},\mathrm{Gini})$ is determined by equations (3-4), solved at the stage of validation of the discriminating power of risk procedures. Assuming that M is given (it is the norm of Net Present Value (NPV) of the product under investigation for the vintage period, taking into account all costs and amortization periods of loans), we can offer a simple formula for the profit from a unit volume of all incoming applicants:

$$\mathrm{P}(\mathrm{x},\mathrm{Gini}) = \mathrm{M}-\mathrm{x}\times\mathrm{M}-\mathrm{EL}(\mathrm{x},\mathrm{Gini}). \qquad (6)$$

The formula for profit (6) simultaneously depends on Type I / II errors, and their balance is determined by external factors - the level of the market default rate and the profitability of the product. Gross margin (6) will have a maximum at a certain level of approval (optimal approval rate), since, with a complete refusal to all, it is fair $\mathrm{P}(1,\mathrm{Gini}) = 0$, if, on the contrary, you approve of everyone, then you can get a loss at $\mathrm{DR}\times LGD > M$.

Determining the areas of parameters where the maximum exists and where it does not is not the task of the presented work. One can only assert that under the condition of the equilibrium activity of the credit market (there is no superprofit and rush demand, there is no global depression and catastrophic risks, etc.) such a maximum takes place. Therefore, it is logical to formulate the metric of the effectiveness of commercial decisions of approval / refusal in terms of the levels of deviation of these decisions from the maximum efficiency, both in the direction of greater approval and less. In Fig. 3 shows the profit curve and its typical zonal levels Tab. 4. Typical zonal levels are not the most stringent. At the same time, of course, each bank can zone this metric for itself based on its own experience and goals.

Table 4. Typical zoning of the level of profit loss from non-optimal decision making

Approval/Refuse Level	**Red zone**	**Yellow zone**	**Green zone**
The range of the level of lost income	50% -100% or negative profit	20%-50%	Less than 20%

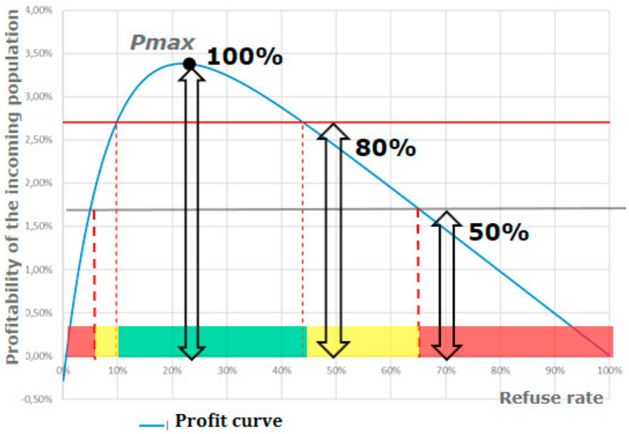

Fig. 3. Zonal representation of approval levels relative to the maximal profit level P_{max}

Acceptable level refuse range α $[X_\alpha^-, X_\alpha^+]$ calculated quite obviously.

1. *1. Optimal refuse point is calculated:*

   $$X_{opt} = \frac{1}{k}\ln\left(\frac{DR \cdot LGD \cdot k}{M \cdot (1-e^{-k})}\right);$$

2. *The following equation is solved (relatively X_α^-, X_α^+):*

   $$(1-\alpha) \cdot P\left(X_{opt}, Gini(k)\right) = P\left(X_\alpha^\pm, Gini(k)\right),$$

   where $P(x, Gini(k))$ calculated from (4),(5),(6).

6. Implementation of the approach in practice

And in the process of validating risk management procedures, it is possible to evaluate all credit products using the key indicators proposed above. Tab. 5 is an example of such a validation evaluation.

Table 5. Validation table of risk management assessment on various credit products

Loan product	Gini index, %	Refuse rate, %	Loss of profitability,%	Gini score	Evaluation of the approval rate
1	46	32	10	Yellow	Green
2	85	28	12	Green	Green
3	33	63	25	Red	Yellow

The analysis of the validation tables obtained by this method is a separate work that should be carried out not only by risk managers, but also by all divisions of the bank involved in the creation and distribution of the credit product. Meanwhile, some typical cases can be distinguished. Tab. 6 presents four common reasons for the weakness of discriminatory procedures in practice, and hypotheses are formed to improve their effectiveness. Ultimately, the goal of validation is to formulate these hypotheses, develop them, and improve the effectiveness of risk management.

Table 6. Typical reasons for risk management weakness

Reason	Improvement hypothesis
Among the clients approved by the bank, a significant part leaves the offer unclaimed or goes to another bank. However, those who use the offer are of lower quality than the average for approved ones. The result is a decrease in Gini.	Segment approved customers by credit quality, offering the best of them more favorable conditions (Risk Based Pricing).
A reduced (increased) level of approval of applicants, a decrease in the commercial effectiveness of the product due to the growth of errors of I/II types.	Regular policy adjustments based on a request for market data (by market segment, by reference group) in the BCH. Adjustment of the optimal approval level taking into account the current lending rates
Low discriminatory power of the credit process in certain segments. Result is Gini zeroing or unreasonably low approval level	Refinement of scoring models, introduction of segment-oriented models, testing and validation of customized or industry-specific scoring
Stagnation of the general level of commercial efficiency of retail lending	Regular validation of risk management procedures, scoring models, a system of rules (stop factors), study of the behavior of “refusers”. Implementation for risk managers and employees of lending departments of motivational tools to improve the efficiency of the credit process

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Appendix. The formula for adjusting the default rate of applicants who applied to the bank for the share of those who are credited by the market, but were refused by the bank

The quality of the applicants included in the bank (for a specific product segment of the bank) will differ from the quality of those included in the statistics of the BCH. This is due to the fact that the bank refuses some of the applicants, therefore, if the applicants who do not get to the bank would never get into the credit market, then it should be expected that the default rate (DR) of the bank's applicants should coincide with the default $DR(M)$ on the market (in the BCH). But this is not the case. At the same time, it should be noted that not all applicants who are refused by the bank then enter the market and participate in the $DR(M)$statistics. Therefore, it is necessary to make a correction for the share of borrowers that have received a refusal from the bank, but find themselves on the credit market.

To do this, it is necessary to conduct a study, relying on the credit report of the BCH on applicants whom the bank refused on a loan application in a statistically sufficient reference period, which is determined so that for each reason for refusal there are at least 1000 applicants. The result of this research will be the parameter p - the average statistical share of abandoned applicants that enter the credit market after a bank refusal. This parameter is purely individual for each bank, its market and product segment.

Let the bank among B applicants credit the number of A, i.e., refuses B-A, then the frequency (share) of defaults for all applicants entering the bank will be calculated as

$DR = \frac{A \cdot DR(A) + (B-A) \cdot DR(B-A)}{B}$,

where $DR(A), DR(B-A)$ – default rate among approved and refused, respectively. At the same time, part of p from B-A participates in the default statistics of the BCH. Taking into account that market default is formed among all those approved by the bank and among the share p of those refused, we obtain the frequency (rate) of defaults in the market in the ratio

$DR(M) = \frac{A \cdot DR(A) + p \cdot (B-A) \cdot DR(B-A)}{A + p \cdot (B-A)}$.

Excluding the unknown $DR(B-A)$ from the ratios above, we obtain the required formula for the default rate of incoming applicants, adjusted for an incomplete share of the return of “refused” applicants to the credit market:

$$DR = DR(M) + \frac{A}{B} \cdot \left(\frac{1}{p} - 1\right) \cdot (DR(M) - DR(A))$$

For each validated segment, the adjusted market share of defaults of the bank's claimants, presented above, shall be used.