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Drivers of Individual Credit Risk of Retail Customers—A Case Study on the Example of the Polish Cooperative Banking Sector

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Abstract: The main aim of the research was to determine the key factors determining the level of credit risk of individual clients (clients in the form of natural persons, excluding companies) on the example of Polish cooperative banks according to the following features: transaction characteristics, socio-demographic characteristics of the customer, the customer's financial situation, the customer's history of cooperation with the cooperative bank where they applied for a loan, and the customer's history of cooperation with other financial institutions. For the research gathered data from 1000 credit applications submitted by individual customers when applying for a credit in five different cooperative banks were used for the analyses. To assess the credit risk of retail clients we use logit regression models, and additionally, score cards were calculated. The results of the research indicate that among the factors with high predictive power there were the features characterizing the client's history of cooperation with the cooperative bank, where they applied for a loan. It may mean that when assessing credit risk related to financing individual customers, cooperative banks due to their local character, have an advantage over other financial institutions.

Keywords: credit risk; score card; credit scoring; logit model; risk drivers

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1. Introduction

An indispensable element of proper functioning of the financial market is to base it on a strong moral foundation (Shiller 2012). This is particularly true in the banking sector, where the contradictions between the interests of the bank and the interests of the customer are increasingly noticeable. Partially, this is due to the transformation that took place in the banking sector at the beginning of the 21st century. It affected the relationship between the bank and the customer within which there was a decline in trust in the banking sector, as customers increasingly found it difficult to recognize the bank as their direct partner (Iannotta et al. 2007). This also translated into the occurrence of a problem related to the assessment of the creditworthiness of customers, as a result of the existence of asymmetry of information between them (Balina and Nowak 2017).

According to the assumptions of neoclassical economics, all market participants are assumed to have the same access to information (Juszczyk et al. 2020). However, economic reality differs from this model, because in many cases this assumption is wrong (Stiglitz et al. 2002). Contemporary economic concepts from the field of game theory, behavioral approach or currents of institutional economics indicate this. These theories assume an imperfect flow of information and knowledge, which in each of these theories is considered in a different context (Walter and Krenchel 2021). In many situations, information asymmetry is a roadblock to a mutually beneficial contract, because it leads either to fraud associated with moral hazard or to abandonment of a transaction by the party that feels misinformed.

This is important in the business of credit institutions because this market is strongly associated with the presence of the problem of information asymmetry, resulting from, among other things, one party to the transaction having less knowledge relevant to the transaction than the other party (Fonteyne 2007). In the case of the loan market, it is assumed that the party generally better informed is the one applying for the loan, as only he/she has full knowledge of their financial situation and the true purpose of spending the funds obtained and their willingness to repay them. Therefore, an important issue related to the problem of information asymmetry in the banking sector is the assessment of creditworthiness of individual customers (Zouhayer et al. 2018).

Bank customers by their behavior can negatively affect the reliability of the result of this assessment, because on their side there is space for actions or omissions that can distort the result of the assessment. Therefore, in the process of creditworthiness assessment, the attitude of the client toward the bank is of great importance. If the customer treats the bank as a partner, they will work with the bank to find a solution that best fits their needs (Arias et al. 2018). There is then a chance that the terms of the loan will be acceptable to both parties and both parties will benefit from the transaction. Therefore, a more favorable situation is one in which customers treat the bank as a partner rather than an adversary. This is also pointed out by Ostrom, who showed that customers who are motivated solely by self-interest will find it fundamentally difficult to act ethically in their relationships with others in situations where they are likely to benefit (Ostrom 1990). With this in mind, banks began to use a variety of tools to reduce uncertainty in lending decisions. The consequence of this has been a change in the relationship between banks and their customers, in which banks have reduced significantly the level of trust in their customers (Kil et al. 2021). Financial institutions began to use increasingly widespread methods to enable banks to reduce a significant part of the risk arising from information asymmetry (Maranga 2013).

The problem of information asymmetry also concerns cooperative banks, however its scale is much smaller than in the case of commercial banks. This is due to the fact that cooperative banks as key elements of local financial and social systems are located very close to their customers and in many cases have excellent knowledge of them. Knowledge of customers and the local market gives cooperative banks an important advantage in the process of credit assessment of individual customers and allows to reduce credit risk in the bank. Therefore, it can be believed that this element may be crucial for the functioning of cooperative banks and should therefore be formally included in the credit evaluation process. Considering the local character of cooperative banks and the roles they play in the development of markets and local communities, it seems to be an important issue to determine the possible consequences of the use of advanced credit assessment methods by cooperative banks in the assessment of their customers, taking into account the relational elements resulting from the cooperative bank's knowledge of customers and the market.

An important issue seems to be the problem of quality of used models of individual credit risk assessment in cooperative banks which, due to their local character, operate on locally diversified markets. Therefore, the risk of improper customer credit assessment may be crucial for their further existence.

The research carried out made it possible to indicate the key factors determining the level of credit risk of individual customers in cooperative banks. This issue has not been analyzed so far in relation to cooperative banks, and the results of the research made it possible to fill this research gap. Additionally, the results of the research pointed out the limitations of using general models to assess the credit risk of individual customers in cooperative banks, which has not been directly articulated so far in relation to this sector.

The research made it possible to identify the key factors determining the level of credit risk of retail customers in cooperative banks and the possibility of developing an individualized approach to its assessment using quantitative, qualitative, and behavioral characteristics. This issue has not been analyzed so far in relation to cooperative banks, and the results of the research made it possible to fill this research gap. Additionally, the results of the research pointed out the limitations of using general models to assess the credit risk of individual customers in cooperative banks, which has not been directly articulated so far in relation to this sector.

The article consists of four parts. First, a review of the literature on the use of scoring models for credit risk assessment is made and on the basis of this review four research hypotheses are formulated. In the second part of the article the research methods are presented and the research sample is characterized. Then in the next part of the paper the results of the research on scoring models for credit risk assessment in the studied cooperative banks are presented. The article ends with a summary indicating the applicability of the developed models.

2. Literature Review

There are many definitions of credit risk in a banking theory, with most of them pointing to its negative aspects. An example is Altman's (2008) view of credit risk, who stated that if credit can be defined as "nothing but the hope of obtaining a sum of money at a certain time", then credit risk is the chance that such hope will not materialize. Van Deventer et al. (2011), on the other hand, emphasize that credit risk is associated with changes in the market value of credit due to faulty models and environment, indicating that the causes of credit risk are either in the environment in which entities operate or in the models used to assess that risk. Fabozzi et al. (2003) primarily associate credit risk with the risk that a borrower will not be able to repay its obligations. Vaughan and Vaughan (2007) also emphasizes that credit risk is associated with the existence of the probability of an unsuccessful deviation from the desired expected return as a result of the borrower's failure to meet the terms of the loan agreement. Rowe (1977) defines risk as a concept consisting of two elements: the occurrence of possible but unwanted consequences or losses, and the uncertainty of those consequences, which is expressed in terms of the probability of the borrower's defaulting on the loan agreement. As can be seen from the above definitions, credit risk is associated with the borrower's failure to meet the terms of the loan agreement, which adversely affects the bank's financial standing. It is worth remembering that this risk is related not only to the behavior of the bank's client but also to the assessment of that risk by the bank.

In order to properly assess individual credit risk, banks, including cooperative banks, perform a number of activities. At the first stage, banks assess the probability of occurrence of a given risk, then estimate the frequency of its occurrence. In the last stage, they determine the potential range of losses that the bank may be exposed to as a result of the materialization of credit risk. The scope and approach to creditworthiness assessment of an individual customer in banks is evolving under the influence of two main factors, which are the experience of banks and the development of quantitative methods. However, based on the available literature three basic approaches to assessing creditworthiness of individual customers can be distinguished (Proniewski and Tarasiuk 2012): the traditional approach, the approach using credit scoring and the approach using various mathematical models.

A common feature of the scoring model approach and the econometric modeling approach is that they seek to create a credit scoring system, or classification of borrowers into specific risk classes. These methods aim to determine whether a given borrower will belong to the groups of customers who will fulfill the credit agreement or will belong to the group of customers who should have been denied credit (Jaki and Ćwięk 2020). Most often, two tiers are used in the credit scoring process. The first one concerns the evaluation of the risk connected with the personal aspect and the second one concerns the evaluation of the risk connected with the economic aspect. The problem and need to assess the creditworthiness of customers, especially the personal aspect results from the occurrence of the phenomenon of information asymmetry, which is defined as one of the market imperfections (Daniłowska 2014). An example of this can be seen in the multifaceted analysis of the problem of information asymmetry conducted by Freixas and Rochet (2008). These researchers showed that the credit market is strongly associated with the occurrence of the problem of information asymmetry, which is the fact that one party to a transaction has a smaller stock of information relevant to the transaction than the other party.

The problem of information asymmetry also concerns cooperative banks, however its scale is much smaller than in the case of commercial banks. This is due to the fact that cooperative banks as key elements of local financial and social systems are located very close to their customers and in many cases have excellent knowledge of them (Idasz-Balina et al. 2020). Knowledge of customers and the local market gives cooperative banks an important advantage in the process of credit assessment of individual customers and allows to reduce credit risk in the bank (Štefko et al. 2021). Therefore, it can be believed that this element may be crucial for the functioning of cooperative banks and therefore should be formally included in the credit evaluation process, especially in scoring models.

Credit scoring is widely used by banks and other financial institutions to assess the risk of default of a customer applying for a loan or credit. It is directly related to the problem of classifying individual customers into groups of "good" and "bad" customers. This problem was addressed in their work by Crook et al. (2007), who defined credit scoring as a set of decision-making models and directly related techniques that assist a lender in the process of granting credit to a customer. These techniques and a model decide who gets the credit, how much a credit amount should be, and what strategy should be applied to a particular customer to increase the profitability from the transaction. On the other hand, Lieli and White (2010) termed credit scoring as a technique that allows financial institutions to benefit from the correct determination of a customer's creditworthiness and risk of default depending on the factors that determine it. When reviewing the literature, it can be observed that in the case of scoring models construction two approaches are most often used. The first one is a descriptive approach and the second one is a stochastic approach. The stochastic approach assumes that the variables describing the borrowers are random variables. Therefore, this approach assumes that the set of borrowers under consideration is a random sample taken from a much larger set, the population. Therefore, the methods used to build scoring models are intended to provide results that allow inferences about this population based on random observations. For example, Thomas (1941) was the first to apply the discriminant analysis method in credit risk assessment system, in 1941. Orgler (1970) in 1970 was the first to use linear regression analysis to evaluate the credit risk of consumer loans. Ten years later, in 1980, Wiginton (1980) attempted to use a logistic regression model to assess customers' behavior in the context of customers' compliance with the terms of their credit agreement. Subsequently, Freed and Glover (1981) used the linear programming method to classify individual customers in terms of a credit risk. In the following years, there has been an intensive development of tools using neural networks to solve numerous problems, including creditworthiness and credit rating (Ma et al. 2021). An example of such an application can be seen in the research conducted by Wang et al. (1999), who in his work attempted to combine the method of discriminant analysis, the method of combined forecasting, and artificial neural networks to assess creditworthiness. With the development of technology, more and more advanced econometric methods began to be implemented to analyze data for assessing the potential credit risk of individual customers in financial institutions (Reske et al. 2015). Examples include the application of support vector machine (SVM) techniques in credit evaluation proposed by Wei et al. (2011), or the use of ongoing data mining (OLDM) to construct Fang's two-level credit risk assessment system. On the other hand, Shi et al. (2002), extended the linear programming model based on data mining technology and proposed multi-criteria linear programming (MCLP) for borrower classification. Then, Hsieh (2004), Lim and Sohn (2007), proposed a dynamic scoring model based on data mining. Furthermore, Nie et al. (2011), used a combination of logistic regression and decision trees to predict the exit risk of bank customers using credit cards. In the literature we can find a rich review of issues related to the construction of scoring models. For example, the works of Anderson (2007), Crook et al. (2007), in which they present a broad description of scoring models.

Reviewing the methods used by researchers around the world, it can be observed that over the years they have used more and more advanced methods and techniques to assess the default risk of bank customers. However, despite such a wide range of analyses, the results obtained by the researchers were similar. Therefore, it can be concluded that the choice of an estimation method of a scoring model does not directly affect the quality of the system of a customer evaluation by the bank. As the research conducted by Ong et al. (2005) shows that it is the selection of variables that are appropriate and adequate to an analyzed issue that significantly affects the quality of a scoring model. Therefore, the selection of variables is such an important element in the construction of scoring models.

Considering the above, the main goal of the research was to determine drivers of individual credit risk of retail customers on the example of Polish cooperative banks according to the following features: transaction characteristics, socio-demographic characteristics of a customer, a customer's financial situation, a customer's history of cooperation with the cooperative bank where they applied for a loan, and a customer's history of cooperation with other financial institutions.

Furthermore, the following research hypothesis were formulated:

Hypothesis 1 (H1). *Considering qualitative, quantitative, and behavioral characteristics of individual customers in credit risk assessment by cooperative banks, we may allow for limiting the effects of market imperfections resulting from information asymmetry and a contract theory.*

Hypothesis 2 (H2). *The biggest contribution to the effectiveness of individual credit risk assessment in Polish cooperative banks comes from the characteristics of the client's past financial situation.*

Hypothesis 3 (H3). *The variation in the effectiveness of individualized scoring models for credit risk assessment in cooperative banks results mainly from taking into account the characteristics of the customer's history of cooperation with a given cooperative bank and other financial institutions.*

Hypothesis 4 (H4). *The use of individualized scoring models in cooperative banks makes it possible to mitigate credit risk to a greater extent than with general model.*

3. Materials and Methods

To achieve the main goal of this paper and to verify the research hypotheses, data from 1000 credit applications submitted by individual customers when applying for a cash credit in cooperative banks were used for the analyses. The cooperative banks included in the study operated in different regions of Poland. The research period covered 2017–2020, with a maximum loan period of 24 months. All loan applications used for analysis were positively processed by the bank during the assessment of creditworthiness and credibility. Which means that these customers were creditworthy, a loan was granted to them, and the bank entered into a loan agreement with them. All the analyzed credit agreements were completed in 2019–2020. The structure of the studied collective made by the institution from which the data were obtained is presented in Table 1. In the studied group of customers, more than 15% of them defaulted on the terms of the credit agreement and were considered "bad" customers and the rest were "good" customers.

Table 1. Structure of the surveyed population.

Specification	Number of "Good" Clients [pcs.]	Number of "Bad" Clients [pcs.]	Total Number of Clients [pcs.]	Share of "Bad" Clients [%]
Bank A	170	35	205	17.07
Bank B	145	30	175	17.14
Bank C	180	30	210	14.29
Bank D	175	30	205	14.63
Bank E	175	30	205	14.63
Total	845	155	1000	15.50

The analysis was based on data on bank customers' compliance with the credit agreement (dependent variable) and 27 features characterizing bank customers at the moment of submitting a credit application (independent variables). It should be mentioned that among these features there were features describing economic and demographic situation of the customer and features concerning customer's cooperation with the bank. The research used a binary explanatory variable that determines whether customer fulfilled the terms of the loan agreement throughout its tenor [Yes, No], which was due to the consideration of data on short-term loan agreements made by banks with customers. In the case of delays in repayment, both the criterion of timeliness, i.e., delays of at least 90 days, and the criterion of significance, i.e., the amount of arrears in the case of a cash loan had to be higher than EUR 50, were used in the classification of customers. The variables were grouped according to the characteristics of the transaction, the customer, and the customer's history of cooperation with the cooperative bank and other financial institutions. The list of variables used in further research is presented below:

1. Characteristics of the transaction [CD]:
   - Loan amount [PLN];
   - Type of collateral [blank promissory note, surety under a bill of exchange/civil law, transfer of ownership/pledge, assignment of rights from an insurance policy, mortgage];
   - Is there a co-borrower [Yes/No];
   - Does the value of the collateral exceed the amount of the loan applied for? [Yes/No];
   - Were there any delays in loan repayment? [Yes/No].
2. Socio-demographic characteristics of the client [CDS]:
   - Age of main applicant [years];
   - Gender of main applicant [female, male];
   - Marital status of main applicant [separated, divorced, widow/widower, single, married];
   - Place of residence [City/Village];
   - Education [primary/high school, basic vocational, secondary, bachelor's/engineer's, higher master's];
   - Number of persons in borrower's household [pcs.];
   - Housing status [tenant, owner/co-owner of house/apartment, other].
3. Characteristics of the client's financial situation [CSF]:
   - Whether there is community of property [Yes/No];
   - Place of work [private sector, public sector, pensioner];
   - Occupation [farmer, manual worker, pensioner, white-collar worker];
   - Borrower's main source of income [civil law contract, permanent employment contract, pension, business activity, fixed-term employment contract, agricultural activity, pre-retirement benefit, pension, other];
   - Declared amount of the applicant's burdens [PLN];
   - Net monthly household income [PLN];
   - Current credit exposure [PLN];
   - Debt to Income ratio (DtI) [%].
4. Characteristics of the client's history with the cooperative bank where he/she applied for credit [CBS]:
   - Does the client have an account with the Cooperative Bank? [Yes/No];
   - Does the customer have other deposit, savings or investment products offered by the Cooperative Bank? [Yes/No];
   - Does the applicant have a bank account limit [Yes/No];
   - Does the applicant have a credit card limit [Yes/No].
5. Characteristics of the customer's history with financial institutions [CIF]:

- Does the client currently have other obligations? [Yes/No];
- Did the client have delays in paying off other (credit/financial) obligations in the period of 3 years prior to submitting the loan application [Yes/No];
- Have there been any collection actions against the applicant? [Yes/No];
- Number of points obtained in BIK or client's rating code if no point value is available.

The characteristic that determines whether there were delays in repayment of the loan granted, was the information on whether the customer complied with the terms of the loan agreement concluded with the bank, i.e., whether he was considered a "good customer" or a "bad customer" (Maranga 2013). In the article we used an explanatory variable that determines whether a customer fulfilled the terms of the loan agreement throughout its tenor. If client fulfilled the terms of the loan agreement he was considered as a good customer and was assigned a value of 1 if not he was considered as a bad customer and was assigned a value 0.

First, the variables characterizing the customers of the banks under study were discretized using the Weight of Evidence Index (*WoE*) (Matuszyk 2015). In performing the clustering of variables in the first step a preliminary analysis of the factors characterizing the borrowers was conducted. According to the literature, the characteristics should be recoded, determining a new scale of their values according to the values of the so-called Weight of evidence (*WoE*) was calculated according to the formula (Thomas 2009):

$$WoE_i = ln\left(\frac{n_i^{Good}/n_{Good}}{n_i^{Bad}/n_{Bad}}\right) \tag{1}$$

where:
n_i^{Good}—the number of good credits for the *i*-th attribute (variation interval) of the predictor value,
n_i^{Bad}—the number of bad credits for the *i*-th attribute (variation interval) of the predictor value,
n_{Good}—number of good credits,
n_{Bad}—number of bad credits,
i—attribute of the explanatory variable

Classification trees were used to group and discretize the characteristics describing the customers of the banks under study. This method was used to obtain the best initial division of the variable range into as homogeneous classes as possible. This division was then processed using a modified CHAID algorithm using the Ch-square test qualitative dependent variable or *F*-test for continuous dependent variable as a criterion for determining the next best distribution in each step (Kass 1980). This modification consists in using the *WoE* difference as a criterion for combining and separating classes. The *WoE* values are a good indicator of the risk profile of borrowers characterized by the values of a given predictor. Large positive values of this indicator show a large share of good loans in relation to bad loans, i.e., a large ability of this category of borrowers to repay their credit obligations. Large negative values of this indicator for a given category testify on the other hand to a large share of bad loans in relation to good ones, and thus to a high propensity of borrowers not to repay their credit obligations (high risk of loan default). The results obtained on WoE_i values were used to select the best predictors, using the information value index (*IV*). At this stage of the research, the *IV* Index calculated according to the following formula was used (Thomas 2009):

$$IV = \sum_{i=1}^{k}\left(\frac{n_i^{Good}}{n_{Good}} - \frac{n_i^{Bad}}{n_{Bad}}\right) * WoE_i \tag{2}$$

WoE_i—value of *WoE* indicator for the *i*-th attribute (ranges of the variable) of the variable value;

n_i^{Good}—number of good loans for the i-th attribute (ranges of the variable) of the variable value;
n_i^{Bad}—number of bad loans for the i-th attribute (ranges of the variable) of the variable value;
n_{Good}—number of good credits;
n_{Bad}—number of bad credits;
i—attribute of the explanatory variable;
k—number of attributes (ranges of the variable) of variable.

It is assumed in the literature that the larger the values of the IV coefficient, the greater the predictive power of the tested predictor (or scoring model) in distinguishing between "good and bad loans". It is assumed that values of IV (Siddiqi 2012):

- Above 0.3 indicate strong predictive power,
- Values between 0.3 and 0.1 indicate medium predictive power,
- Values between 0.1 and 0.02 indicate weak predictive power,
- Values below 0.02 indicate no predictive power.

The maximum likelihood estimation method and the backward stepwise method were used throughout the study to estimate only statistically significant model parameters (Balina 2018). The use of this type of modeling was due, among other things, to the fact that the variables used for analysis in many cases were expressed by variables of a qualitative nature. These variables, by their very nature, were most often zero-one variables. In the case of the scoring model, this variable determines whether the customer belongs to the group of good or bad customers. With this approach, the zero-one variable model has the form:

$$y_i^* = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + u_i \tag{3}$$

β_0; β_j—estimated parameters of the logit model,
y_i^*—latent variable specifying that the customer belongs to one of the groups, i.e., good or bad customer,
x_{ij}—independent variables (quantitative or qualitative) characterizing the bank's customer after its discretized using the weight of evidence index (WoE) according to the Equation (1),
u_i—rest in the model.
where y_i^* is the latent variable. This model is called a probability model, where a logit model of the form is often used:

$$y_i^* = ln\frac{P_i}{1-P_i} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + u_i \tag{4}$$

where y_i^* is called the logit and P_i is the probability of the dependent variable determining the customer's membership in one of two categories determined from the logistic distribution from equation:

$$\frac{P_i}{1-P_i} = e^{y_i^*} = e^{\beta_0 + \sum\limits_{j=1}^{k} \beta_j x_{ij} + u_i} \tag{5}$$

hence:

$$\hat{P}_i = \frac{1}{1+e^{-y_i^*}} = \frac{1}{1+e^{-(\beta_0 + \sum_{j=1}^{k} \beta_j x_{ij})}} \tag{6}$$

Next, on the basis of the estimated logit regression model determining the level of risk related to financing individual customers in the banks studied and the model for the entire population studied, the parameters of scoring cards were estimated. The score for individual borrowers was determined using linear scaling, which expresses the linear relationship between the score and the so-called Odds Ratio, which is the ratio of the probability of repayment to non-payment of a loan (Siddiqi 2012):

$$Score = a_0 + a_1 \cdot ln(Odds) = a_0 + a_1 \cdot ln\left(\frac{p_{Good}}{1 - p_{Good}}\right) \quad (7)$$

where p_{Good} is likelihood of being a good customer

In order to determine the scoring, the *pdo* parameter is also introduced, which specifies how many scoring points double the chance of loan repayment. It is expressed by the relation below (Thomas 2009).

$$Score + pdo = a_0 + a_1 \cdot ln(2 \cdot Odds) \quad (8)$$

Solving the system of Equations (7) and (8) gives the formulae for the estimation of parameters a_0 and a_1

$$\begin{cases} a_0 = ScoreC - a_1 \cdot ln(Odds) \\ a_1 = \frac{pdo}{ln(2)} \end{cases} \quad (9)$$

For the study, it was assumed that the score would be 100 (*ScoreC*) and that there is a chance like 50:1, (*Odds* = 50) of repaying the loan and that every 20 points (*pdo*) the chance doubles. With this in mind, estimates were obtained for the parameters: a_0 = 28.8539 *i* a_1 = −12.8771.

For the logit model there is a relation:

$$ln\left(\frac{p_{good}}{1 - p_{good}}\right) = \beta_0 + \sum_{i=1}^{n} \beta_i X_i \quad (10)$$

where β_i are the estimates of the parameters of the logit model, then from relation (7) after transformations the formula is obtained, expressing the total score of the borrower as the sum of scores for individual attributes of each predictor as follows:

$$Score = \sum_{i=1}^{n}\left(\frac{a_0 + a_1\beta_0}{n} + a_i\beta_i X_i\right) = \sum_{i=1}^{n}(Score_i) \quad (11)$$

Due to the importance of the possibility of using scoring cards in assessing the credit risk of individual customers of the banks studied, an important part of this process was to determine the optimal cut-off point, which divided borrowers into two groups: a good one with a low risk of loan default and a bad one with a high risk. There are several ways to determine the optimal cut-off point. For the purpose of the analysis, a method was used consisting in finding such a cut-off score for which the following optimization task is fulfilled (Zweig and Campbell 1993):

$$SP_2 - m \cdot BP_1 \rightarrow max \quad (12)$$

where:

SP_2—cut-off score

$$m = \frac{k_{NP_2}}{k_{NP_1}} \cdot \frac{1 - p}{p} \quad (13)$$

k_{NP_2}—costs of misclassifying good borrowers,
k_{NP_1}—costs of misclassifying bad borrowers,
p—probability of belonging to a class: "bad".

After determining the cut-off points for each model. The quality of the scoring card was evaluated based on the classification performance of the borrowers.

Among other things, the model accuracy assessment matrix was used to evaluate the classification accuracy of the companies. This is a tool that provides a summary on the accuracy of the indications of the estimated model (Card 1993; Congalton 1991; Li and Racine 2007).

4. Results

The results obtained were used to rank the predictors that have the greatest predictive power in distinguishing between "good and bad customers", bearing in mind that the larger the values taken by the IV, the greater the predictive power of the factor under study in distinguishing between "good" and "bad" loans.

The analysis using the IV coefficient showed that different variables were significant in each of the banks studied, and, given the assumptions made, no variable was significant in each of the banks analyzed and simultaneously in the entire study population (see Table 2). Based on the results for the IV coefficient for the entire sample of bank customers, the following characteristics were the best predictors: Has the client defaulted on any obligations within 3 years from the date of application? (Yes/No), Does the applicant have a credit card limit [Yes/No], Current credit exposure (PLN), Does the client have an account with the Cooperative Bank? [Yes/No], Whether there is a community of property (yes/no), Declared amount of the applicant's burdens (PLN), Loan amount (PLN), Borrower's main source of income, Occupation, Housing status, Debt to Income ratio (DtI) [%], Age of the main applicant (years), and Place of work. In the case of bank-by-bank analyses, the results indicated that a different number of variables were significant in each bank: Bank A—9 variables, Bank B—12 variables, Bank C—13 variables, Bank D—11 variables, and Bank E—9 variables. Interestingly, the variables that were significant for individual banks were largely consistent with the variables that were significant for the entire collective. Namely, in the case of the surveyed banks, the number of significant characteristics that were also significant for the whole collective was relatively high and amounted respectively for Bank A—8 variables, Bank B—7 variables, Bank C—11 variables, Bank D—7 variables, and Bank E—6 variables.

The features that occurred most frequently among the set of significant variables in the studied cooperative banks were as the following: a declared amount of applicant's burdens (PLN), a loan amount (PLN), a borrower's main source of income, which were present in 4 out of 5 banks studied and at the same time were significant for the analyses conducted for the whole set of customers. Variables such as: if the client had delays in paying off other (credit/financial) obligations within 3 years prior to submitting the loan application [Yes/No], an occupation, a debt to Income ratio (DtI) [%], age of the main applicant (years), and a place of work were significant both for the whole sample of clients and in 3 out of 5 banks analyzed.

The remaining variables appeared among the significant predictors less than two times. This situation also indicates that cooperative banks should individualize their approach to credit risk assessment, keeping in mind the key variables for the entire sector, which may constitute a significant part of credit risk assessment of a given client, but should be supplemented with individual features reflecting the local conditions in the area where the cooperative bank operates. It is also worth paying special attention to the variables for which the value of coefficient IV exceeded 0.5. In the case of the whole sample group these were two variables: if the client had delays in paying off other (credit/financial) obligations within 3 years prior to submitting the loan application [Yes/No] and if the applicant has a credit card limit (yes/no). In Bank A and B this level was exceeded by one variable if the client had delays in paying off other (credit/financial) obligations within 3 years prior to submitting the loan application [Yes/No]. In Bank C, on the other hand, there were as many as 6 such variables, among which the following predictors were found: if the client had delays in paying off other (credit/financial) obligations in the period of 3 years prior to submitting the loan application [Yes/No], if the applicant has a credit card limit (yes/no), a current credit exposure (PLN), a declared amount of the applicant's burdens [PLN], the age of the main applicant (years), and a net monthly household income (PLN). In Bank D, the IV coefficient exceeded the level of 0.5 for the variable indicating the number of persons in a borrower's household (pcs.), and in Bank E this level was exceeded for the characteristic indicating monthly net household income (PLN). This may be indicated by the high level of significance of variables related to the client's previous relationships with financial institutions, especially in terms of the service of obligations and the financial situation of clients. Table 3 presents a summary of significant features by their category.

Table 2. Information value index values for the studied traits.

Specification	Bank A	Bank B	Bank C	Bank D	Bank E	Total
Characteristics of the client's financial situation [CSF]						
Current credit exposure	0.07	0.02	0.96	0.30	0.38	0.31
Whether there is community of property	0.08	0.01	0.12	0.01	0.19	0.22
Declared amount of the applicant's burdens	0.13	0.26	0.92	0.16	0.29	0.21
Borrower's main source of income	0.15	0.43	0.40	0.04	0.20	0.19
Occupation	0.00	0.41	0.24	0.22	0.02	0.17
Debt to Income ratio (DtI)	0.02	0.11	0.15	0.02	0.10	0.13
Place of work	0.21	0.21	0.09	0.16	0.02	0.11
Net monthly household income	0.29	0.02	1.00	0.06	0.51	0.10
Socio-demographic characteristics of the client [CDS]						
Housing status	0.01	0.00	0.10	0.12	0.03	0.17
Age of main applicant	0.24	0.22	0.54	0.36	0.09	0.12
Marital status of main applicant	0.02	0.00	0.03	0.28	0.09	0.06
Number of persons in borrower's household	0.06	0.01	0.17	0.75	0.05	0.04
Place of residence	0.01	0.26	0.06	0.05	0.00	0.01
Gender of main applicant	0.01	0.14	0.02	0.50	0.02	0.01
Education	0.01	0.15	0.09	0.05	0.06	0.01
Characteristics of the customer's history with financial institutions [CIF]						
Has the client defaulted on any obligations within 3 years from the date of application?	0.67	1.64	2.57	0.00	0.00	2.06
Does the client currently have other obligations?	0.08	0.00	0.00	0.00	0.00	0.10
Number of points obtained in BIK or client's rating code if no point value is available	0.02	0.28	0.01	0.00	0.08	0.09
Characteristics of the transaction [CD]						
Loan amount	0.25	0.02	0.26	0.39	0.35	0.19
Does the value of the collateral exceed the amount of the loan applied for?	0.01	0.02	0.00	0.00	0.00	0.07
Is there a co-borrower	0.02	0.02	0.00	0.42	0.10	0.07
Type of collateral	0.06	0.01	0.00	0.00	0.00	0.02
Characteristics of the client's history with the cooperative bank where he/she applied for credit [CBS]						
Does the applicant have a credit card limit?	0.14	0.01	1.88	0.00	0.00	0.68
Does the client have an account with the Cooperative Bank?	0.12	0.21	0.00	0.00	0.00	0.31
Does the customer have other deposit, savings or investment products offered by the Cooperative Bank?	0.05	0.05	0.01	0.01	0.00	0.00
Does the applicant have a bank account limit?	0.02	0.08	0.04	0.00	0.24	0.00

Table 3. Number of significant features in terms of IV index values by feature category.

Specification	Total	Bank A	Bank B	Bank C	Bank D	Bank E
Characteristics of the customer's history with financial institutions [CIF]	1	1	2	1	0	0
Characteristics of the client's history with the cooperative bank where he/she applied for credit [CBS]	2	2	1	1	0	1
Characteristics of the client's financial situation [CSF]	7	4	5	7	4	6
Characteristics of the transaction [CD]	1	1	0	1	2	2
Socio-demographic characteristics of the customer [CSD]	2	1	4	3	5	0

When analyzing the significance of the considered set of variables, it is worth noting that the largest number of significant features concerned the financial situation of the customer. This indicates the high relevance of this type of information in determining the credit risk of a customer applying for a loan in the studied cooperative banks. The research showed that an important element in the assessment of creditworthiness of individual customers in cooperative banks was the current financial situation, therefore the hypothesis stating that the greatest influence on the adequacy of individual credit risk assessment in Polish cooperative banks has the features characterizing the current financial situation of the customer was confirmed. However, the results obtained in relation to the whole population of the surveyed banks indicate that if a customer had previously fallen behind in repayment of any liabilities within 3 years since the date of submitting the application, there was a high risk that this situation would recur. Similar results were also obtained for Bank A, Bank B, and Bank C. For Banks D and E, no such relationship was found due to the lack of an adequate number of observations regarding this characteristic on the part of bad customers. On the basis of this result we estimated the logit models to assess credit risk in analyzed clients population and separately in each bank.

The analysis conducted revealed that in the case of estimating a logit model to assess the risk of a customer defaulting on a loan agreement (see Table 4), seven variables were found to be significant for the entire study population i.e.,: if the customer had delays in paying other liabilities (credit/financial) in the period of 3 years prior to submitting the loan application [Yes/No], the age of the main applicant [years], whether there is property community [Yes/No], declared amount of the applicant's burdens [PLN], loan amount [PLN], whether an applicant has a credit card limit [Yes/No] and an occupation. In the case of the first variable, the situation in which the customer over a period of 3 years since the date of filling a credit application was not in default with repayment of any obligations had a positive impact on the customer's creditworthiness—which was confirmed by a positive regression coefficient. In case of the second variable defining the age of the main applicant, the regression coefficient for the following ranges proved to be significant: from 25 to 58 years and over 74 years. It should be noted that in the case of the age range of 25 to 58 years, the regression coefficient was negative which indicates a higher level of credit risk associated with granting credit to this customer. For the range above 74 years, the relationship was opposite. This indicates that the age of the customer in a non-linear way affects the level of creditworthiness of an individual customer in the banks studied. In case of the feature determining the presence of community of property, we may conclude from the analyses that significant presence of community of property among persons applying for a loan in the examined cooperative banks positively influenced their creditworthiness and significantly reduced the level of credit risk related to granting a loan to such a customer. When considering the amount of the applicant's declared debts it was found that the most advantageous situation in terms of the possibility to reduce the credit risk associated with the borrower took place when it was below PLN 850. In the model for the entire population of cooperative bank customers examined, the variable determining the amount of the loan applied for was also significant. It is interesting to note that loans between PLN 251 and 16015 were associated with the lowest level of risk because the regression coefficient for this range was the highest and at the same time statistically significant. Additionally, the level of credit risk of an individual customer in the banks studied was influenced by the fact that the applicant had a credit card limit. As the research shows, the customers who had such a limit were characterized by a lower level of risk than customers who did not have one. Importantly, in the case of the estimated model for the entire sample, the last variable was the occupation of the bank customer. The research also showed that it was significant that the borrower was a farmer. This fact had a positive impact on reducing the level of risk associated with lending to this group of customers.

Table 4. Credit risk logit model for the entire study sample.

Trait	Trait Attribute	Coefficient	Wald's Statistics	p-Value
Has the client defaulted on any obligations within 3 years from the date of application?	Yes	1.43	138.65	0.001
	No	n.d.	n.d.	n.d.
Age of main applicant	under 24	0.78	3.44	0.064
	from 25 to 58	−0.46	4.39	0.036
	from 59 to 65	n.d.	n.d.	n.d.
	from 66 to 73	−0.42	1.18	0.276
	over 74	1.17	7.51	0.006
Whether there is community of property	Yes	0.84	16.57	0.001
	No	−0.36	3.34	0.068
Declared amount of the applicant's burdens	under 850	0.46	6.02	0.014
	from 851 to 1675	−0.25	2.22	0.136
	above 1676	n.d.	n.d.	n.d.
Loan amount	under 250	−0.14	0.66	0.416
	from 251 to 16,015	1.32	10.74	0.001
	from 16,016 to 32,150	−0.36	2.00	0.157
	above 32,151	n.d.	n.d.	n.d.
Does the applicant have a credit card limit?	Yes	n.d.	n.d.	n.d.
	No	0.51	15.60	0.001
Occupation	farmer	0.57	6.92	0.009
	pensioner	n.d.	n.d.	n.d.
	other	−0.01	0.00	0.950

The parameters of the logit models were then estimated for each of the cooperative banks under study. The detailed results are presented in Tables 5–9. In the model developed for Bank A (see Table 5), five variables were significant i.e., net monthly household income [PLN], a loan amount [PLN], if the customer had delays in paying other liabilities (credit/financial) within 3 years prior to submitting the loan application [Yes/No], if the client has an account with the Cooperative Bank? [Yes/No], and the age of the main applicant [years]. Analyzing the significance of each attribute within the characteristics that were included in the model, it should be stated that in the case of the first variable, the level of net household income between 2801 and 3075 PLN was significant. In the case of this range, the regression coefficient was positive, which indicated that the household income in this range had a positive effect on credit risk reduction. Interestingly, in case of the next characteristic of a loan transaction, i.e., the loan amount applied for, two ranges turned out to be significant. Namely, when the customer applied for a loan up to the amount of PLN 1300 it did not cause an increase in credit risk but rather a decrease, which indicates that in the case of Bank A low-amount loans were repaid regularly. The second range that was statistically significant was the range above PLN 21501, for which a negative value of the regression coefficient was recorded. This means that if the customer applied for a loan exceeding this amount, the risk associated with servicing it increased, as indicated by the value of the regression coefficient.

Table 5. Credit risk logit model for Bank A.

Trait	Trait Attribute	Coefficient	Wald's Statistics	*p*-Value
Net monthly household income	under 2800	n.d.	n.d.	n.d.
	from 2801 to 3075	1.59	13.77	0.001
	above 3076	−0.37	1.16	0.281
Loan amount	under 1300	1.77	13.33	0.001
	from 1301 to 21,500	n.d.	n.d.	n.d.
	above 21,501	−0.96	4.80	0.028
Has the client defaulted on any obligations within 3 years from the date of application	Yes	n.d.	n.d.	n.d.
	No	0.94	16.08	0.001
Does the client have an account with the Cooperative Bank?	Yes	0.75	9.86	0.002
	No	n.d.	n.d.	n.d.
Age of main applicant	under 36	−0.37	0.90	0.343
	from 37 to 40	n.d.	n.d.	n.d.
	over 41	1.12	6.10	0.014

Table 6. Credit risk logit model for Bank B.

Trait	Trait Attribute	Coefficient	Wald's Statistics	*p*-Value
Has the client defaulted on any obligations within 3 years from the date of application	Yes	n.d.	n.d.	n.d.
	No	1.72	37.23	0.000
Age of main applicant	under 29	n.d.	n.d.	n.d.
	from 30 to 54	1.23	6.21	0.013
	over 55	−0.36	0.90	0.343
Place of residence	City	n.d.	n.d.	n.d.
	Village	0.52	4.00	0.045
Declared amount of the applicant's burdens	under 214	n.d.	n.d.	n.d.
	from 215 to 1900	2.01	5.60	0.018
	above 1901	−0.58	1.20	0.274

Table 7. Credit risk logit model for Bank C.

Trait	Trait Attribute	Coefficient	Wald's Statistics	*p*-Value
Has the client defaulted on any obligations within 3 years from the date of application	Yes	n.d.	n.d.	n.d.
	No	3.25	22.56	0.000
Net monthly household income	under 2435	1.17	1.69	0.194
	from 2436 to 3256	1.80	7.74	0.005
	from 3255 to 4,30	−1.77	3.15	0.076
	from 4631 to 5078	0.12	0.01	0.906
	from 5079 to 8704	n.d.	n.d.	n.d.
	from 8705 to 9395	3.40	6.44	0.011
	above 9396	−1.15	0.80	0.370
Current credit exposure	under 230	n.d.	n.d.	n.d.
	from 231 to 5384	2.49	12.83	0.000
	above 5385	−1.77	3.87	0.049
Loan amount	under 7499	0.09	0.04	0.841
	from 7500 to 15,499	1.87	10.19	0.001
	above 15,500	n.d.	n.d.	n.d.

Table 8. Credit risk logit model for Bank D.

Trait	Trait Attribute	Coefficient	Wald's Statistics	*p*-Value
Number of persons in borrower's household	1 or less	0.85	10.46	0.001
	2 and more	n.d.	n.d.	n.d.
Gender of main applicant	female	0.71	8.23	0.004
	male	n.d.	n.d.	n.d.
Place of work	pensioner/business activity	n.d.	n.d.	n.d.
	private sector/public sector	0.57	3.85	0.050
Loan amount	under 2599	0.75	6.42	0.011
	above 2600	n.d.	n.d.	n.d.
Age of main applicant	under 33	1.29	21.25	0.000
	over 34	n.d.	n.d.	n.d.
Declared amount of the applicant's burdens	below 1045	0.55	5.10	0.024
	above 1046	n.d.	n.d.	n.d.

Table 9. Credit risk logit model for Bank E.

Trait	Trait Attribute	Coefficient	Wald's Statistics	*p*-Value
Net monthly household income	under 1799	n.d.	n.d.	n.d.
	above 1800	1.41	25.82	0.000
Current credit exposure	under 619	0.59	5.61	0.018
	above 620	n.d.	n.d.	n.d.
Whether there is community of property	Yes	0.64	7.27	0.007
	No	n.d.	n.d.	n.d.
Declared amount of the applicant's burdens	below 1170	0.76	8.55	0.003
	above 1171	n.d.	n.d.	n.d.
Does the applicant have a bank account limit	Yes	0.69	6.43	0.011
	No	n.d.	n.d.	n.d.

The third variable concerned the customer's history of servicing prior obligations. As in the case of the model developed for the whole group of customers, in the case of Bank A, the regression coefficient for the variant in which the customer had not been in arrears in repayment of any obligations during the three-year period was positive, indicating that if the customer had not been in arrears in repayment of obligations during this period, the risk associated with granting him a loan was lower than in the situation when such delays occurred. Another variable that was included in the model was whether the customer had an account at the cooperative bank where he applied for a loan. As the analyses show, customers who had an account at Bank A had a lower level of risk than customers who did not have an account at that bank.

The last variable that was included in the model was the age of the primary applicant. For this characteristic, the statistically significant age range was over 41, meaning that customers who were older than 41 were better borrowers than younger individuals. This may have been due to the fact that people of this age tended to have an established economic and financial situation, which translated into a lower risk of defaulting on their loan obligations.

The model estimated for Bank B finally included four variables (see Table 6): if the customer had delays in paying other liabilities (credit/financial) in the 3 years prior to submitting the loan application [Yes/No], the age of the main applicant [years], a place of residence [City/Village] and declared amount of the applicant's burdens [PLN]. In the model developed for Bank B, one of the variables was information about the customer's arrears in the last 3 years and, as in previous models, the absence of arrears in this period worked in favor of the customer in the credit evaluation process, as it indicated a lower level of risk than in the case of customers who showed such arrears. For the variable indicating the age of the main applicant, the range of 30 to 54 years proved to be significant, for which the regression coefficient was positive. It was interesting to note that for the customers of this bank, the variable indicating the place of residence of the customer turned out to be significant, with the situation where the customer lived in a rural area being more favorable than if the customer lived in an urban area, since the regression coefficient for the customer attribute of rural residence was positive. Moreover, in the logit model developed for Bank B, the level of declared financial burden of the applicant between 190 and 1900 PLN was significant.

In the case of Bank C (see Table 7), the final version of the logit model included four variables i.e., Has the client defaulted on any obligations within 3 years from the date of application [Yes/No], Net monthly household income [PLN], Current credit exposure [PLN], and Loan amount [PLN]. The first variable, like the previous models, indicated the importance of the client's positive history of cooperation with financial institutions in terms of debt service. In the case of the variable determining monthly net household income, the range between PLN 2436 and PLN 3256 and between PLN 8705 and PLN 9395 was significant. In the case of these values, the risk of the customer's defaulting on the loan agreement was the lowest and resulted from the fact that such an income level allowed meeting the current needs of the borrower and servicing the debt. Importantly, current credit exposure was also important in explaining the creditworthiness of Bank C's individual customers. The value of this exposure in the amount between PLN 231 and PLN 5384 was associated with lower risk than in the case when the exposure exceeded PLN 5385. This was due to the fact that too high a level of credit exposure reduced a client's ability to service the debt in the long term, and thus exposed the bank to a greater credit risk associated with servicing such a client. The model also included a variable for the amount of a credit a customer applied for. Interestingly, the highest regression coefficient was recorded for the range from PLN 7500 to PLN 15499, indicating that customers taking out debt in Bank C were characterized by a high level of reliability.

The final form of the credit risk assessment model developed for Bank D included six characteristics describing the profile of a customer applying for a loan with that bank (see Table 8). This model included a variable for the number of people in the borrower's household, where it was preferable for the borrower to have one or fewer people in the household, which was because this characteristic was related to the borrower's cost of living and economic situation, as a larger number of household members resulted in a reduction in the borrower's ability to service the debt.

Another variable was the gender of the principal applicant, where it was desirable for the bank customer to be female, which was associated with a lower risk of default to the bank. In Bank D, the characteristic that determined the place of work of the main applicant was also important. The analyses conducted showed that in the case of Bank D, customers who earned income from private or government jobs had a lower level of risk than customers who earned income from other sources.

In addition, the model included a variable specifying the amount of credit requested by the customer. In the credit risk assessment of an individual customer in Bank D, the amount below PLN 2599 was significant, for which the risk was lower than in the case of higher loan amounts. The high significance, of loans with low amounts may also have been important, due to the fact that in the case of the variable determining the age of the main applicant, the analyses showed that the highest regression coefficient was for the age below 33 years. What indicates that Bank D was crucial to finance young people with a stable family situation and not burdened with other liabilities, as in the case of the last variable the level of declared amount of the applicant's burden below PLN 1045 was significant.

Table 9 shows the estimation results of the logit model for Bank E. There were six variables in the final version of the model. Among the significant attributes, all of them had two attributes each, of which only one was statistically significant. In the case of the variable of net monthly household income, its amount above PLN 1800 had a positive effect on the customer's creditworthiness. A customer's level of credit exposure below PLN 619 had the same effect. An important element in the assessment of credit risk in this bank was the existence of a community of property in the main applicant, which contributed to an increase in the probability of the customer's compliance with the loan agreement. In addition, the credit risk assessment of Bank E included the applicant's declared debts below PLN 1170 and the possession of a bank account limit.

Analyzing the variables that were included in the estimated logit regression models, it was found that in each of the banks studied, a different set of characteristics characterizing the borrower was significant (see Table 10). However, taking into account the nature of these variables, it was noted that in the general model, out of seven variables, three of them were related to characteristics of the customer's financial situation. In the model estimated for Bank A, out of five variables, each of them concerned a different area describing the customer profile. In the case of Bank B, which included four variables, two of them were related to the sociodemographic situation of the customer. The model developed for Bank C also included four variables, two of which specified the financial situation of the bank customer. In the model developed for Bank D, on the other hand, six variables were significant, among which three were related to sociodemographic characteristics defining the customer and the other two characteristics were related to the financial situation of the applicant. The model developed for Bank E consisted of five variables, within which there were as many as four variables related to the financial situation of the customer.

Table 10. Summary of variables in estimated credit risk logit regression models in analyzed banks by feature category.

Specification	General Model	Bank A	Bank B	Bank C	Bank D	Bank E
Characteristics of the customer's history with financial institutions [CIF]	1	1	1	1	0	0
Characteristics of the client's history with the cooperative bank where he/she applied for credit [CBS]	1	1	0	0	0	1
Characteristics of the client's financial situation [CSF]	3	1	1	2	2	4
Characteristics of the transaction [CD]	1	1	0	1	1	0
Socio-demographic characteristics of the customer [CSD]	1	1	2	0	3	0
Total	7	5	4	4	6	5

These results indicate that among the characteristics of the customer and the associated credit risk, the most significant were the variables describing the financial situation of the customer, which was primarily with the ability of the customer to service the debt. Therefore, it may be assumed that the hypothesis stating that the differentiation of the effectiveness of individualized scoring models for credit risk assessment in cooperative banks results mainly from taking into account the features characterizing the history of cooperation of a customer with a given cooperative bank and other financial institutions was confirmed.

Using the above assumptions, a scoring card was determined for the assessment of an individual customer in the cases considered. The details of the analyses are presented in Table 11. The results of the developed scoring cards coincide with the results obtained from the developed logit regression models.

Table 11. Scoring cards for the studied cooperative banks.

Specification	General Model		Bank A		Bank B		Bank C		Bank D		Bank E	
	Trait Attribute	Points	Trait Attribute	Points	Trait Attribute	Points	Trait Attribute	Points	Trait Attribute	Points	Trait Attribute	Points
Has the client defaulted on any obligations within 3 years from the date of application [Yes/No]	Yes	28	Yes	0	Yes	0	Yes	0	—	—	—	—
	No	28	No	28	No	37	No	81	—	—	—	—
Age of main applicant	under 24	23	under 36	−10	under 29	0	—	—	under 33	37	—	—
	from 25 to 58 years	−13	from 37 to 40	0	from 30 to 54	36	—	—	over 34	0	—	—
	from 59 to 65 years	0	over 41	32	over 55	−10	—	—	—	—	—	—
	from 66 to 73 years	−12	—	—	—	—	—	—	—	—	—	—
	over 74 years	34	—	—	—	—	—	—	—	—	—	—
Whether there is community of property	Yes	24	—	—	—	—	—	—	—	—	Yes	19
	No	−10	—	—	—	—	—	—	—	—	No	0
Declared amount of the applicant's burdens	under 850	13	—	—	under 214	0	—	—	under 1045	16	under 1170	22
	from 851 to 1675	−7	—	—	from 215 to 1900	56	—	—	above 1046	0	above 1171	0
	above 1676	0	—	—	above 1901	−17	—	—	—	—	—	—
Loan amount	under 250	−4	under 1300	50	—	—	under 7499	3	under 2599	22	—	—
	from 251 to 16,015	38	from 1301 to 21,500	0	—	—	from 7500 to 15,499	53	above 2600	0	—	—
	from 16,016 to 32,150	−10	above 21,501	−27	—	—	above 15,500	0	—	—	—	—
	above 32,151	0	—	—	—	—	—	—	—	—	—	—
Does the applicant have a credit card limit	Yes	0	—	—	—	—	—	—	—	—	—	—
	No	15	—	—	—	—	—	—	—	—	—	—

Table 11. *Cont.*

Specification	General Model		Bank A		Bank B		Bank C		Bank D		Bank E	
	Trait Attribute	**Points**	**Trait Attribute**	**Points**	**Trait Attribute**	**Points**	**Trait Attribute**	**Points**	**Trait Attribute**	**Points**	**Trait Attribute**	**Points**
Occupation	farmer	17	—	—	—	—	—	—	—	—	—	—
	pensioner	0	—	—	—	—	—	—	—	—	—	—
	manual worker white-collar worker	−1	—	—	—	—	—	—	—	—	—	—
Net monthly household income	—	—	under 2800	0	—	—	under 2435	33	—	—	under 1799	0
	—	—	from 2801 to 3075	33	—	—	from 2436 to 3256	52	—	—	above 1800	28
	—	—	above 3076	32	—	—	from 3255 to 4630	−51	—	—	—	—
	—	—	—	—	—	—	from 4631 to 5078	3	—	—	—	—
	—	—	—	—	—	—	from 5079 to 8704	0	—	—	—	—
	—	—	—	—	—	—	from 8705 to 9395	98	—	—	—	—
	—	—	—	—	—	—	above 9396	−33	—	—	—	—
Does the client have an account with the Cooperative Bank?	—	—	Yes	21	—	—			—	—	—	—
	—	—	No	0	—	—			—	—	—	—
Place of residence	—	—	—	—	City	0			—	—	—	—
	—	—	—	—	Village	15			—	—	—	—
Current credit exposure	—	—	—	—	—	—	under 230	0	—	—	under 619	17
	—	—	—	—	—	—	from 231 to 5384	71	—	—	above 620	0
	—	—	—	—	—	—	above 5385	−51	—	—	—	—
Number of persons in borrower's household	—	—	—	—	—	—	—	—	1 or less	12	—	—
	—	—	—	—	—	—	—	—	2 and more	0	—	—
Gender of main applicant	—	—	—	—	—	—	—	—	female	21	—	—
	—	—	—	—	—	—	—	—	male	0	—	—

Table 11. *Cont.*

Specification	General Model		Bank A		Bank B		Bank C		Bank D		Bank E	
	Trait Attribute	**Points**	**Trait Attribute**	**Points**	**Trait Attribute**	**Points**	**Trait Attribute**	**Points**	**Trait Attribute**	**Points**	**Trait Attribute**	**Points**
Place of work	—	—	—	—	—	—	—	—	pensione business activity	0	—	—
	—	—	—	—	—	—	—	—	private sec-tor/public sector	17	—	—
Does the applicant have a bank account limit	—	—	—	—	—	—	—	—	—	—	Yes	20
	—	—	—	—	—	—	—	—	—	—	No	0

With this and the previous research results in mind, a score below which the probability that a customer will default on a loan agreement will meet the assumptions made was determined. The cut-off value separating good and bad customers for the scoring cards developed for individual banks and the general population was set at the level of respectively: Card for the general population: 82 points, Bank A: 76 points, Bank B: 69 points, Bank C: 75 points, Bank D: 62 points, Bank E: 57 points. This meant that if the number of points was below the cut-off value then the customer was considered as a "bad" customer and if the value was above or equal to the cut-off value the customer was considered as a "good" customer.

Table 12 shows the results on the efficiency of the developed scoring cards. The data presented in this table shows that all of the developed scoring cards had a very high level of overall efficiency, which ranged from 90.48% for the model developed for Bank C to 92.37% for the model developed for Bank C. Such a high level of overall efficiency of the developed scoring cards indicates that the developed cards, taking into account the specificity of the individual banks, gave satisfactory results on a general level. The developed scoring cards were also characterized by a very high level of efficiency of the second level, which indicated the percentage of correctly identified "good" customers, in the case of developed cards this level ranged from 92.41% for the model developed for Bank D to 94.69% for the model developed for Bank B. This meant, errors in recognizing "good" customers were less than 8%, which should be considered a satisfactory level.

Table 12. Evaluation of the effectiveness of the estimated scoring cards.

Model Efficiency	General Model	Bank A	Bank B	Bank C	Bank D	Bank E
First efficiency level	78.32%	75.00%	75.86%	71.43%	82.76%	75.86%
Second efficiency level	93.30%	92.56%	94.69%	92.65%	92.41%	92.74%
Overall efficiency	91.67%	90.74%	92.37%	90.48%	91.35%	90.87%

An important element of the evaluation of individual customers in the banks studied was the level of efficiency I degree, which determined what proportion of "bad" customers the model developed identified correctly. In this respect the results varied, because in the case of the model developed for Bank C the level of efficiency of the first degree was 71.43%, and for the model developed for Bank D this efficiency was 82.76%. This means that out of the population of "bad" customers, the models developed for the banks studied recognized more than 70% of them correctly, which can be considered a satisfactory level, because the application of these models could contribute to a significant reduction in credit risk in the banks studied, by eliminating a significant proportion of "bad" customers (see Table 13).

Table 13. Summary of the overall efficiency level of the developed scoring models to evaluate customers in other banks.

The Sample to Which the Model Was Applied	General Scorecard	Scorecard for Bank A	Scorecard for Bank B	Scorecard for Bank C	Scorecard for Bank D	Scorecard for Bank E
Whole sample	91.67%	87.16%	87.08%	80.28%	90.98%	91.36%
Bank A	82.22%	90.74%	85.19%	67.78%	91.48%	81.85%
Bank B	81.78%	66.95%	92.37%	67.80%	82.20%	82.20%
Bank C	86.81%	66.67%	75.82%	90.48%	86.45%	76.56%
Bank D	76.69%	91.73%	81.95%	78.57%	91.35%	81.95%
Bank E	76.43%	87.07%	87.45%	82.51%	82.51%	90.87%

In the next stage of the research, the application of the individualized scoring cards developed for each bank was simulated in relation to the other banks studied. This simulation was designed to determine the suitability of the individualized models for credit risk assessment at other entities. Tables 14 and 15 show the levels of efficiency in the application of the individualized scoring cards with respect to the banks studied. Table 14 shows the overall efficiency of the individual scoring cards with respect to the banks under study and the entire sample. The results showed that the estimated general model had the highest level of overall efficiency with respect to the whole sample. The use of this card for creditworthiness assessment in the surveyed banks yielded worse results than when a bank-specific model was used for risk assessment. This trend was evident for both overall efficiency and first and second tier weldability. This indicates that individualized credit assessment models contributed to credit risk reduction in the banks studied. Thus, it can be concluded that the hypothesis stating that the use of individualized scoring models in cooperative banks allows credit risk mitigation to a greater extent than with the use of general model was confirmed.

Table 14. Summary of the second efficiency level of the developed scoring models to evaluate customers in other banks.

The Sample to Which the Model Was Applied	General Scorecard	Scorecard for Bank A	Scorecard for Bank B	Scorecard for Bank C	Scorecard for Bank D	Scorecard for Bank E
Whole sample	93.30%	93.82%	92.19%	86.78%	95.62%	97.85%
Bank A	86.78%	92.56%	90.91%	73.55%	95.04%	83.06%
Bank B	87.92%	73.91%	94.69%	72.46%	91.02%	85.02%
Bank C	91.02%	67.76%	77.96%	92.65%	92.41%	76.33%
Bank D	84.39%	94.94%	85.65%	84.39%	92.41%	86.08%
Bank E	82.05%	93.16%	92.31%	89.32%	87.61%	90.87%

Table 15. Summary of the first efficiency level of the developed scoring models to evaluate customers in other banks.

The Sample to Which the Model Was Applied	General Scorecard	Scorecard for Bank A	Scorecard for Bank B	Scorecard for Bank C	Scorecard for Bank D	Scorecard for Bank E
Whole sample	78.32%	32.87%	45.45%	27.27%	53.15%	38.46%
Bank A	42.86%	75.00%	35.71%	17.86%	60.71%	71.43%
Bank B	37.93%	17.24%	75.86%	34.48%	51.72%	62.07%
Bank C	50.00%	57.14%	57.14%	71.43%	46.43%	78.57%
Bank D	13.79%	65.52%	51.72%	31.03%	82.76%	48.28%
Bank E	75.86%	37.93%	48.28%	27.59%	41.38%	75.86%

However, it is worth noting that in a few cases the overall effectiveness of individualized scoring cards developed for a particular bank was lower than when a scoring card developed for another bank was used (see Table 14). An example of such a situation was the model developed for Bank A, whose application to the assessment of Bank D's customers produced a slightly better result than the application of the model developed for that bank. A similar situation was observed in the case of a card developed for Bank D, the application of which to Bank A gave better results than the use of a card dedicated to that bank. It should be emphasized, however, that these differences were insignificant.

The overall fitness results were due to the fact that the individualized scoring sheets developed for each bank, often had higher levels of the second-tier fitness relative to other banks than they were developed. An example is the model developed for Bank A, which best identified Bank D's "good" customers. Similarly, the card developed for B, produced better results in terms of second-level efficiency for Bank E than the model developed for that bank. The scoring card model developed for Bank D, on the other hand, had the highest level of efficiency in recognizing "good" customers when applied to the entire sample. In addition, its use in assessing Bank A's customers produced better results than the card developed specifically for that bank.

However, when looking at the first-level efficiency of the developed scoring cards in terms of their recognition of "bad" customers, it was found that in all of the analyzed cases the model developed for a given bank was characterized by the highest level of efficiency. Thus, it can be concluded that the scoring cards dedicated to credit risk assessment were best at recognizing "bad" customers when used in the bank for which they were developed. This is particularly important due to the fact that proper identification of "bad" clients, i.e., those who did not meet the terms of the loan agreement concluded with the bank, is crucial for credit risk management in a cooperative bank. It is interesting to note that there are significant discrepancies between the first and second tier efficiency levels. Such significant discrepancies are due to the application of a bank-dedicated model to another bank. This indicates the necessity of applying an individualized approach to the construction of scoring models in cooperative banks.

5. Conclusions

An important element in a cooperative bank's assessment of a customer is the quality of the relationships that exist between stakeholders. These are particularly important in the case of financing individual customers, since in their case a good knowledge of the customer by the bank can facilitate the data collection process and contribute to the use of much more information during the credit assessment than in the case of unknown customers. Many researchers also point out that larger banks, particularly commercial banks, are less likely than cooperative banks to process and provide "soft and relational" information through their hierarchical structures. This contributes to the fact that cooperative banks, to a greater extent, respond to the needs of their customers and thus provide them with adequate financial support. The results of the research indicate that among the factors with high predictive power were the features characterizing the client's history of cooperation with the cooperative bank, where they applied for a loan. It may mean that when assessing credit risk related to financing individual customers cooperative banks, due to their local character, have an advantage over other financial institutions. Therefore, it seems justified to use this element in the assessment of individual clients by cooperative banks.

The estimated logit regression models showed that a different set of a borrower characteristics was significant in each of the banks studied. However, taking into account the nature of these variables, it was noted that the variables characterizing the financial situation were crucial, since in most of the developed models they constituted a significant part of it. In the general model, out of 7 variables, three of them were related to the characteristics of the customer's financial situation. In the models estimated for Bank A and Bank A, only one variable concerning the customer's financial situation appeared. In the other individualized models, variables of a financial nature appeared more frequently. The model developed for Bank C also contained 4 variables, two of which specified the financial situation of the bank's customer. In the model developed for Bank D, on the other hand, 6 variables were significant, among which 3 were related to sociodemographic characteristics defining the customer and another 2 characteristics were related to the financial situation of the applicant. The model developed for Bank E, consisted of 5 variables, within which there were as many as 4 variables related to the financial situation of a customer. This allowed us to verify positively the hypothesis stating that the biggest influence on the adequacy of an individual credit risk assessment in Polish cooperative banks has the features characterizing the previous financial situation of a customer.

In assessing an individual credit risk, a cooperative bank should use individualized models for its credit assessment process because, as the research showed, a different set of borrower characteristics was important in each of the developed individualized scoring models. Additionally, the discretization and clustering of the variables themselves indicate a significant difference in this regard among the cooperative banks studied. Of the thirteen variables that were included in the individualized scoring models, none of the variables occurred in all of the developed scorecards. Four variables indicating whether the client was in arrears on any obligations within 3 years of the application date, age of the primary applicant, declared amount of the applicant's debts, loan amount, and net monthly household income, occurred in three out of five individualized scoring models developed. These results allowed us to conclude that the hypothesis stating that the variation in the effectiveness of individualized scoring models for credit risk assessment in cooperative banks results mainly from taking into account the characteristics of the customer's history of cooperation with a given cooperative bank and other financial institutions was confirmed.

The scoring model built for one cooperative bank should not be used directly in another bank, especially when it applies to different products and different customer groups. The research indicated significant differences in general efficiency as well as in efficiency of the first and second degree of the developed models, therefore the model developed for one cooperative bank should not be directly implemented in another cooperative bank, because it is connected with the risk of its mismatch to the area of bank's activity and profile of its clients. Therefore, it may be concluded that individualized scoring models dedicated to a given bank give the best results. Moreover, implementing ready-made solutions developed on data from a large number of cooperative banks without statistical research may expose the bank to misestimation of risk and financial loss. Hence, it was concluded that the hypothesis stating that the use of individualized scoring models in cooperative banks allows for a credit risk reduction to a greater extent than using general model was confirmed.

The research made it possible to identify the key factors determining the level of a credit risk of individual customers in cooperative banks and to develop individualized models for the assessment of this risk using quantitative, qualitative, and behavioral characteristics, which has not yet been carried out in relation to cooperative banks. Additionally, the results of the research pointed out the limitations of using general models to assess credit risk of individual customers in cooperative banks, which has not been directly confirmed so far in relation to this sector. Moreover, the analysis of credit risk assessment in cooperative banks on the basis of contract theory made it possible to indicate the importance of relationality in contacts with customers in credit risk reduction. Thus, it allowed to include new elements in the definition of credit scoring in relation to cooperative banks. As the research carried out allowed us to conclude that credit scoring is a diagnostic tool measuring the probability of a potential borrower′s defaulting on a loan agreement, in the context of the borrower′s handling of a new loan commitment, with particular reference to the bank's past experience in assessing individual customers and quantitative, qualitative and behavioral characteristics. Such a definition of credit scoring allowed us to include all its elements so far discussed in the literature and to complement its definition with the element related to the cooperative bank's knowledge of its customers.

An important element in a cooperative bank's assessment of a customer is the quality of the relationship that exists between them. These are particularly important in the case of financing individual customers, since in their case a good knowledge of the customer by the bank can facilitate the data collection process and contribute to the use of much more information during the credit assessment than in the case of unknown customers. Many researchers also point out that larger banks, particularly commercial banks, are less able to process and communicate "soft and relational" information through their hierarchical structures than cooperative banks. This state of affairs contributes to the fact that cooperative banks, to a greater extent, respond to the needs of their customers and thus provide them with adequate financial support. It is also indicated by the results of the research, which show that among the factors with high predictive power were the features characterizing the client's history of cooperation with the cooperative bank, where he applied for a loan. It may mean that cooperative banks, due to their local character, have an advantage over other financial institutions when assessing credit risk related to financing individual customers. Therefore, it seems reasonable for cooperative banks to use this element in assessing individual customers. The individualized scoring models developed on the basis of the studied banks included quantitative, qualitative, and behavioral variables. The combination of these features made it possible to construct models that were significantly adjusted to the bank's profiles, owing to which the banks were able to significantly reduce credit risk related to lending to individual customers. At the same time, basing the risk assessment on the variables which were included in the individualized scoring models allowed cooperative banks to reduce the effects of asymmetric information which is a part of uncertainty related to the conclusion of a credit agreement. The use of three perspectives for customer evaluation in the analysis gave better results than the previous methods used in the studied banks. Therefore, it was concluded that the hypothesis stating that the inclusion by cooperative banks in the credit risk assessment of qualitative, quantitative, and behavioral characteristics of individual customers may allow to reduce the effects of market imperfections resulting from asymmetry of information and contract theory was confirmed.

The study involved a limited number of cooperative banks and their customers, therefore its scope is limited and provides possibilities for further work in the field of searching pivotal factors determining the level of credit risk of retail customers using a wider range of data and diversified multidimensional methods. Nonetheless, the results may serve as an auxiliary source of information for cooperative bank managers regarding the determinants of individual credit risk assessment and as a basis for further research in this area.

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