VILNIUS UNIVERSITY

RENATAS ŠPICAS

STATISTICAL CREDIT RISK ASSESSMENT MODEL OF SMALL AND VERY SMALL ENTERPRISES FOR LITHUANIAN CREDIT UNIONS

Summary of doctoral dissertation

Social Sciences, Economics (04S)

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VILNIAUS UNIVERSITETAS

RENATAS ŠPICAS

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Daktaro disertacijos santrauka

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Introduction

The relevance of the topic. The provision of loans to the members is the main area of activity of the credit unions. Having summarised the reviews of the credit union performance by the Bank of Lithuania for the last five years, it is observed that the interest from the loans granted generate the major part of the income of these institutions, and the loans to the members make up the largest part of the assets of the credit unions (the Bank of Lithuania, 2016; 2015; 2014; 2013; 2012), it is, therefore, fair to say that the risk arising from the lending activity is the most significant risk faced by credit unions when performing regular activities. Naturally, in order to ensure the continuity and stability for both individual credit unions and the sector as a whole, it is necessary to assess and manage the taken credit risk properly.

In the scientific literature (O'Connel, 2012; Fonteyne, 2007; MacPherson, 2007) it is stated that the credit unions operating within the community have an innate ability to manage information asymmetry better and that allows them to effectively assess credit risk through the expert methods. However, in the literature it is pointed out that with the development and growth of credit unions, they begin to operate beyond the community, and the social control element that helps to assess credit risk more accurately for small credit unions becomes weaker (O'Connel, 2012; Fonteyne, 2007; MacPherson, 2007). Fonteyne (2007) argues that the credit union operating model has been developed for small institutions, which now have become complex financial conglomerates. These facts allow to assume that the expert methods of credit risk assessment function only at a nascent development stage of the credit unions and as long as the unions have the ability to use the social control element for reduction of information asymmetry. For this reason, the sustainable development of credit unions cannot take place without appropriate credit risk assessment models. It was claimed by Kaupelytė (2007) that the sector of Lithuanian credit unions is in a transition stage of development. Five years later and then after nine years McKillop and Wilson (2015; 2011) claimed that Lithuanian credit unions were still in a transitional stage of development. It can be presumed that the development of credit union sector stagnates due to inability to assess and manage credit risk properly.

Evaluation of the ability to assess credit risk by Lithuanian credit unions may be performed having summarized the documents of the Bank of Lithuania as a key supervisory authority in the sector. Having analysed the history of the efficiency measures applied in the credit union sector by the Supervision Board of the Bank of Lithuania (LB) from 1 January 2013 to 1 May 2016 (LB, 2013-2016) it is observed that during a 30-month period LB applied 32 efficiency measures for the credit unions where 25 were linked to the inadequate credit risk assessment. It constitutes 78% of the total efficiency measures applied. In the annual and quarterly operation surveys of the credit unions and Lithuanian Central Credit Union, the Bank of Lithuania consistently notes the lack of the credit union ability to properly assess the taken credit risk, too big appetite of credit risk and lack of the equity to cover losses increasing due to non-performing loans (LB, 2016; 2015; 2014; 2013; 2012). These and some other causes have encouraged the LB to initialise the reform of credit union sector. For this purpose, the Bank of Lithuania has prepared a draft reform of the credit union sector and announced it as a document for the public debate. The Bank of Lithuania, with a description of the context and justification of the reforms, has introduced five key factors, where three of them are related to the misuse of credit risk assessment and management, determining the reform of credit unions (LB, 2014a).

In contemporary scientific literature dealing with credit risk assessment (Dzidzevičiūtė, 2013; Valvonis, 2008; Thomas, 2009; Anderson, 2007; Siddiqi, 2006), it is recognised that the statistical models of credit risk assessment separate the reliable debtors more accurately than expert models do. When applying more accurate models, the credit institutions operate more efficiently: firstly, less loans are granted to unreliable clients (type I error); secondly, a more precise assessment allows to provide more loans to trusted clients (avoiding type II error), thereby increasing the income of a credit institution from the interest. The statistical methods are also suggested to be applied by Basel Committee on Banking Supervision (BCBS, 2004).

The appropriateness of the statistical model to be applied in the activities of the credit institution mainly depends on two factors: *the first* is accuracy, which to a great extend depends on the quality of the statistical sample and compliance to the target credit segment of the credit institution, and the *second* is the compliance to the needs of credit institution business. In the scientific literature, it is recognised that the credit union operation model is different from the operation models of commercial banks or other financial institutions (Fonteyne 2007). Therefore, it can be assumed that the models of the credit risk assessment suggested in contemporary scientific literature are not applicable to the sector of Lithuanian credit unions due to the differences in the demands of the business of credit institutions and non-compliance of applied statistical sampling to target credit segment of credit unions. From a theoretical point of view, the most issues related to the credit risk should be come across by the credit unions being in a transition and mature stage of development, but this issue has not been addressed so far neither by Lithuanian nor foreign investigators.

The extent of research on the subject. It is generally stated that the pioneer of modern statistical evaluation of credit risk is Altman, who in 1968 introduced the discriminant credit risk assessment model for the enterprises[1] (Altman, 1968). After Altman, discriminant models were suggested by Martin (1977), and Tafler and Tisshaw (1977), Springate (1978), Lis (1982), Fulmer (1984) and the others (Mackevičius, 2007; Altman, 2000; Altman, Saunders, 1998) as well. In 1974, the logistic regression model for the credit risk assessment was suggested firstly by Chesser and after him logistic regression for this purpose was applied by: Martin (1997), Ohlson (1980), Zmijewski (1984), West (1985), Koh (1991), Platt et al. (1991), Hopwood et al. (1994) (Dzidzevičiūtė, 2010; Mackevičius, Silvanavičiūtė, 2006; Lennox, 1999; Altman, Saunders, 1998). The statistical methods is widely applied in the assessment of the credit risk in the following researches (Fernandes, Artes, 2016; Sousa et al. 2016; Petropoulos et al. 2016; Sohn et al. 2016; Xiao et al. 2016; Lessmann et al. 2015; Danėnas, Garšva 2015; Manab et al. 2015; Fei et al. 2015; Florez-Lopez, Ramon-Jeronimo 2015; Tomczak, Zięba 2015; Harris 2015; Van Vlasselaer et al. 2015; Wang et al. 2015; Bekhet, Eletter 2014; Gupta et al. 2014; Niklis et al. 2014; Ju, Sohn 2014; Verbraken et al. 2014).

For the first time, artificial intelligence techniques were applied for prediction of the insolvency by Tam (1991), who created a neural network model to predict the insolvency of commercial banks. In addition to the neural networks in credit risk

[1] Due to the simplicity of the adaptation of Altman's model, as well as its interpretability and versatility, the models suggested by the author have become popular rapidly and have been widely applied in the research. At the time of the preparation of this dissertation, according to Prado et al. (2016), Altman was the most quoted author in the field of credit risk assessment.

assessment, other artificial intelligence techniques are widely applicable, where the most popular are the decision trees (Florez-Lopez, Ramon-Jerome's 2015; Tomczak, Zięba 2015) and support vector machines (Cardoso and others by 2016; Petropoulos et al. 2016; Xiao et al. 2016). Artificial intelligence techniques are rapidly gaining popularity, however, their practical application in the activities of credit institutions are limited because of the low explainability of results regarding incompatibility with recommendations of the Basel Committee of Banking Supervision. The popularity of artificial intelligence techniques is determined by their high level of accuracy and the possibility of practical application in the financial institutions that are applied different legal regulation than the one recommended in the Basel documents. Typically, these financial institutions do not accept deposits insured by the state, for instance, crowdfunding and peer-to-peer lending companies, instant credit and leasing service companies.

One of the first Lithuanian researchers dealing with the credit risk evaluation methods in the context of bankruptcy prediction was Grigaravičius (2003; 2003a) who applied logistic regression model to predict company bankruptcy. Comprehensive scientific analysis of the issues of credit risk was made by Valvonis (Valvonis 2004, 2006, 2006a, 2008a, 2009; Savickaitė, Valvonis, 2007; Kamienas, Valvonis, 2004; Jasevičienė, Valvonis 2003). In the dissertation Valvonis (2008) developed a summarized theoretical credit risk assessment model applied by commercial banks in Lithuania. Dzidzevičiūtė (2010; 2010a; 2013) analysed in detail the methodology of the development and application of the statistical models for credit risk assessment in commercial banks. In the dissertation (Dzidzevičiūtė, 2013) she offered a statistical model of the credit risk assessment of the Lithuanian enterprises set up on the basis of logistic regression model. Danėnas and Garšva (2015; 2012; 2011; 2010; 2009) and Danėnas et al. (2011) applied support vector machines for the credit risk assessment and examined their accuracy in operation. Moreover, the publications on the credit risk assessment issues have been published lately by these Lithuanian researchers: Butkus et al. (2014); Mileris (2014; 2012; 2009); Budrikienė, Paliulytė (2012); Bivainis, Garškaitė (2010); Mackevičius (2010); Vasiliauskaitė, Cvilikas (2008); Garškaitė (2008); Mackevičius Silvanavičiūtė (2006); Merkevičius et al. (2004); Jasevičienė, Valvonis (2003). In Lithuania, lately the following dissertations where credit risk assessment issues have been dealt with have been defended: Danėnas (2013), Dzidzevičiūtė (2013), Stulpinienė (2013), Mileris (2011), Pridotkienė (2009), Merkevičius (2008), Valvonis (2008), Valužis (2007), Grigaravičius (2003). It should be noted that the issues of the credit risk assessment are more often analysed in dissertations on mathematics and computer science than in the economics or management science areas.

Credit risk assessment issues in the scientific literature have become significantly more popular since 2009, which may be linked to the global financial crisis in a connection to the poor credit risk assessment (Prado et al. 2016). Although the assessment issues of the credit risk were widely analysed in the past and this has remained the focus of the researchers recently credit risk assessment in cooperative banking has been researched occasionally only. Peculiarities of credit union performance in Lithuania and risks related to it were analysed by Kėdaitis, Žilinskas (2013), Kaupelytė, McCarthy (2006). Moreover, activities of the credit unions have been recently analysed by Jasevičienė et al. (2015, 2015a, 2014); Jasevičienė (2014); Dubauskas (2012); Igarytė, Ramanauskas (2011); Lukoševičius (2005); Bubnys, Kaupelytė (2004); Levišauskaitė, Kaupelytė (2003). However, these studies have not looked upon the issues of the enterprise credit risk assessment in credit unions.

Abroad, credit risk assessment model created on the basis of support vector machines for Barbados credit unions was suggested by Harris (2013), credit risk assessment model based on neural network for activities of credit unions was proposed by Desai et al. (1996). It should be noted that although these authors used targeted segments of credit unions corresponding to the data samples, but when concluding the credit risk assessment models, the operational features, issues, the external surrounding and the business needs of the credit unions and requirements for models in the process of development have not been analysed. In addition, these models are not suitable for use in the sector of Lithuanian credit unions due to the nonconformity between regulatory and target credit segment. Also, it should be noted that in Lithuania the legal entities, corresponding to the definition of small and very small enterprises, may be associate members of credit unions (Official Gazette, 2016, XII-2567), as it is defined by the Republic of Lithuania Law on Small and Medium-sized Business Development (Official Gazette, 1998, 105-4689). So far, for the segment of small and very small enterprises in Lithuania the credit risk assessment models have not been developed, as well as in the context of this segment other issues related to the assessment of the credit risk have not been analysed.

To sum up, it can be argued that there is a general lack of research in scientific literature dealing with credit risk assessment issues in credit unions, and cooperative banking in general. So far, the researchers have not analysed business needs of credit unions for credit risk assessment models, and there are models corresponding to target credit segment of credit unions, i.e. small and very small enterprises created. The lack of attention for cooperative banking from the researchers is observed not only in the area of credit risk analysis as in the context of cooperative banking there has been little analysis so far on other types of banking risk, for instance, operating risk, market risk, liquidity risk, etc.

The scientific definition of the problem. In the process of development of credit unions when expanding their activities outside the community, the element of social control partially or completely stops functioning, so credit unions face difficulties in assessing credit risk. In regard to this, the issue dealt with in the dissertation is the creation and application of statistical credit risk assessment models in credit unions, taking into account their specificity, the needs of the business and the external surroundings where the credit unions function.

The object of the dissertation is the enterprise credit risk assessment in the credit unions applying statistical models.

The aim of the dissertation: to create a statistical model of enterprise credit risk assessment for Lithuanian credit unions having examined the issues, needs and requirements of credit risk assessment in credit unions.

The objectives of dissertation:

1. To define the concept and nature of the risk, and to provide a theoretical analysis of the different types of risks in the credit union activity.
2. To provide a theoretical analysis of different aspects of credit risk assessment during various stages of credit union development.
3. To define and analyse the main model’s development stages and factors affecting methods and data choice for model development.

4. Having analysed the issues of activities of Lithuanian credit unions, to identify the needs, expectations, and requirements of credit unions for statistical credit risk assessment model.
5. With regard to the identified business needs, expectations, and requirements of credit unions for credit risk assessment model, to develop the model creation sample and choose the proper methods for model development.
6. To create a statistical model of credit risk assessment for the Lithuanian credit unions.
7. To apply a developed model when analysing the business loan portfolio of Lithuanian credit unions and to carry out back-testing of the model.

The research methods. When writing the thesis, the scientific literature, legislation, documents have been analysed and the information they contain has been abstracted, systematised and critically analysed. Other general scientific methods were applied.

When dealing with the sector of Lithuanian credit unions the following quantitative methods were applied: a survey (interview), and survey by phone. Survey data is summarised and structured, forming a statistical sample. When processing statistical data, MS Excel and R Software Package were employed. For the presentation of the results of the research visual information Circos Software Package was used as well.

When creating the statistical credit risk assessment model, the following mathematical and statistical methods were applied: Markov chain, the visual data rendering techniques, methods based on entropy measure (information value, further IV), regression analysis. The methods applied for the assessment of binary classification models were used to evaluate the reliability of model: the ROC curve, AUC measure, the Gini index and the graph of forecasted probabilities. In order identify the optimal cut off point the method of expected maximum profit (EMP) calculation was applied.

The scientific novelty. Taking into account the already carried out research and identified areas analysed fragmentary, the scientific novelty of this dissertation is defined as follows:

1. The specific features of the activities of the credit unions were identified and their cause and effect relation with particular risks of credit union operating were determined.

2. Different aspects of credit risk assessment during various stages of credit union development were revealed.
3. The factors affecting the choice of methods and data for the development of credit risk assessment model identified.
4. Following detailed research of the sector of Lithuanian credit unions, the problematic aspects of Lithuanian credit unions, targeted segments of credit and the requirements for statistical credit risk assessment model were defined.
5. The new method of definition formulating of a "good" and "bad" loans for the segment of small and very small enterprises was developed and presented in detail.
6. The statistical credit risk assessment model of small and very small enterprises using a statistical sample corresponding to the target segment of Lithuanian credit unions and taking into account the requirements and needs of the credit union was developed.
7. The provided recommendations of integration of the model in the decision-making support system of credit unions allow including the Central Credit Union into the credit decision-making process. Moreover, the proposed integration method provides the ability to exploit the broad capabilities of the credit unions network more effectively when sharing the rejected applications.

The main defended statements:

1. The expert assessment of the credit risk in the performance of credit unions can be effective only as long as the credit union is in the early stage of the development, and has the ability to use the social control element to reduce information asymmetry.
2. Contemporary credit risk assessment models (including the combined and applied other types of credit institutions and credit offices) are not suitable for the use in the activities of Lithuanian credit unions since when they are created the analysis is not performed from three perspectives: credit institutions, external factors and homogeneous risk groups.
3. The developed statistical credit risk assessment model for small and very small businesses is an effective tool for credit risk assessment in credit unions when they are in transition and maturity development stages.

The practical significance of the dissertation. The results of this research were used by the author to create interactive credit risk modelling system, which has been successfully installed in various types of credit institutions in Lithuania and abroad. Currently, the system is adapted for the activities of the central credit unions in order to assess and manage risk at the systematic level.

The main directions of further research:

1. To adapt the developed model for dichotomous nature of credit unions, including the factor of created social value.

The essential research assumptions and limitations:

1. At the time of the survey of credit unions there were 72 credit unions operating in the country that constituted the research population. In order to ensure the accuracy of the research, the entire research population was intended to be surveyed, however, only 56 credit unions agreed to participate.
2. One of the inhomogeneity features of the credit unions is that they have different target crediting segments. Nevertheless, the survey data were generalised for the entire survey population making a summary compilation of the business needs of the credit unions that is used for ***enterprise*** credit risk assessment model. (Ignoring the fact that some of the respondents did not provide credits for the legal entities).
3. The activities of credit unions are limited by the territorial principle (Official Gazette, 1995). When creating enterprise credit risk assessment model, statistical sample of the enterprises including enterprises from different geographical areas of Lithuania was used. Thus, it was assumed that small and very small enterprises operating in different geographical areas constitute a single homogeneous risk segment.
4. For the creation of the model, a maximum sample of 1252 enterprises, with regard to the actual possibilities, was used.
5. Whereas there were no data on rejected applications in the statistical sample, appropriately, the problem of rejected inference was not analysed.

The structure of the dissertation. The dissertation consists of an introduction, three chapters and conclusions (Fig. 1).

The first chapter of the dissertation develops the theoretical discussion. This chapter defines the concept of risk, highlights the usual features of the activities of credit unions, reveals the cause-effect links to operating risks of credit unions, analyses the credit risk assessment peculiarities in different stages of credit union development. The scarcity of expert credit risk assessment methods is distinguished and the stages and methods of the credit risk assessment model development are considered. The procedure of statistical credit risk assessment model composition is analysed and the factors determining methods applied for the model creation and the data used are identified. Also, the basic model development techniques, distinguishing their advantages, disadvantages and limitations of application are dealt with in the first chapter.

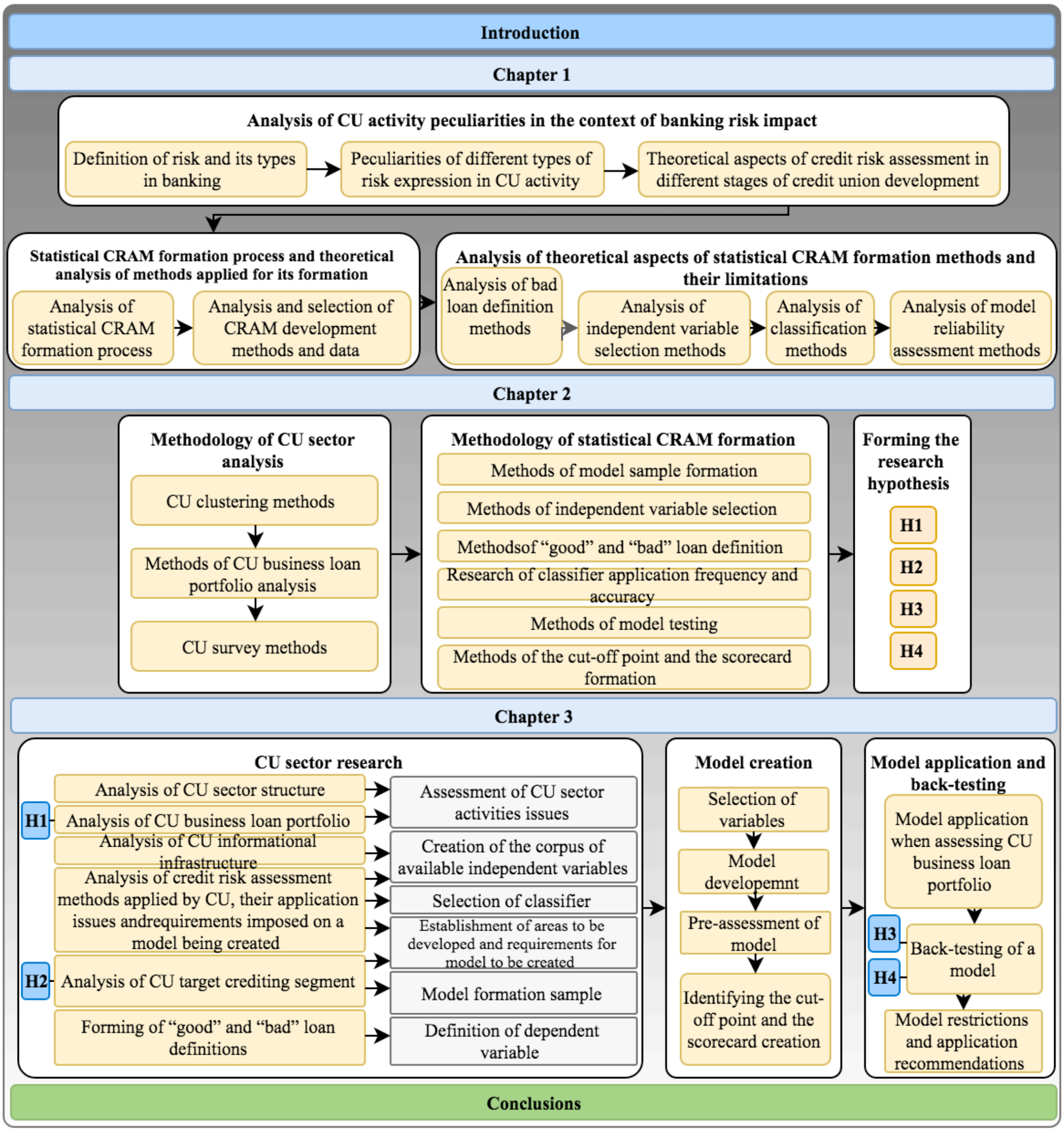

Fig. 1. The layout of dissertation structure and logical sequence.

The second chapter provides the model creation methodology. In this chapter, the survey methodology of credit union sector is developed with regard to clustering of comprising credit unions, the study of the business loan portfolio and the survey of credit unions. Moreover, the methodology of the statistical model creation is presented in this chapter and research hypotheses are formulated.

The third empirical chapter of the dissertation presents the results. At first, the results of the credit union sector are introduced, providing the ability to choose methods and data suitable for model development for the credit unions. Secondly, the logistic regression model is designed and its pre-assessment was made. Thirdly, the model back-testing is performed. Fourthly, the recommendations for the model application are submitted and the model integration into the decision-making support system for credit unions is suggested.

List of publications on the subject of dissertation

1. Špicas, R., Kanapickienė, R.; Vijūnas, M.; Kirka, R. (2017), "Development of enterprise credit risk assessment model for Lithuanian credit unions", *Transformations in Business & Economics* (in press).
2. Kanapickienė, Rasa; Špicas, Renatas (2016). Bankruptcy Prediction Models: Case of the Construction and Transport & Storage Sector in Lithuania. *Perspectives of Business and Entrepreneuship Development - 2016*, p. 344-357.
3. Špicas, Renatas; Vijūnas, Mindaugas; Kanapickienė Rasa (2016). Setting optimal performance period and bad loan definition for credit risk assessment model for Lithuanian credit unions. *Perspectives of Business and Entrepreneuship Development - 2016*, p. 713-728.
4. Špicas, Renatas; Vijūnas, Mindaugas (2016). The early history of credit unions and the development of the business model. *Economics and Management: Issues and Perspectives*, No. 1 (38), p. 118-128.
5. Špicas, Renatas; Kanapickienė, Rasa; Ivaškevičiūtė, Monika (2015). *Perspectives of Business and Entrepreneuship Development*. 15th International Conference at Brno University of Technology, Brno, p. 147-161.

The presentations in the international scientific conferences on the subject of dissertation

1. In the conference "International scientific conference of Ernestas Galvanauskas" (Šiauliai, 2016). The topic of presentation "The early history of credit unions and the development of the business model".
2. In the conference "New Challenges of Economic and Business Development" (Ryga, 2016). The topic of presentation "Setting optimal performance period and bad loan definition for credit risk assessment model for Lithuanian credit unions".
3. In the conference "New Challenges of Economic and Business Development" (Ryga, 2016). The topic of presentation "Bankruptcy Prediction Models: Case of the Construction and Transport & Storage Sector in Lithuania".

Chapter 1. Theoretical aspects of credit risk assessment in the credit unions.

The peculiarities of risk occurrence in the cooperative banking. Having summarised the research of scientific and professional literature dealing with the issues of theoretical definition of risk (iso.org, 2016; SRA, 2015; Crouhy et al. 2014; Kungwani 2014; Coleman 2011; Rutkauskas, Stasytytė 2011. Webster's, 1993; Knight, 1921), it can be said that there is no universal definition of risk. In the context of this dissertation research, the risk is understood as the probability that in the future the actual results of the creditor activities will be different from the planned ones.

In the scientific literature dealing with risk issues of banking activities the different classifications of the banking risk appear, but it can be argued that the majority of sources (BCBS, 2013 p. 57; Gudelytė, Valužis, 2012; Glantz, Mun, 2010; Goyal, 2010; Valvonis 2008; Altman, Hotchkiss, 2006) make a distinction between the following basic types of risks: *operational risk, market risk, liquidity risk, and credit risk.* In the broad sense, the activities of cooperative banking are identical to those of commercial banking, therefore, when analysing the cooperative banking it is appropriate to exclude the same types of risks. When analysing the forms of risk occurrence in the activities of credit unions, it is necessary to research the factor of uniqueness of credit union activities. In the case of specific financial institutions, the traditional kinds of risks in the activities of credit unions are manifested under influence of other risk factors as well as the specific features of the activities of credit unions.

The link between the credit risk, activities peculiarities of credit unions and other types of risk. In the scientific literature dealing with cooperative banking issues, the following typical features of cooperative credit unions are highlighted most often: cooperative ownership structure, cooperative management form, the dichotomous nature of credit unions, the relation of association, small size of the organisation and specific legal regulation (McKillop, Wilson, 2015; Fonteyne, 2007; Kupelytė, 2007; MacPherson, 2007; Baarda, 2006; Davis, 2001; Wolf, 1983). The link of these features with the risks typical for credit unions is illustrated in Figure 2.

In cooperative banking, unlike in traditional one, the risk of adverse selection, moral risk, difficulties in equity attraction, which are typical for other types of banking, however, their manifestation in cooperative banking is associated with the peculiarities of this kind of banking features. The particular risk factors have to be distinguished: the overlap between the interests, the low market depth, the application of expert credit risk assessment models, limited possibilities of attraction of deposits and their high cost. As presented in the figure (Fig. 2), all kinds of risks and factors are related by cause-effect relations and affect the overall risk of the activities of credit unions, which is generally higher than in regular financial organisations.

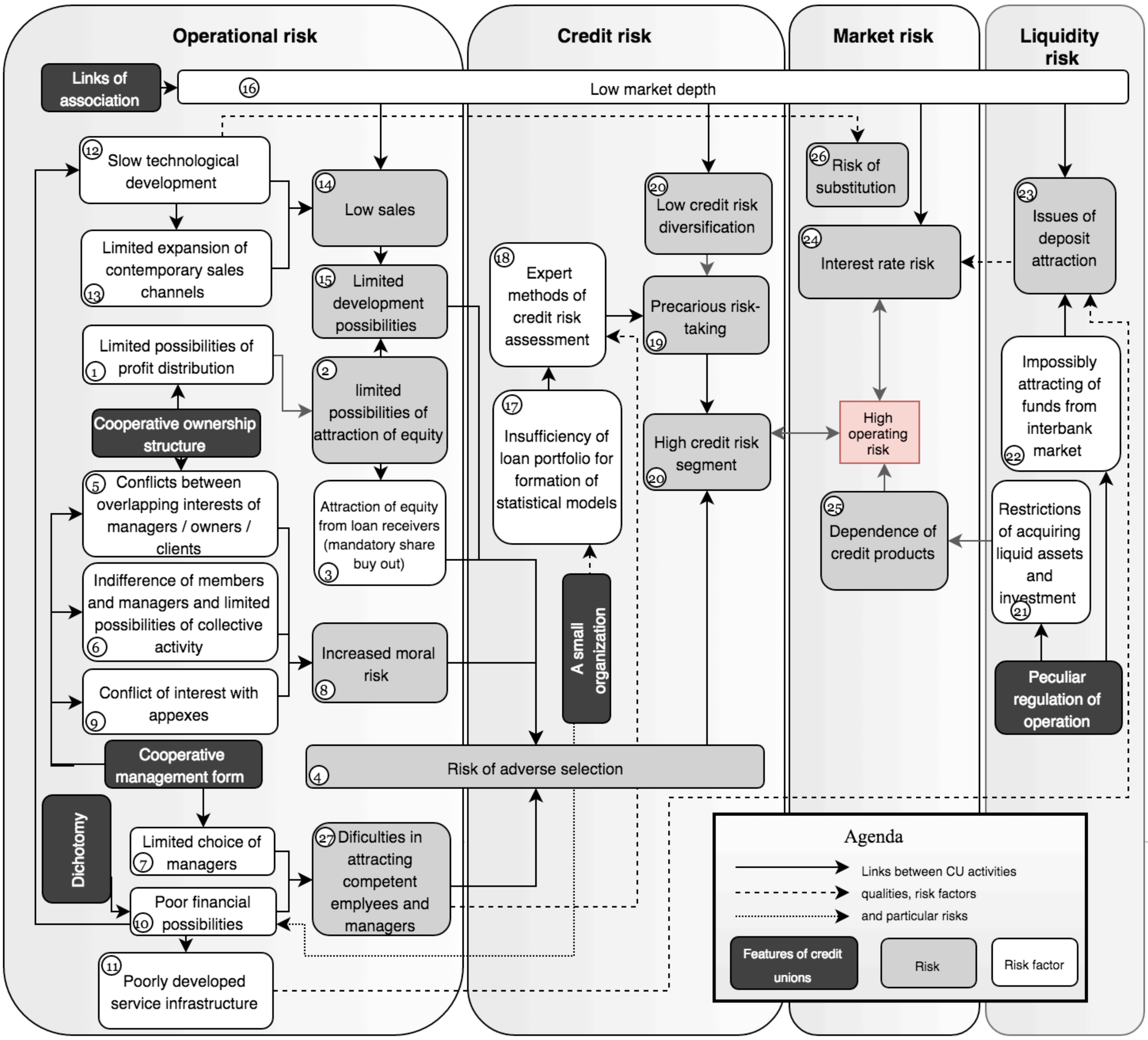

Fig. 2. Features of credit unions and their relationship with the representative operating risks of the credit unions

Created by the author

Theoretical aspects of credit risk assessment in different stages of the credit union development. For a long time the activities of the credit unions were of social orientation, which in the scientific literature is most often associated with poverty reduction and financial seclusion of union members (McKillop, Wilson, 2015; Macdonald, Jazwinski, 2012; Birkenmaier, Curley, 2009; Jones, 2008, 2005, 2004; Westricht, Bush, 2005). This operation model of credit unions applied in different countries until 1980-2000 is called "social" or "traditional" credit union operating model in literature. Social model was marked by orientation to small communities, personnel operating on voluntary basis and socially oriented philosophy (Chambers, Ryder, 2008; Jones, 2008; Richardson, Lennon, 2001). Most of the authors, who dealt with the ability of credit unions to perform a social function, agree that the impact of credit unions on poverty level and the reduction of financial exclusion is questionable (Jones, 2008; Richardson and Lennon, 2001).

These circumstances encouraged the credit unions and their associations to overview their operational principles, segment, objectives and methods. The world's largest association of credit unions announced new strategic plans and the formation of a "new model" (Chambers, Ryder, 2008; Ferguson, McKillop, 2006). The issues of application of a new operating model is related not only to the established values of the credit unions, but also with the significant environmental changes in the credit risk assessment. In the scientific literature, it is often noted that credit unions have an innate ability to manage information asymmetries better than traditional credit institutions, through social control element, but social relation decreases when the unions expand (Power et al. 2014; MacPherson, 2007; Guinnane, 1994; Fonteyne 2007). It is also observed that the structure of credit unions itself and the risk assessment and management methods applied in activities have been adapted to small credit institutions on the basis of existing communities (Fonteyne 2007). The new credit union operating model, which is focused on economic efficiency, operational efficiency and economies of scale, presupposes an imminent growth of credit unions and the provision of services outside the community losing the social control element and the advantage when managing the information asymmetry. Thus, it can be argued that the credit risk assessment methods should vary according to the stage of credit union development.

It can be stated that under the new operating model, with a view to efficiency and economies of scale, the credit unions must evolve and this evolution will meet in accordance with its essence the stages of development defined by Sibbald et al. (2002), namely, nascent, transition and mature. During the different stages of the union development, depending on the analytical information received by credit union, available human, technological and financial resources, the unions should employ different methods for the assessment of the credit risk, in order to assess as accurately as possible, the credit risk of the potential credit recipients.

As already mentioned, at a nascent stage of the credit union development, the credit unions can quite effectively assess the credit risk by applying expert credit risk assessment methods by means of social control element. At the transition stage of development, the activity of the enterprises is expanded outside the community, the social element of control becomes weaker, therefore, the quantitative methods must be applied by invoking analytical information. Typically, this stage of the development of credit unions have not collected yet a sufficient amount of data to create statistical models and, therefore, in a transition period the expert developed assessment models may be applied on the basis of the rules. However, in order to assess the credit risk of the potential loan recipient as accurately as possible, the unions should aim at starting applying the statistical models for credit risk assessment in the shortest possible period of time.

Theoretical framework of the development of the statistical credit risk assessment model. When analysing the formation methods of statistical models theoretically, at first the *concept* of *theoretical model development* is formulated. In the most general meaning, the *model* can be defined as a logical or mathematical description of the components and/or functions, reflecting the significant characteristics of the structure of an object or phenomenon in the process. *Statistical credit risk assessment model* is a tool of the creditor in the decision-making process that helps to calculate the probability of default according to the primary data of potential loan recipient and the decision on the grant of the loan is made.

The formation of statistical credit risk assessment model is a complex process that can be divided into six basic stages. The figure presents the main six development stages of statistical credit risk assessment model (Fig. 3).

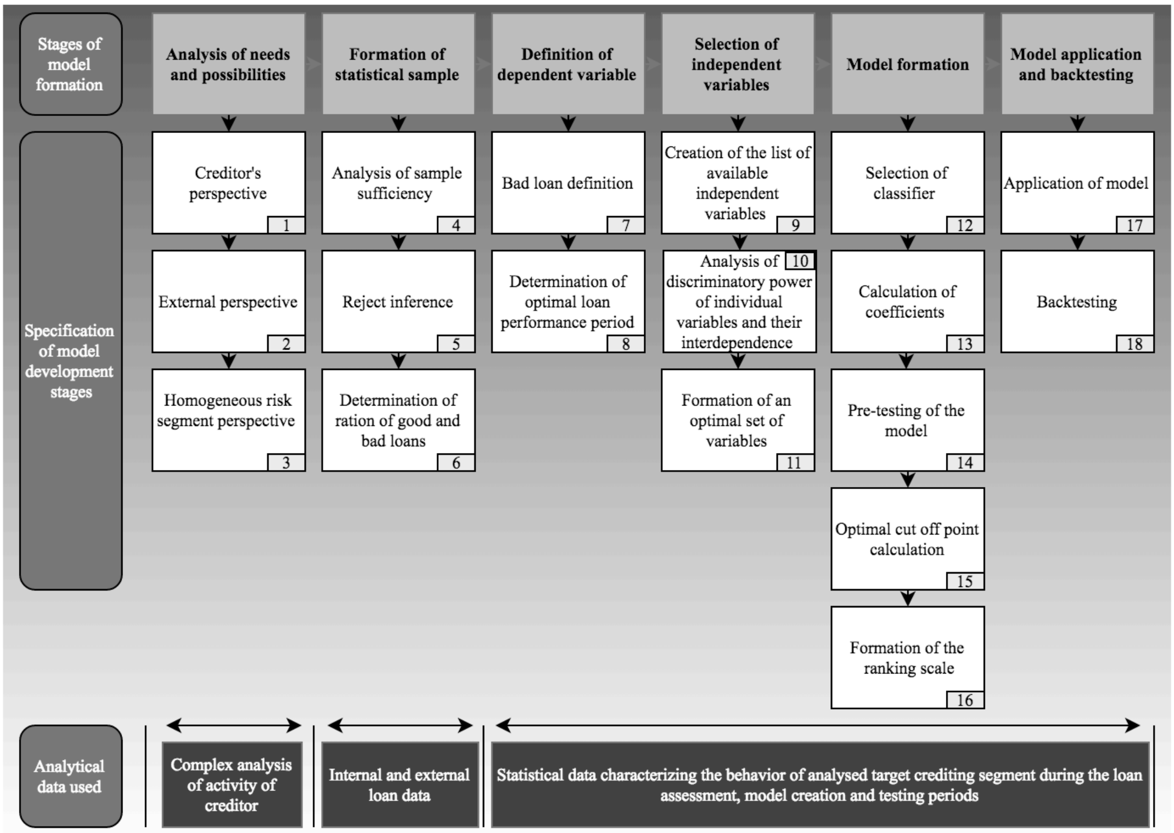

Fig. 3. The development stages of statistical credit risk assessment model and analytical information

Created by the author in accordance with Garcia et al. (2015); Anderson (2007); Siddiqi (2006)

The development process of credit risk assessment model presented in the figure (Figure 3) corresponds to the classical approach to the development of credit risk assessment models, which is followed in the scientific literature (Garcia et al., 2015; Dzidzevičiūtė, 2013; Anderson, 2007; Siddiqi, 2006). This process is uniform and generally should not be different from the selected target credit group, credit institution that will apply this model, or the external environment for the application of the model.

Having summarised the scientific literature (Dzidzevičiūtė, 2013; Anderson, 2007; Siddiqi, 2006), it can be stated that **the methods and data** applied in the development of credit risk assessment model determine the basic properties of **the model characteristics**: **the discriminating power with respect to the results of the analysed segment, the explainability of the model results, the risk tolerance level, compliance with the existing requirements for the creditor and other business needs of the creditor.**

Prior the decision-making on the methods to be applied and data to be used, it is appropriate to carry out an analysis from three perspectives: *credit institutions* (which will apply the model), *forecasted homogeneous groups* and *perspectives of external factors* (Fig.3, 1-3). In order to show how the results of this analysis determine the other model development stages, and to reveal the cause-effect relations, the process of model development (Fig. 3) is presented through perspectives distinguished by the author (Fig. 4).

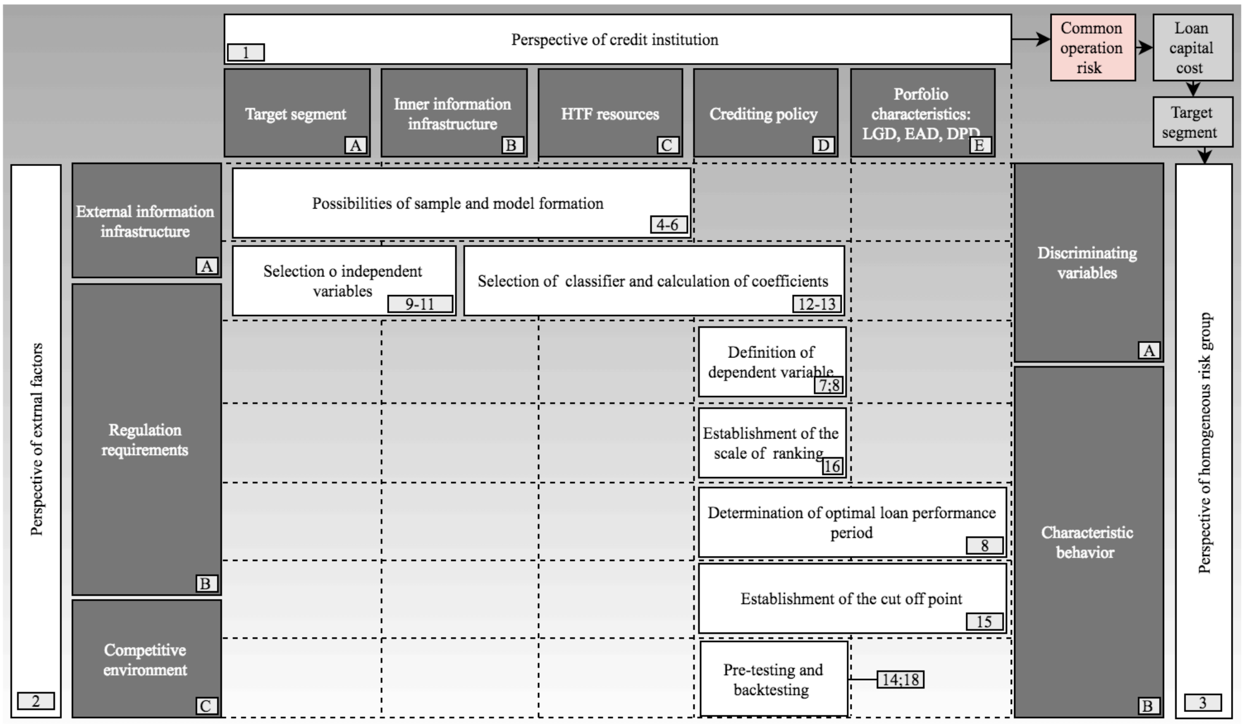

Fig. 4 Factors affecting the model development methods applied for data selection and the characteristics of the model

Created by the author

Abbreviations: DPD – days past due.

In the figures (Fig. 3; Fig. 4) the stages of model development process are numbered (1-17). At is can be observed, the model development process begins with the model development needs and the analysis of possibilities, which is carried out from three perspectives (Fig. 4, stages 1-3). In Fig. 4, these three perspectives of analysis are presented as dimensions determining the methods of other model development stages, the data used and by this the characteristics of the full model to be developed. The model development stages are further discussed in detail.

The information used in the model development can be divided into external and internal. It is generally acknowledged that the overall *information infrastructure* quality available for modelling, *price*, and the availability of *human, technological and financial* *resources* in the company (hereinafter referred to as HTF resources), determine significantly whether the model can be developed and whether it is developed in the organisation or through a third party. In the case when the creditor's internal data is not sufficient for the model development, the data or its part may be acquired from the outside: credit bureaus, associations, etc. In the case when there is not enough data for the model development or when the model development is economically irrational, the creditors may apply external models or expert models (otherwise known as the expert assessment systems or rule-based models).

When the creditor chooses the target credit segment, it is necessary to ensure that the segment is homogeneous from the risk point of view and define the modelled *dependent variable*. The definition of the dependent variable is usually associated with the definition of loss event – non-performing loan. In the scientific literature dealing with the credit risk assessment issues, when defining "bad" loans commonly the feature of payment delay of 90 days or more days is applied (Sorokin, 2014; Nguen, 2014; Rajan et al., 2010; Bloem, Freeman, 2005; Thomas, 2009, 2000; Jiménez et al., 2014; Beck et al., 2013; Leow, Crook, 2016, 2014; Bendendo, Bruno, 2012; Khemraj, Pasha, 2009).

For the quantitative definition of bad loan Markov migration matrices and their modifications are usually applied (Choy, Laik, 2009; Anderson, 2007; Siddiqi, 2006). When applying these methods, it is assumed that the passage of the loan from one state of delay to another meets the Markov chain process. This assumption means that the migration between the status of the loans is going homogeneously with respect to time. In other words, the application of the method of Markov chains, the stage of maturity of the loans is not taken into account, and it is considered that the probability of migration during the period of observation is the same.

Once a variable is determined, the *optimal performance period of the loan* is defined, which depends on the behaviour of the target segment, the regulations applied to the creditor and the credit policy. The Basel Committee on Banking Supervision refers to the not shorter, than one-year loan period of observation (BCBS, 2004).

For quantitative determination of optimal loan performance period, the cohort analysis is the used most commonly (Choy, Laik, 2009; Anderson, 2007; Siddiqi, 2006). This analysis consists of several steps. First, the loans issued in different months are combined into homogeneous groups - cohorts. Second, the average delay is calculated for each cohort. Third, the results are displayed graphically and analysed. By applying this method, a variety of time delay settings are available (Choy, Laik, 2009; Siddiqi, 2006). The essence of this graphic method is to determine such an observation period, during which the average number of delay days is growing rapidly. The sample of the model is modelled from "mature loans", which are less likely to occur in the group of the bad loans.

Available *independent variables* are determined by taking into account the specific behaviour of the selected credit segment, the modelled dependent variable, internal and external information infrastructure. It is important to ensure that the selected independent variables would be qualitatively homogeneous and uniform within the meaning of the content of both the development of the statistical model back-testing samples, and practical application of the model in the process. Typically, the creation process of final set of independent variables consists of two stages: 1) *creation of the corpus of available independent variables* (the formation of the set of independent variables) and 2) t*he selection of independent variables included in the model*. When selecting independent variables, their individual discriminatory power and the correlation between them are take into account.

In the assessment of the individual discriminatory properties of individual independent variables, the method of information value is the most frequently used (Bolton, 2009), rarer X^2(Chi square test). For the evaluation of the relationship between the variables Spearmen correlation coefficient is most frequently applied (Oreski, Oreski, 2014; Dzidzevičiūtė 2013; Tsai Hsiao, 2010; Ioniţă I., Şchiopu D. 2010; Hörkkö 2010; Lee, 2009; Enke, Thawornwong 2009; Tsai 2009; Karakoulas Roobaert, 2006; Shin et al 2005; Atiya 2001).

The *classification method applied* in the model is selected taking into account the regulations applied to the creditor, the credit policy (for instance, the need to interpret the model answers, and/or the expectations for the accuracy of the model), the amount of distinguished independent variables and HTF resources available. In the scientific literature, it is recognised that the models developed on the basis of artificial intelligence are more accurate, but the Basel Committee on Banking Supervision stress to apply statistical models whose performance can be explained and documented in detail (BCBS, 2004, p. 410). It should be noted that the methods of artificial intelligence require larger HTF resources, therefore, it is rarely applied in small credit institutions.

One of the most popular methods of statistical classification, used in the area of credit risk assessment is logistic regression (Dzidzevičiūtė, 2010; Kamienas, Valvonis, 2004). Formula of logistical regression is logical sigmoid function:

$$P = \frac{1}{1 + e^{-(\beta_1 + \beta_1 X_{1i} \cdots \beta_n X_{ni})}} \tag{1}$$

In the formula: P – dependent variable, in this case – the default probability, where the possible values are logistically distributed between 0 and 1, β_1, ... β_n – factor variables, while X_1, ... X_{ni} – coefficients (weights) of factor variables.

When performing *the pre-assessment of the model*, the model discrimination power is analysed compared to quantitative characteristics of other models (according to available information). During the forehand inspection of the model and the back-testing it must be taken into account whether the created model corresponds to the objectives set prior to the model development. According to the content of information analysis, discriminatory power assessment methods of binary models can be of two types:

1) methods, indicating the discriminatory properties of the model in the selected cut-off point, of which classification matrices and correct classification ratios are the most widely applied;
2) methods, showing general discriminatory characteristics of the model, regardless of the selected cut off point, where the graphic methods such as receiver operating characteristic curve (ROC) and the area under the curve (AUC) are the most widely applied.

The model assessment methods analysed in the scientific literature are usually applied in two stages: the first on is pre-assessment of the model, and the second one is back-testing. At the time of these assessments, the same methods discussed in this chapter are applied. The difference is that when performing pre-assessment, the breaking point is set by the expert way (most commonly by setting it at 0.5), and the properties of the model shall be assessed in the sample, which is developed from the primary available sample. The performing the back-testing, the model is tested in the real-life environment (such as the simulation of model in the credit institution which it is created for).

The method for determination of cut-off point is selected according to the creditor's credit policy (for instance, risk tolerance), the main characteristics of the loan portfolio (LGD, EAD) and the specific behaviour inherent to the debtor. It should be noted that the selection of breaking point has a direct impact on acceptance rate, competitiveness of the creditor and attractiveness in the market, therefore, when determining the breaking point, the competitive environment should be taken into consideration as well. In the scientific literature, two types of methods for optimal setting of cut-off point are identified (Verbraken et al., 2014; Bravo et al. 2013): 1) prove by an analysis of the accuracy of the classification and 2) prove by economic[2] benefit optimisation analysis. Recent research shows that, in the case of credit risk assessment, the latter method is more efficient (Verbraken et al. 2013 2014; 2013; Bravo et al. 2013; Hand, 2009; Dompuos et al., 2002; West, 2000).

Scorecard is formed in accordance with the regulations applied to the creditor, and taking into account the specific characteristics of the selected target segment of behaviour (for example, a prior PD). Credit institutions which are directly or *mutatis mutandis* applied the regulations of the Basel Committee on Banking Supervision have to apply the ranking from not less than 8 ranks where 6 ranks possibly for those meeting the liabilities and 2 for failing to meet their liabilities (BCBS, 2001, p. 198).

The author of the dissertation research takes the view that the compulsory integral part of development process of the credit risk assessment model is the complex analysis of the model development and opportunities, including research along with the creditor, the external factors and the prospects for the modelled segment.

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[5] When models are developed for the non-profit organisations non-economic benefits can be analysed as well. For instance, Bravo et al. (2013) included the variable reflecting social welfare of the granted loan into determination methodology of separation point:

Part II. Composition methodology for credit risk assessment model.

The theoretical analysis conducted in Chapter 1 of the dissertation allows creating a statistical enterprise credit risk assessment model taking into account the specific features, needs, requirements and external factors of activities of credit unions. In order to create a statistical enterprise credit risk assessment model, the research has been carried out consisting of four research stages.

The first stage of the research dealt with the comprehensive analysis of the Lithuanian credit union sector. *Firstly*, the Lithuanian credit union sector and its structure was analysed. During the analysis, the size of each market maintained by the credit union was estimated, the additional features of the maintained market, the loan portfolio and the size of assets were assigned to credit unions, and the cluster analysis was performed applying the method of k-means and circular diagrams. *Secondly*, the issues of credit risk assessment of enterprises in the sector of credit unions were studied. The sample of business loan data in the sector and the results of cluster analysis were invoked for the research, the method of cohorts was applied. *Thirdly*, the survey of credit unions was performed. During the survey, the requirements of credit unions for general properties of the credit risk assessment model were determined and the difficulties arising when improving the existing credit risk assessment model and/or developing the new one were analysed. The enterprise credit risk assessment model used by credit unions was examined, the issues of its application and limitation were considered, the information infrastructure of credit unions was extensively analysed in order to define the data that can be used in the composition of the model. The analysis sought to determine the target crediting segments of credit unions. In addition, the survey intended to establish the prevailing definition of a bad loan in the sector. *The main task of this stage of the research was to properly identify methods for the development of the model and to select data for the composition of the model taking into account the features of activities of credit unions, the target segment and external factors.*

In *the second stage of the research*, the samples for the composition and testing of the model were formed. *Firstly*, in order to objectively define the dependent variable of the model and the optimal loan performance period, the quantitative analysis was performed applying the Markov chain method, and cohorts were formed. The sample of business loans of Lithuanian credit unions was invoked to define the dependent variable of the model. The additional method for checking the business continuity proposed by the author was additionally applied to define good loans. *Secondly*, the samples for the composition and testing of the model were formed out of statistical sample[3] of small and very small Lithuanian enterprises provided by the credit bureau “Creditinfo Lietuva”, Ltd. *Thirdly*, after a detailed analysis of scientific and professional literature and taking into account the results of information infrastructure analysis, the collection of available independent variables was composed. *Fourthly*, the model variables were selected out of the composed collection of indicators. Apart from general scientific methods, the method of information value correlation matrix was applied to select the model variables and the backward stepwise regression was applied for choosing optimal set of variables.

In *the third stage of the research*, *firstly*, using the samples formed in the second stage of the research, a statistical model was composed on the basis of logistic regression and the pre-assessment of the model was conducted. The model was composed using the R statistical software package (R-team, 2015). *Secondly*, the pre-assessment of the model was performed. The model indicators, the values of corresponding coefficients and the log odds were analysed, the Wald criterion was estimated. The model was analysed calculating the (pseudo) determination coefficient and the Akaike’s criterion. The discriminatory power of the model was checked, i. e. the model receiver operating characteristic (ROC) curves and the graphs of predicted probabilities were drawn, the AUC measure and other indicators of classification accuracy were calculated. *Thirdly*, applying the EMP method introduced by Verbraken et al. (2014, 2013), the optimal cut-off point was determined. *Fourthly*, taking into account the determined cut off point, the scale of 10 ranks was formed with an a priori PD assigned for each rank.

In *the fourth stage of the research*, the composed model was applied to assess CCUL business loan applications, and the back-testing of the model was performed, i. e. the discriminatory properties of the model were assessed at the determined cut off point and of the entire model generally. During the back-testing evaluation of the model, the additional comprehensive analysis of compliance of the composed model with the requirements of credit unions identified during the survey was conducted. After having

[3] The data for the research were provided by the credit bureau UAB “Creditinfo Lietuva”, Ltd.

ascertained that the model is suitable for usage in the activities of credit unions, the method of integration of the model into the decision-making support system of credit unions was proposed.

The following hypotheses of empirical research were formulated (Table 1):

Table 1. Hypotheses of empirical research

H1	**Business loan portfolios of credit unions operating in small markets are of higher quality than of credit unions operating in large markets.** The author presumes that the element of social control characteristic to credit unions operating on the basis of small communities and is functioning in credit unions that operate in small markets. This factor determines that in credit unions operating in small markets, the share of non-performing loans in the total loan portfolio is lower. The confirmation of hypothesis would provide significant grounds to claim that when credit unions operate outside the community, the element of social control weakens and the need for a statistical credit risk assessment model occurs.
H2	**Most commonly credit unions face issues of credit risk assessment in assessing the credit risk of small and very small enterprises and consumer loans.** The author assumes that in respect of credit risk assessment the most problematic segments for credit unions are those which are traditionally assessed through statistical methods of credit risk assessment. The confirmation of hypothesis would allow to argue the application of statistical credit risk assessment models would facilitate the activities of credit unions and would simplify the loan granting process.
H3	**A significant number of enterprises with non-performing loans granted by credit unions do not go bankrupt.** The author presumes that a significant number of small and very small enterprises do not go bankrupt after faced with financial difficulties. Such a phenomenon can be explained in two ways: *firstly*, at the exposure of economic, moral and social factors, business owners tend to pay the enterprise's debts out of their personal funds, and *secondly*, creditors do not tend to litigate for the collection of an insignificant amount of debt. Should the hypothesis be confirmed, when composing statistical credit risk assessment models of small and very small enterprises, it would be expedient to form a modified definition of a "bad" loan including business continuity features within a specified period of observation. This method is provided by author in this dissertation.
H4	**The composed statistical credit risk assessment model of small and very small enterprises will enable a more accurate credit risk assessment of business loans granted by credit unions.** The author presumes that the application of the developed model in the activities of credit unions would result in a lower share of non-performing loans within the loan portfolio of credit unions. Should the hypothesis be confirmed, the developed model could be proposed to the credit union associations. The application of the developed model would contribute to the stability of the credit union sector and the efficiency of the credit union activities.

Part III. Credit risk assessment model of enterprises for Lithuanian credit unions

Problems of credit risk assessment in the sector of Lithuanian credit unions and requirements for the developed model. After *the clusterisation of respondents by attributes*, two conclusions can be drawn. *First*, credit unions are non-homogeneous, there are significant differences – they operate in markets of different sizes, have different structure of assets, follow different strategies of asset management and have significantly different both loan portfolios and the assets in general. *Second*, the majority of Lithuanian credit unions are small by the size of assets at their disposal and loan portfolios. Although the majority of credit unions operate in small markets and Lithuanian credit unions operate in accordance with the territorial principle, it is obvious that this is not the main factor impeding the development of credit unions – a considerable number of credit unions operating in medium-size and large markets are also small (in the sense of both assets and loan portfolios at their disposal, Fig. 5). This situation in the sector of Lithuanian credit unions suggests that credit unions face difficulties in shifting from socially-oriented (or "the old") to business-oriented (or "the new") activity model.

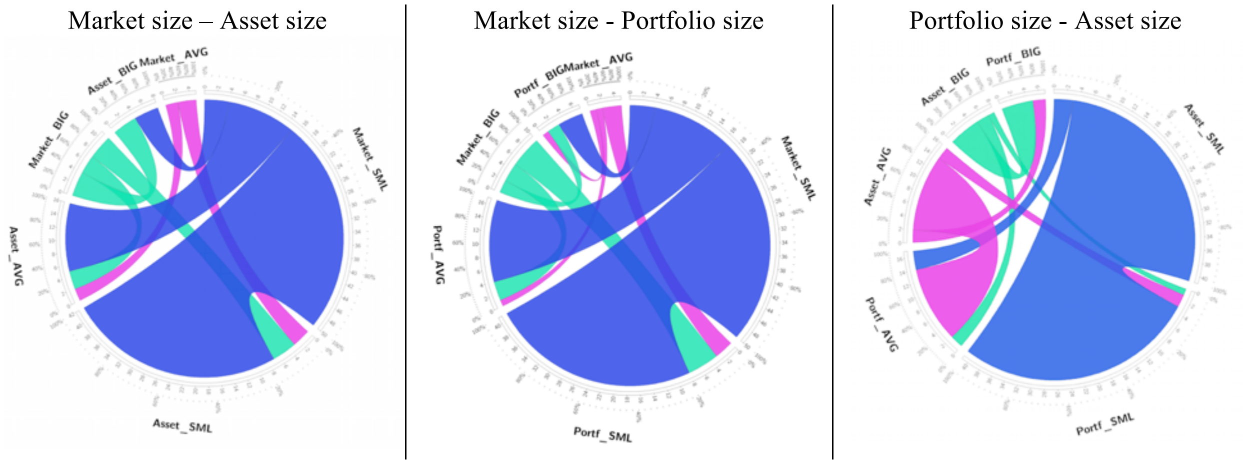
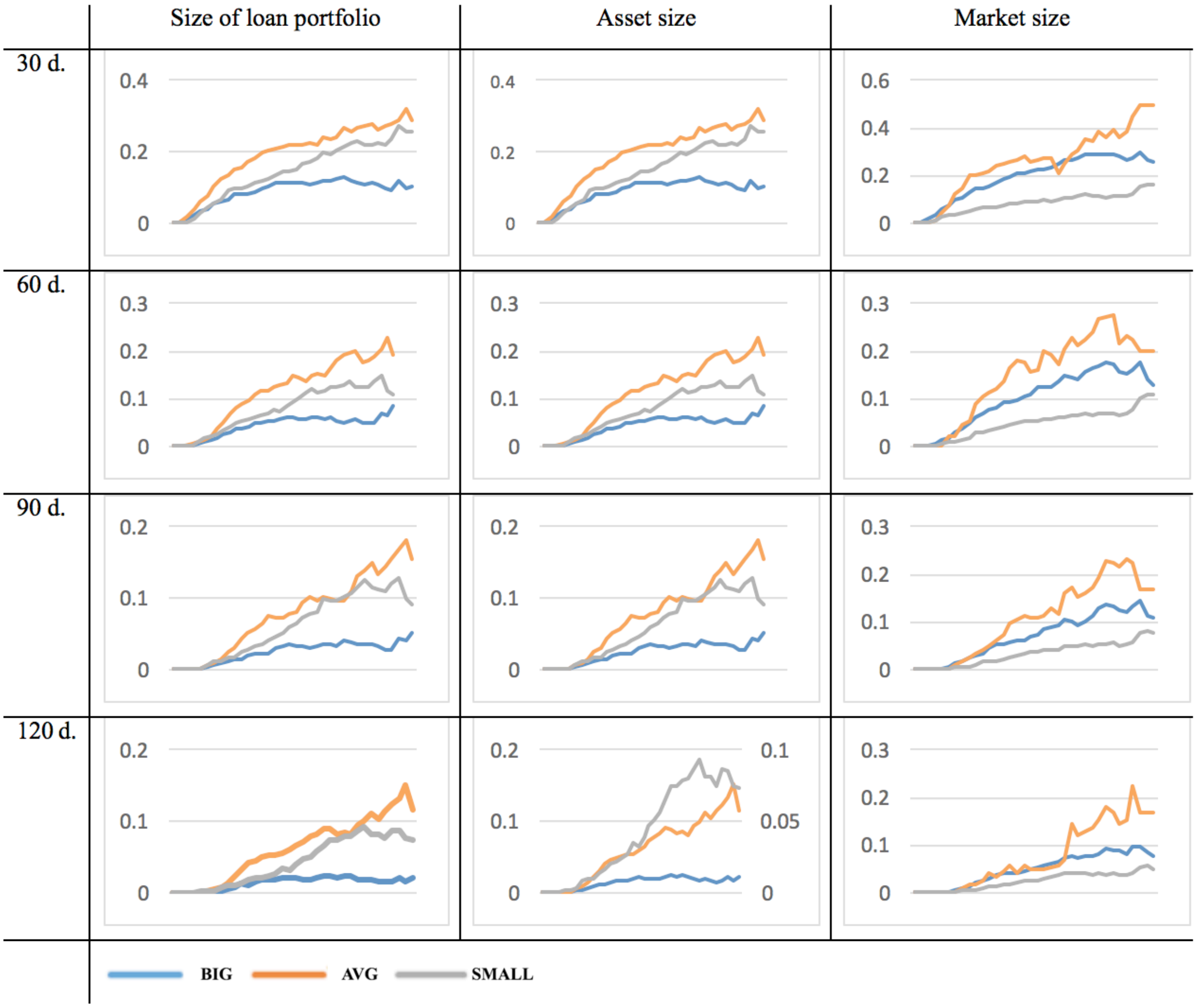


Fig. 5. Structured distribution of analysed credit unions by attributed features

Composed by the author based on Krzywinski et al (2009)

The analysis of credit union business loan delay dynamics allows to confirm hypothesis H1. The analysis results (Table 2) show that loan portfolios of the credit unions operating in small markets are of significantly higher quality than of those operating in medium-size and large markets. These results suggest that the element of social control is more efficient in small markets and weakens when the activity expands outside the community. This fact confirms the need for statistical credit risk assessment models when credit unions expand their activities outside the community. It should be noted that the study results are consistent with the individual stages of development of credit unions distinguished in the literature and the approach of modern researchers to the role of the element of social control in the process of credit risk assessment and in the overall evolution of credit unions.

Table 2. The structure of business loan portfolios in the Lithuanian credit union sector by an average amount of days past due and different segments of credit unions



* In the figures, BIG. – large, AVG. – medium, SMALL – small credit unions.

The analysis of credit risk assessment methods applied by credit unions and the requirements for the developed model. After the survey of credit unions, the limitation of the credit risk assessment model used by credit unions was determined: the model is not suitable for use in the activity of credit unions operating in medium-size and large markets. It should also be noted that the model used by credit unions is incompatible with recommendations of the Basel Committee on Banking Supervision because of an exclusive number of ranks in the scale. When improving and/or developing the new model, credit unions face most difficulties due to the limited human, technological and financial resources and the lack of political will among management bodies. In addition, the requirements of credit unions for the developed model were determined: the high discriminatory power, the interpretability of model results and the inclusion of available external information (in the form of independent variables) in the model, including financial and non-financial information.

The performed analysis of *target crediting segments* of credit unions and their problems allows to confirm hypothesis H2. Firstly, the analysis reveal that in the credit risk assessment, credit unions face most difficulties in examining loan applications of natural persons and business entities. The results allow to presume that the application of a statistical credit risk assessment model in the activities of credit unions would facilitate the process of examination of applications and would positively contribute to the efficiency of activities of credit unions. Secondly, the analysis of target crediting segments of credit unions leads to the reasoned definition of the targeted model segment: small and very small enterprises as defined by the Law of the Republic of Lithuania on Small and Medium-Size Business Development (1998, No. 109-2993).

During the survey, respondents were asked to specify the *criteria defining a "bad" loan* in their credit unions. As a leading factor defining a "bad" loan, the number of days past due of payment of loan instalments was chosen. It was determined that the largest share of respondents (38 %) considered the delay of payment for 90 days to be the key feature of a "bad" loan. Such a definition of a "bad" loan coincides with the most common definition used in the scientific and professional literature, the EU legislation and recommendations of the Basel Committee on Banking Supervision. Slightly less respondents (34 %) tolerated up to 60 days past due, and 17 % - up to 30 days past due. Only 7 % of respondents used the criterion of non-performing loans referred to in the legislation of the Republic of Lithuania, i. e. 180 days, to define a "bad" loan.

Statistical enterprise credit risk assessment model for Lithuanian credit unions.

Revision of the definition of a "bad" loan. In order to qualitatively determine the definition of a "bad" loan, the business loan portfolio data of the Central Credit Union of Lithuania were invoked for the research, for the period from 1 January 2010 to 12 September 2015, i. e. the history of monthly repayment of 1955 loans in total. Firstly, after forming cohorts of loans granted in different months, the rates of loans which were delayed at least once are indicated distinguishing delays of 30, 60, 90, 120 and 180 days past due. After the analysis of formed cohorts, the two-year period was established for the monitoring of loan performance (Fig. 6).

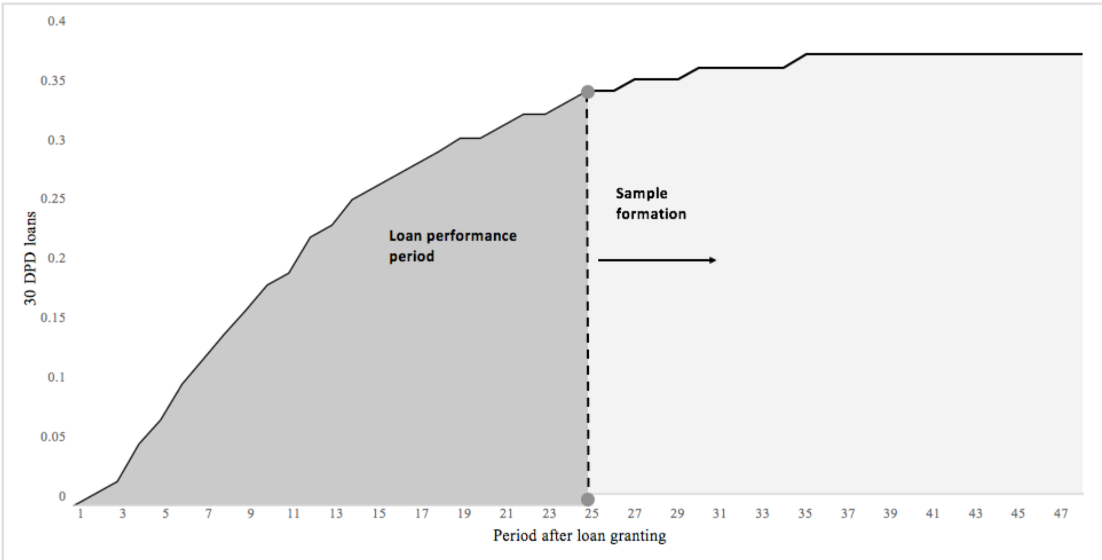


Fig. 6. The determination of optimal loan performance and sample formation periods by an observation of average rate of 30 days past due

Created by the author

After establishing the optimal loan performance period, the annual migration period is chosen for further research. The research includes only those loans with the duration from the moment of granting not less than the established optimal loan performance period (24 months). In the relevant case, such loans comprise 1383 loans within the research sample. During the research, the maximum delay of payment of each loan is assessed in the first year and the second year. The Markov's migration probability matrix is composed (Table 3):

Table 3. Migration probability matrix

	No delay	30+ DPD	60+ DPD	90+ DPD	120+ DPD	Write off
No delay	92,1%	4,1%	1,1%	0,9%	1,3%	0,4%
30+ DPD	36,8%	21,5%	16,0%	8,3%	9,7%	7,6%
60+ DPD	27,1%	6,8%	15,3%	20,3%	17,0%	13,6%
90+ DPD	28,6%	2,4%	2,4%	7,1%	33,3%	26,2%
120+ DPD	36,1%	0,0%	0,0%	0,0%	13,9%	50,0%
Write off						100%

Calculations by the author

Abbreviations: DPD – days past due

In order for the developed model to meet the definition of a "bad" loan prevailing in the sector of credit unions as much as possible, the author of the dissertation has decided to apply a 24-month period of observation and the delay of payment for 90 days past due as the key features of a "bad" loan.

The formation of model development sample. 28 580 companies meeting the criteria determined in the dissertation were operating in Lithuania during the analysed period. The random sample composed for the research included financial and non-financial corporate data for the period 2010-2012, the total research sample consisted of 2150 records and 64 variables. Financial data included the data from enterprises' balance sheets and profit (loss) reports, non-financial data – information about the assets distrain applied to the enterprises, credit history, number of employees. After eliminating inaccurate and false data from the research, 1799 records remained in the sample.

When forming the sample, the definition of a "good" loan was adjusted. The initial model development sample consisted of 1799 companies, out of which 650 went bankrupt or became bankrupt during a 24-month period of observation, and 48 had significant debts. Accordingly, the sample of companies not meeting the criteria applied to "bad" loans comprised 1 101 companies. From the conventional point of view, all these enterprises complied with the definition of a "good" loan. However, after the additional checks of business continuity of companies conducted in accordance with the additional verification algorithm proposed by the author (Fig. 7), it turned out that a considerable number of these companies should not have been considered as "good", i. e. 34 % of companies which were considered as "good" were not operating, had significant debts to the Social Insurance Fund or other business disorders. These findings allowed to reasonably argue that hypothesis H3 was likely to be correct, therefore, in this stage of the research, it was not rejected during the preliminary inspection and would be repeatedly checked in the sample of model back-testing when the final decision on its approval or rejection was to be made.

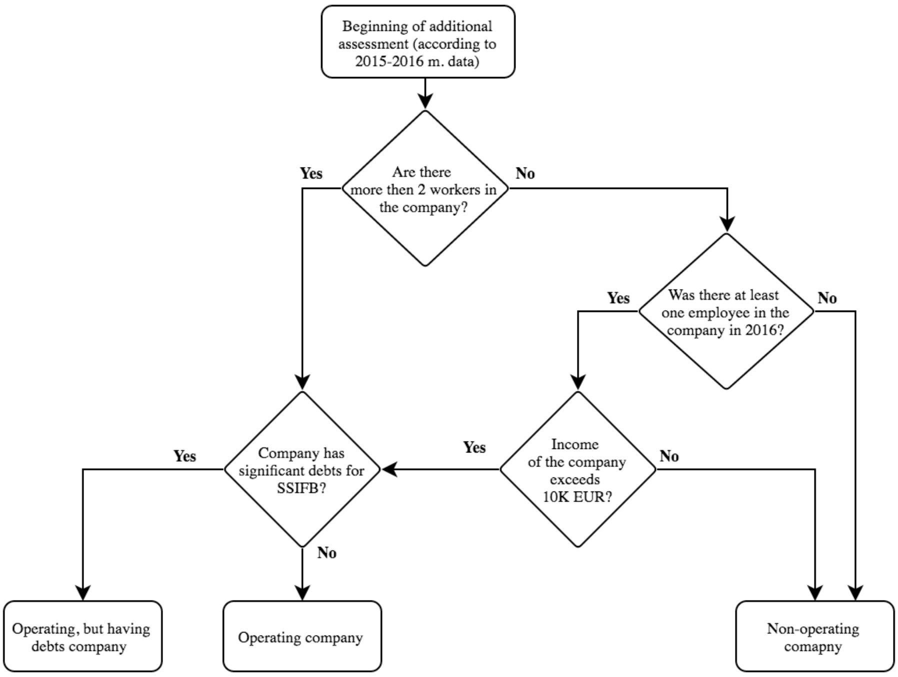


Fig. 7. The additional verification algorithm of business continuity of enterprises

Created by the author

In addition, the research also excluded those companies, which in 2010 met the definition of a "bad" company[4]. The remainder of the sample consisted of 1 252 companies, out of which 525 were "bad" companies and 727 were "good" companies. This sample was further used in the research for the assessment of independent variables, for the selection and the determination of their weights of evidence (WOE). After having randomly divided this research sample, the samples of model development and testing were obtained. It was decided to attribute some of "bad" companies (275 records) for testing, and the remaining ones (250 records) – for the formation of model development sample, and to attribute 350 "good" companies for model testing, and the remaining 375 "good" companies – for the formation of model development sample. In this way, the model development sample consisting of 625 companies and the model testing sample consisting of 627 companies were obtained.

[4] In accordance with the logic, if already during the analysis, the company meets the formed definition of a "bad" loan, there is no point in calculating the probability that it will become "bad" in the next two years.

As recommended in the scientific literature, in the formed model development sample, none of the values of dependable variable are prevailing, and the number of records corresponding the feature of expected event comprised 40 % and can be considered to be sufficient (Čekanavičius, 2011). It is estimated that the formed model development sample allows predicting PD with the probability of 95 % and the error of 7 %.

The composition of a compilation of independent variables available for use. In order to compose a compilation of the most frequently employed relative financial values that are used for selecting relative financial values at later stages of the model creation, a detailed analysis of the scientific literature was conducted, works of 40 authors were analysed, 101 different credit risk assessment and bankruptcy prediction methods in total (Altman, 1968; Altman, Sabato, 2007; Angelini et al, 2008; Bužius et al, 2010; Chen, Du, 2009; Cubiles-De-La-Vega et al, 2013; Danėnas et al, 2011; De Andres et al 2011; Dimitras et al, 1999; Dzidzevičiūtė et al 2010; Frydman et al, 1985; Fulmer, 1984; Grigaravičius, 2003; Gurny, Gurny, 2013; Huang et al, 2004; Lin, 2009; Lorca et al, 2013; Mileris, 2012; Min, Jeong, 2009; Min, Lee, 2005; Mori, Yasushi, 2007; Nikolic, 2013; Ohlson, 1980; Olson, 2012; Pacelli, Azzollini, 2011; Pompe, Feelders, 1997; Ryser, Denzler, 2009; Springate, 1978; Tafler, Tisshaw, 1977; Tseng, Hu, 2001; Tseng, Hu, 2010; Varetto, 1998; Vasiliauskaitė, Cvilikas, 2008; Wang et al, 2005; Wang, Ma, 2012; Wu, Hsu, 2012; Zhang, Hardle, 2008; Zhou, Tian, 2006; Zmijevski, 1984; Zopoudinis, Doumpos, 1999). Authors employed 218 different relative financial values in the literature analysed.

The set of independent variables is composed from the initial companies' data. From the financial data contained in the data sample, 54 financial ratios, most frequently employed in the field of the credit risk assessment, were calculated. Initial variables describing non-financial data were transformed: by converting these values into categorical, dummy variables were deduced that were employed to complement the current data sample. It was decided to perform this transformation by a knowledge-based method. In total, 64 independent values were deduced.

The selection of independent variables and the composition of a statistical model

The selection of a classifier of a model. When choosing a classifier, firstly, a general compilation of requirements for a model is composed. The requirements are selected to be included into the compilation taking into account the credit policy study of credit unions (carried out during CU surveys), results of a study on the frequency and accuracy of the classification methods implementation as well as the most important regulatory requirements wile implementing credit risk assessment models. Therefore, taking into account these factors, this compilation is composed from four main requirements for the characteristics of a model (Table 4).

Table 4. The compilation of requirements imposed on a model being created

No.	A requirement	The basis for a requirement
1.	The model must be characterised by a high discriminatory power, the AUC value should not be less than 75.	It was established during the survey of the CU sector that respondents consider the accuracy of a model to be one of its most important characteristics. A minimal AUC is determined by taking into account a conducted study on the frequency and accuracy of different classifiers.
2.	The high interpretability of results of a model.	Firstly, it was established during the survey of the CU sector that respondents name the interpretability of a result of a model as one of its most important characteristics. Secondly, the Basel Committee on Banking Supervision recommends implementing statistical models whose operation may be exhaustively explained and documented (BCBS, 2004, p. 410).
3.	The implementation of a model, a periodical review, calibration and the interpretation of results of a model should not require special knowledge in the fields of statistics and information technology.	It was established during the survey of the CU sector that HTF resources of credit unions are particularly limited for the creation, maintenance and implementation of a model of a credit risk assessment. Respondents noted that human resources and competences are particularly lacking in the fields of statistics and information technology.
4.	A model must be probabilistic, i. e. the model's answer must be PD - a probability that a debtor will default after a specific period of time.	Statistical as well as methods are recommended to be implemented in recommendation documents of the Basel Committee on Banking Supervision as well. The probability of the loan and portfolio non-solvency (PD) is one of the main values that are recommended to be calculated in a banking activity (BCBS, 2004).

Created by the author

The types of classifiers available for use are determined by conducting a detailed analysis of scientific and professional literature, whereby the frequency and accuracy of 21 types of classifiers were assessed. Implementation possibilities of all analysed classifiers were assessed during the creation of a model. The selection of a classifier was carried out in a few stages. *Firstly*, the average accuracy of classifiers was assessed. It was determined that the average accuracy of analysed methods corresponded to the established minimal accuracy requirement (Table 4, No. 1). *Secondly*, artificial intelligence methods, i. e. classification methods of artificial neuron networks, genetic programming, decision trees, support vectors, and ensemble learning methods, were eliminated from the further study due to limited possibilities of result interpretability (did not fulfil regulatory requirements and the CU credit policy, table 4, no. 2). *Thirdly*, the following classifiers were eliminated form further selection due to an infrequent employment in the scientific and professional literature as well as the complexity of a model's implementation, modification and calibration (taking into account particularly limited HTF resources of credit unions, Table 4, No. 3): Classifiers NB, PR, CR, MARS, RLR and LLR. *Fourthly*, discriminant classification methods were eliminated in order to leave classification methods only that determine the PD (Table 4, No. 4). It should be noted that discriminant classification methods were rejected, because of their strictness for the normality of data as well (Čekanavičius, 2011). Therefore, the following methods were included into the compilation of intermediate options: the logistic regression (LR) and the nearest neighbour algorithm (KNN).

When deciding between the logistic regression and the nearest neighbour methods, the logistic regression has been chosen due to its higher accuracy that was assessed taking into account the conducted detailed analysis of scientific and professional literature.

The selection of independent variables and the composition of a logistic regression model. Firstly, variables with a direct link to a dependent variable were eliminated. *Secondly*, the analysis of missing values was conducted. *Thirdly*, an analysis of individual discriminatory power of independent variables was performed. The analysis was conducted by the means of calculating the value information value (IV) of each variable. The analysis revealed that ratios of the asset structure possess the greatest discriminatory power. In spite of the fact that non-financial variables turned out to be in possession of a weak discriminatory power, it was decided to eliminate only one non-financial value from the further process – the number of inquiries (in Credit Bureau). *Fourthly*, a correlation matrix is formed. In instances when values significantly correlated among each other, the value with a weaker discriminatory power is eliminated.

Fifthly, the weight of evidence (WOE) was calculated and analysed. The WOE was calculated for every analysed independent variable. Original values of variables that were decided to be left for a further analysis were substituted by calculated WOE values. *Sixthly*, backward stepwise regression is employed.

Seventhly, a logistic regression model is composed by calculating coefficients of selected variables. In accordance with the composed model, the probability of default (PD) is calculated in the following manner[5]:

$$PD = \frac{1}{1 + e^{-z}} \tag{2}$$

$$z = -1{,}241 - 0{,}627 \cdot EQ\_TA - 0{,}326 \cdot CA\_EQ + 0{,}669 \cdot CUA\_TL\_CA - 0{,}229 \cdot WC\_S - 0{,}679 \cdot NP\_TA + n^{*} + k^{**} \tag{3}$$

* jei NSVVT > 4, n=0,885; jei ne – 0;

** jei A > 0, k=0,939; jei ne – 0.

After calculating a company's PD by the means of this formula, if PD=1, the company is considered to have a 100 percent chance to become "bad", and if PD=0, 100 % probability to remain "good". After the creation of a model, its pre-assessment was carried out in the following sequence:

1. It can be seen from the provided formula (3) that in general the regressors of the model correspond to economic logic and cover main operation areas of companies that are supposed to be analysed by determining the default probability.
2. While analysing *the values of coefficients assigned to regressors,* it may be observed that they correspond to economic logic.
3. *Log odds* of all regressors demonstrate that regressors are significant.
4. *The Wald test for regression* demonstrated that variables included into a model are statistically significant.
5. After calculating the *(pseudo) coefficient of Determination* R^2 = 0,62 and *Aikake criterion = 582*, it was established that the model is suitable for the data.
6. The graphic analysis of the model's discriminatory power is performed by analysing *receiver operating characteristic* (ROC) curve as well as the chart of predicted probabilities.
7. The total discriminatory power of a created model was assessed (without excluding the cut off point): AUC = 0,86; Gini=AR=2·AUC-1=0,72. As it may be seen, the model fulfils the imposed requirements for a minimal discriminatory

[5] See fig. 8 for explanation of variables abbreviations.

power (AUC=0,75). Furthermore, having compared the discriminatory power of the created model with the accuracy of logistic regression models in recent scientific studies, it may be stated that the discriminatory power of the created model may be assessed as great.

The discriminatory power of a model in a specific breaking point is presented in the classification table (table 5).

Table 5. The accuracy classification table of a suggested model in the vicinity of the breaking point 0.4

		The calculated result of model	
		0 („Good”)	1 („Bad”)
The actual state	„Good”	267 (TP)	83 (FN)
	„Bad”	71 (FP)	222 (TN)

Calculations by the author

Main classification accuracy assessment values were submitted, the cut-off point taken to be 0,4 (Table 6).

Table 6. Main classification accuracy values of a suggested model in the vicinity of the cut-off point at 0,4

Ar	0,76	PPV	0,79
CCR	1,6	NPV	0,73
MCR	0,5	α	0,54
Se	0,76	β	0,24
Sp	0,76	F	0,78
BAC	0,76	G-mean	1,23
MCC=AC	0,52	ACP	0,76

Calculations made by the author

To sum up, it may be stated that the results of a pre-assessment of the model allow presupposing that the composed model of logistic regression if of high quality and may be suitable to be employed in the operation of credit unions. Hereafter it is aimed at optimally determining the cut-off point of the model, composing a ranking scale and performing a back-testing of a model.

The determination of the cut-off point and the formation of a ranking scale. Taking into account the peculiarities of credit risk assessment issues and the difference of economic influence of false positive and false negative classification errors, it was decided to employ the EMP method suggested by Verbraken et al (2014; 2013) for the determination of an optimal cut-off point. It was determined that the composed maximum profit is received from one credit after discarding 52,46% of credits with the highest risk, i. e. the optimal cut-off point is T=0,48.

The ranking scale of scorecard is composed taking into account the recommendations from the Basel Committee on Banking Supervision and the determined cut-off point *T*. It is recommended in Basel documents to compose a scale from no less than 8 ranks, no less than 6 ranks of which fulfil their obligations and 2 are defaulters, who do not (BCBS, 2001, p. 198). Therefore, it is aimed at the cut-off point *T* corresponding to the 7th or 8th rank's lowest strip value. The allocation of strips of ranks is determined expertly, taking into account the distribution of companies in composed ranks. A relative and absolute distribution of "good" and "bad" companies, average ODF values of ranks and the distribution of all companies in composed ranks were analysed. In order to graphically present the structure of a composed model, the analysed operation fields of companies, selected ratios, their coefficients and the influence of the values on PD of the company being analysed, hereafter, the graphic summary of z parameter of a composed model and the composed rank scale are being analysed (Fig. 8).

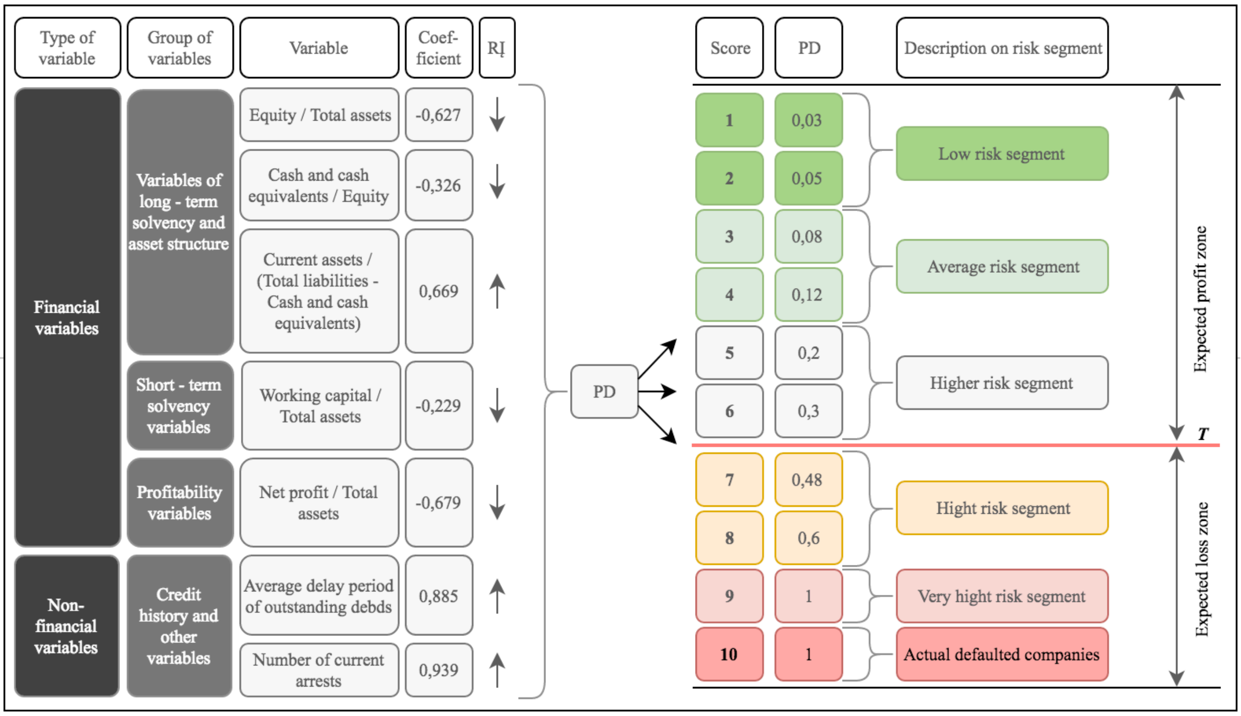


Fig. 8. The graphic summary of the composed model and the scorecard

Created by the author

The explanation of abbreviations used in the figure: VI – value influence on PD, with the increasing indicator value; *T* – the cut-off point.

Hereafter the model composed in the work is employed while analysing the data sample of business loans provided by Lithuanian Central credit union (thereafter LCCU). After the implementation of the model, its back-testing is carried out.

The implementation of the composed model in the Lithuania credit union sector

The back-testing and the compliance with requirements of credit unions of the composed model. In order to perform a reversible assessment of the composed model, the data sample of business loans actually provided by credit unions belonging to LCCU. The companies being analysed were involved in the study on the basis of the same criteria as the composition of the data sample of the model creation. While selecting appropriate companies for the study the aim was to select companies that would have provided loans no less than two years ago, i. e. so that during the assessment the loan monitoring (or maturity) period would have been finished. In total, 84 companies were included in the study.

During the analysis of "bad" companies, it has been noted that only 9 companies out of 37 that were assigned the "bad" feature are currently undergoing a bankruptcy, are bankrupt or liquidated. This fact together with the results of the study of model composition and credit unions data sample, **allow confirming the hypothesis H3** that presumed that a significant number of enterprises with non-performing loans granted by credit unions do not go bankrupt. The confirmation of this hypothesis demonstrates that during the development of the model the implemented methods for defining "good" and "bad" enterprises were chosen reasonably.

In order to assess the accuracy of the model, the following calculations were carried out. *Firstly*, the overall accuracy of the model was assessed (without excluding the cut-off point). It was determined that: model AUC=89,62, model Gini=AUC $\cdot$ 2-1=79,24, the ROC and predicted probability charts were composed. *Secondly*, values of classification accuracy in the determined breaking point 0.48 were calculated. The accuracy classification table was composed (Table 7).

Table 7. Accuracy classification table of the composed model in the vicinity of the breaking point 0.4

		The calculated result of model	
		0 ("Good")	1 ("Bad")
The actual state	"Good"	44 (TP)	8 (FN)
	"Bad"	3 (FP)	29 (TN)

Compiled by the author

Thirdly, classification accuracy values were calculated (table 8).

Table 8. Main classification accuracy values of the composed model in the vicinity of the cut-off point 0.4

Ar	0,87	PPV	0,94
CCR	1,97	NPV	0,78
MCR	0,30	α	0,73
Se	0,85	β	0,09
Sp	0,91	F	0,89
BAC	0,88	G-mean	1,32
MCC=AC	0,74	ACP	0,87

Compiled by the author

After the development of the model, it is important to make certain once more that methods implemented for the composition of the model and the employed data fulfil the requirements imposed after carrying out the study from three perspectives – a credit institution, external factors and simulated homogeneous risk groups. The study revealed that the model was composed after a detailed complex study of the sector of credit unions. The methods of model composition were selected by assessing the specificity of a creditor's operation, risk tolerance and applicable regulatory requirements. The data sample of the model creation was composed taking into account the creditor's credit target segment, and it corresponds to a simulated homogeneous group. The model variables were selected after performing a detailed analysis of the scientific and professional literature and assessing the possibilities of their practical implementation after analysing the external information infrastructure of credit unions. The composed scorecard of the composed model corresponds to the recommendations of the Basel Committee on Banking Supervision. The cut-off point of the scale was determined by statistical methods after assessing the peculiarities of business loans portfolio of credit unions, credit margin as well as the LDG of a portfolio. The discriminatory power of a model was assessed statistically and compared to recent results of scientific studies.

Taking into account the assessment results of the model, the model may be reasonably considered to be reliable and appropriate for use in the operation of credit unions. ***It allows confirming the hypothesis H4 and reasonably state that the composed statistical credit risk assessment model of small and very small enterprises will enable a more accurate credit risk assessment of business loans granted by credit unions.*** *Hereafter in the work, recommendations for the implementation of the model and its integration into the general decision-making system are provided.*

The implementation of the composed model and recommendations on the integration into the decision support system. After the development of a statistical credit risk assessment model, some issues regarding its limits and forms in the implementation in the credit risk assessment process remain. In the last subdivision of the doctoral thesis recommendations, taking into account the operational issues of credit unions established during the study, are provided regarding the implementation of the model and its integration into the decision-making support system of credit unions. Firstly, the implementation restrictions of the composed model are provided in the subdivision. Secondly, taking into account the results of the study and the insights of the author of the thesis, recommendations on the model's implementation into the operation of credit unions are provided.

The composed statistical model of the credit risk assessment is featured by the following implementation restrictions:

1. *The composed model should be understood as a part of a general decision support system; therefore, it should be employed with its implementation into the general decision-making support system of credit unions whose integral part is the set of credit rules.* This restriction is important due to the fact that during the composition of the model, some non-financial ratios with a great discriminatory power that should be included into the set of credit rules were not incorporated[6];
2. *The model is suitable for assessing only those enterprises that have been operating at least two years before the assessment* [7];
3. *The model is adapted to one target credit segment of credit unions during the study, due to this reason it is suitable only for assessing small and very small*[8] *enterprises operating in Lithuania.*

At the end of the study of this thesis the methodology for the implementation of the model is presented that are composed in accordance with the analysed operational range of problems of credit unions' sector of Lithuania. The novelty of this methodology may be described by two main aspects. *Firstly*, the Central credit union is involved in the

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[6] An exemplary credit decision-making process that also covers the assessment of credit rules is provided in the thesis.

[7] This restriction is important due to the facts that credit unions provide government-guaranteed loans to new companies as well. The composed model is not suitable for the assessment of this credit segment.

[8] It is taken to be as defined in the Law of the Republic of Lithuania on Small and Medium-Sized Business Development (1998, No. 109-2993).

credit decision-making process. This change grants the Central credit union a possibility to efficiently manage the credit risk assumed by the participants of the solvency assurance system. *Secondly*, the offered process allows using the possibilities of a wide network of credit unions more effectively by sharing rejected applications. Apart from other advantages, this point of view will increase the acceptance rate of financed applications, the whole sector of credit unions, as well as the appeal to the end user.

Conclusions:

1. In the study of this thesis, the risk is defined as a probability that factual results of credit institutions will be different from the planned ones in the future. The risk may be statistically measured by expressing it as a probability that may be determined by analysing the factors that arise due to the operation of a credit institution and condition the risk formation. In the operation of credit unions as well as in the commercial banking, four main risk types are distinguished: operational, credit, market and liquidity.

   In cooperative banking, in contrast to the traditional, such risk as adverse selection, moral, issues in raising equity that are characteristic to other banking types emerge, but in cooperative banking, their exhibition is related to the peculiarities of the features of this banking type. Exceptional and unique risk factors: the overlapping of interests, small market depth, the implementation of expert credit risk assessment models, limited possibilities to procure a borrowed capital and a high price for a borrowed capital. All risk types and factors are interrelated by cause-and-effect relations - and influence the common risk of the operation of credit unions.
2. It was determined after conducting the analysis of the scientific literature that operating in accordance with the new operational model aiming at operation effectiveness and the economy of scale, credit unions must evolve and their development essentially will correspond to development stages defined by Sibbald et al (2002). In different stages of development of unions, depending on the analytical information being received by credit unions, human, technology and financial resources that are available, unions should implement different credit risk assessment methods in order to assess the credit risk of potential receivers of

loans as accurately as possible. *During the early* stage of development credit unions may relatively effectively assess the credit risk by expert credit risk assessment methods, employing the element of social management.

During the transition stage, the operation of unions is enhanced beyond the community, the element of social control weakens, and, therefore, credit unions should employ quantitative methods by using objective analytical information. Normally, during this development stage credit unions have not yet accumulated a sufficient amount of data for the creation of statistical models, therefore, during the intermediate period, assessment models expertly composed rule-based models may be implemented. However, in order to assess the credit risk of potential loan receivers as accurate as possible, credit unions should aim at implementing statistical credit risk assessment models as soon as possible. *During the maturity* stage, the social control element disappears or is particularly insignificant, hence, statistical credit risk assessment methods should be implemented during this stage.

3. The development of a statistical credit risk assessment model is a complex process that may be divided into six main steps: 1) the analysis of model composition requirement and possibility, 2) the compilation of statistical data sample, 3) the definition of a dependent variable, 4) the definition of independent variables, 5) the composition of a model, 6) the assessment of qualitative and quantitative features of a model.
    a. The thesis broadens the first step of the model creation and suggests *a theoretical concept of the model development* that provides an opportunity to assess the possibility to compose a statistical model, to select model creation methods and data employed for the model creation during the analysis from three perspectives: a creditor's, external factors and a homogenous risk segment's. While conducting the analysis form *the perspective of a creditor*, a creditor's target credit segment is established, the internal information infrastructure as well as HTF resource available are assessed, credit policy and loan portfolio are analysed. While conducting the analysis form *the perspective of external factors*, the external information infrastructure and regulatory requirements are

analysed, and the competitive environment is assessed. While conducting the analysis form *the perspective of a predicted segment* that is analysed in the context of a binary event, potential discriminatory variables are determined, and the typical behaviour is assessed. The thesis demonstrates that applied methods and employed data determine main features of a composed model: the discriminatory power regarding the segment being analysed, the interpretability of model results, the risk tolerance level, the compliance with the regulatory requirements applicable to a creditor as well as other business requirements of a creditor.

b. *The definition of a dependent variable* signifies the definition of a "bad" loan in the context of credit risk assessment. Defining a "bad" loan answers two questions: *firstly*, what feature or set of features may characterise the analysed loan as a "bad" one; *secondly*, what is the optimal loan performance period. Most frequently, various signs of the non-compliance with a loan agreement, i. e. a bankruptcy, insolvency or prolonged payment delay are the main features of a "bad" loan. The analysis of the scientific literature conducted in this work demonstrated that the most frequently employed definition of a "bad" loan is a payment delayed for more than 90 days. Such a maximum period for late payment tolerance is established by Bank for International Settlements. The most frequently applied method for statistical definition of a "bad" loan is Markov's transition matrix. The essence of optimal loan performance period determination is to determine such a monitoring period during which the average number of days for delayed payments of the selected loan segment grows rapidly. Most frequently, a cohort analysis is implemented for this cause.

c. *The selection of independent variables* is performed in three stages. *Firstly*, a set of variables available for use is composed. *Secondly*, an analysis of values is carried out, whereby variables of low discriminatory power and interrelated variables are eliminated. During this stage, filter methods are the most widely employed methods that allow assessing an individual discriminatory power of variables and their interdependence. *Thirdly*, an optimal set of independent variables is composed that is included into the final model. During this stage, backward stepwise regression is most widely used.

d. *While developing the model*, a classification method is selected and implemented. *Classification methods* are usually grouped into statistical and artificial intelligence. In the work, it is determined that most widely implemented classification methods are discriminant analysis, logistic regression, neuron networks and decision trees. These theoretical approaches were presented in the work.

e. *The discriminatory power assessment methods of a model* may be divided into two types: *Assessment taking the cut-off point into account* and *assessment not taking the cut-off point into account*. Graphic methods are attributed to the first type: receiver operating characteristics curve (ROC), cumulative accuracy curve (CAP). The following values are related to these graphic methods: area under the curve (AUC), accuracy rate (AR), the Gini index, the Pietra index. It is demonstrated in the work that these assessment methods are connected by linear relations. If *the cut-off point is selected near assessment methods* various classification accuracy assessment values that are calculated from the classification matrix data are applicable. These model assessment methods are applied while conducting a pre-assessment or a back-testing of a model.

f. *In order to determine an optimal cut-off point,* two types of methods are distinguished in the scientific literature: based on the classification accuracy analysis and based on profit optimization analysis. Due to the differences in losses in case of first and second type classification errors, profit maximization methods are more appropriate.

4. Exhaustive analysis of the Lithuanian sector of credit unions was performed in order to make a credit risk assessment model conforming to needs of Lithuanian credit unions. *First of all* – the Lithuanian sector of credit unions was analysed as well as structure thereof and the portfolio of business credits at the credit unions. Issues faced by the credit unions when evaluating credit risks of enterprises were identified. *Second*, credit unions were surveyed. Requirements of the credit

unions for general features of the credit risk assessment model were identified by the survey, difficulties in improvement of the current credit risk assessment model or in creation of a new one were analysed.

a. The performed *analysis of structure of the sector* led to two conclusions. *First* – credit unions are non-homogeneous, significant differences are obvious – they operate in markets of different sizes, have different structure of assets, follow different strategies of property management, their sizes are significantly different, loan portfolios and the general assets alike. *Second,* the majority of Lithuanian credit unions are small considering the size of assets at their disposal and loan portfolio. Although the majority of credit unions operate in small markets, and Lithuanian credit unions operate according to the territorial principle, it is obviously not the main factor preventing the credit unions from development – a significant part of credit unions operating in medium and large markets are also small (both in terms of assets and loan portfolio at their disposal). Such situation in the Lithuanian sector of credit unions leads to an assumption that credit unions face difficulties when transferring from socially oriented model to business activity.
b. *Analysis of business loan portfolio* of the credit unions disclosed that the quality of loan portfolios at credit unions operating in small markets is significantly higher compared to those in medium and large markets. These results lead to a conclusion that the social control element is more effective in small markets and it decreases when the activities are expanded beyond the community. It confirms the need for statistic credit risk assessment models when credit unions expand their activities beyond the community. The result of this analysis leads to definition of limitation of the credit risk assessment model used by the credit unions – the model is not suitable in activities of credit unions operating in medium and large markets. It should also be noted that the model used by the credit unions does not conform to recommendations of the Basel Committee on Banking Supervision regarding a number of grades that should be on the scorecard.
c. *Analysis of target crediting segments and related issues* shows that most

difficulties in credit risk evaluation are faced by the credit union when analysing applications for credit by natural persons and legal entities. Such results lead to a presumption that using a statistic credit risk assessment model in activities of credit unions would simplify application analysis process and would have a positive effect on efficiency of activities of the credit unions. The results of analysis of target crediting segments and related issues lead to a motivated definition of the target crediting segment – small and very small companies, as defined in the Lithuanian Law on Development of Small and Medium-Sized Companies (1998, No. 109-2993).

d. Analysis of *corporate needs and requirements for the model to be created* disclosed that most difficulties in improvement of the current credit risk assessment model or in creation of a new one were faced by the credit unions due to limited HTF resources and lack of political willpower of management bodies. Requirements of the credit unions for the model to be created were also identified: high discriminatory power, explainability of the results provided by the model and inclusion of available external information (as independent variables) into model composition, including financial and non-financial information.

5. Model formation methods were selected and model formation sample was formed in consideration of issues in activities of the credit unions and identified needs of the credit unions, as well as requirements for the credit risk assessment model.

   a. In accordance with the Lithuanian Law on Credit Unions, survey results of the sector and in consideration of the maximum possible amount of one loan that the credit unions can grant to one member, the segment of small and very small enterprises were chosen for model development.

   b. *The dependent variable* was defined in accordance with definition of a bad loan as established in the sector of credit unions. The survey of Lithuanian credit unions disclosed that loan repayment delay (DPD) is usually applied on the definition of a "bad" loan. To summarise the analysis, the majority of respondents consider payment delay of 90 or 60 days to be the main feature of a "bad" loan. In consideration of the fact that the analysed segment of credit unions was revealed to be non-homogeneous in respect of the definition of a "bad" loan, statistical methods were used to determine the definition of a "bad" loan: Markov chains and cohorts. Statistical analysis was performed using the business loan portfolios of the Central Credit Union of Lithuania as a sample. It was disclosed that the following shall be considered a "bad" debtor: an enterprise that bankrupted or was late to pay to one of the creditors (according to available data) for more than 90 calendar days within an observation period of 24 months, where the total delayed amount was 2000 or more EUR, and the total amount of delayed loans were two or more.

c. Additional inspection of the sample of "good" enterprises using the method suggested by the author disclosed that a significant part of "good" enterprises should not be considered as "good". Such results lead to the conclusion that a significant part of companies granted with loans that become non-performing do not go bankrupt. These results also lead to the conclusion that the segment of small and very small enterprises forms a separate homogeneous risk group where specific methods for credit risk evaluation are required, other than those previously suggested in scientific and professional literature.

d. A modified definition of a "good" enterprise was applied when forming the *model formation sample* in accordance with the results of the additional inspection of the "good" companies. Companies not conforming to established definitions of "good" and "bad" companies were removed from the model formation sample. According to calculations, the formed model formation sample allows 95% probability and 7% error in PD estimation.

e. A list of possible *independent variables* is comprised of two parts. First, a set of financial independent variables to be used was formed after an exhaustive analysis of scientific and professional literature. Second, nonfinancial variables were selected after an analysis of external informational infrastructure of the credit unions. The financial and nonfinancial data were joined and a list of possible independent variables was formed.

f. In consideration of the possible accuracy of the *classifiers*, frequency of their application, possibilities of explainability of the results of the model, the logistic regression method was selected for formation of the statistical model of company credit risk evaluation.

g. In consideration of importance of profitability of activities of credit unions, the expected maximum profit method (EMP) was selected for determination of the cut-off point. The scorecard was formed in consideration of the determined cut-off point and recommendations of the Basel Committee on Banking Supervision.

h. When assessing the model, most attention was paid to the features that were considered the most important by the credit unions. The economical logic of model operation was thoroughly evaluated, as well as discriminatory power, explainability of the results and possibility to apply the model in automated or semi-automated mode.

6. A model of company credit risk assessment was created for Lithuanian credit unions using logistic regression as a basis. Pre-assessment of the model revealed that variables included in formation of the model have strong discriminatory power and are statistically important. In terms of economical logic, the selected variables are considered important because they analyse important areas of activities of the enterprises and include both financial and non-financial data.

    a. It was found that using the created model, Lithuanian credit unions would possibly maximise the profit of credits to companies, if the established cut-off point would be set at T=0,48.

    b. The scorecard of the model consists of 10 ranks, 6 of them are for enterprises executing their obligations, 3 – for those non-executing their obligations and 1 (the 10th one) – for factually insolvent companies. Such method of ranking conforms to recommendations of the Basel Committee on Banking Supervision.

7. To summarise the results of model application and back-testing, the discriminatory power of the model is excellent. Analysis of suitability of the model in activities of the credit unions shows that the model was created after an exhaustive complex analysis of the sector of credit unions. Model making

methods were selected in consideration of specifics of activities of the creditor, risk tolerance and applied regulatory requirements. The model making sample was formed in consideration of the target crediting segment of the creditor, the sample conforms to the shaped homogeneous group. Variables of the model were selected after an exhaustive analysis of scientific and professional literature and possibilities of practical implementation, as well as external informational infrastructure of the credit unions. The discriminatory power of the model was statistically evaluated and compared to the results of latest scientific research. The method of model application was presented as an additional result of the research.

About the author:

Renatas Špicas was born on 7 of June, 1985 in Telšiai (Lithuania).

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2013 – 2017 – doctoral studies (Economics), Vilnius University, Lithuania;

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DAKTARO DISERTACIJOS SANTRAUKA

Temos aktualumas. Paskolų teikimas nariams – pagrindinė kredito unijų veiklos sritis. Apibendrinus Lietuvos banko rengtas kredito unijų veiklos apžvalgas už pastaruosius penkis metus, matyti, kad palūkanos iš suteiktų paskolų generuoja didžiausią dalį šių įstaigų pajamų, o paskolos nariams sudaro didžiausią dalį kredito unijų turto (LB, 2016; 2015; 2014; 2013; 2012), todėl teisinga teigti, jog iš kreditavimo veiklos kylanti rizika yra reikšmingiausia rizika, su kuria susiduria kredito unijos vykdydamos tipinę veiklą. Suprantama, kad siekiant užtikrinti tiek pavienių kredito unijų, tiek ir viso sektoriaus veiklos tęstinumą bei stabilumą, būtina tinkamai vertinti ir valdyti prisiimamą kredito riziką.

Mokslinėje literatūroje (O'Connel, 2012; Fonteyne, 2007; MacPherson, 2007) teigiama, kad kredito unijos, veikdamos bendruomenės ribose, gali lengviau valdyti informacijos asimetriją ir tai suteikia joms galimybę efektyviai vertinti kredito riziką pasitelkus ekspertinius metodus. Literatūroje teigiama ir tai, kad augdamos kredito unijos pradeda veikti už bendruomenės ribų, tada socialinis ryšys, padedantis tiksliau vertinti kredito riziką kredito unijoms esant mažo dydžio, silpsta (O'Connel, 2012; Fonteyne, 2007; MacPherson, 2007). Fonteyne (2007) teigia, kad kredito unijų veiklos modelis buvo kurtas mažoms įstaigoms, kurios dabar tapo sudėtingais finansų konglomeratais. Šie faktai leidžia preziumuoti, kad ekspertiniai kredito rizikos vertinimo metodai veikia tik unijų ankstyvajame raidos etape ir tik tol, kol unijos turi galimybę savo veikloje naudoti socialinį kontrolės elementą informacijos asimetrijai mažinti. Dėl šios priežasties tvari kredito unijų raida negali vykti be tinkamų kredito rizikos vertinimo modelių. Kaupelytė (2007) disertacijoje teigia, kad šiuo metu Lietuvos kredito unijų sektorius yra tranzitiniame raidos etape. McKillop ir Wilson (2015; 2011) po penkerių ir vėliau, po devynerių metų, taip pat teigė, kad Lietuvos kredito unijų sektorius vis dar yra tame pačiame etape. Tad galima daryti prielaidą, kad kredito unijų sektoriaus raida stagnuoja dėl negebėjimo tinkamai vertinti ir valdyti kredito riziką.

Lietuvos kredito unijų gebėjimą vertinti kredito riziką galima apibendrinus Lietuvos banko, kaip pagrindinės sektoriaus priežiūros institucijos, dokumentus. Išanalizavus Lietuvos banko Priežiūros tarnybos (toliau LB PT) kredito unijų sektoriuje taikytų poveikių priemonių istoriją nuo 2013 m. sausio 1 d. iki 2016 m. gegužės 1 d.

(lb.lt, 2013–2016) matyti, kad per 30 mėnesių laikotarpį LB PT kredito unijoms taikė 32 poveikio priemones, iš kurių 25 buvo susijusios su netinkamu kredito rizikos vertinimu. Tai sudaro 78 % visų poveikio priemonių, taikytų sektoriuje. Lietuvos bankas metinėse ir ketvirtinėse kredito unijų ir Lietuvos Centrinės kredito unijos veiklos apžvalgose nuolatos pastebi nepakankamą kredito unijų gebėjimą tinkamai įvertinti prisiimamą kredito riziką, per didelį kredito rizikos apetitą bei nepakankamą kapitalą augantiems nuostoliams dėl neveiksnių paskolų amortizuoti (LB, 2016; 2015; 2014; 2013; 2012). Šios ir kai kurios kitos priežastys paskatino LB PT inicijuoti kredito unijų sektoriaus reformą. Realizuodamas šį tikslą, Lietuvos bankas parengė kredito unijų sektoriaus reformos projektą ir paskelbė jį dokumente viešai diskusijai. Lietuvos bankas, aprašydamas teikiamų unijų reformų kontekstą ir pagrindimą, pristatė penkis pagrindinius kredito unijų reformą lėmusius veiksnius, iš kurių trys yra susiję su netinkamu kredito rizikos vertinimu ir valdymu (LB, 2014a).

Šiuolaikinėje mokslinėje literatūroje, analizuojančioje kredito rizikos vertinimo klausimus (Dzidzevičiūtė, 2013; Valvonis, 2008; Thomas, 2009; Anderson, 2007; Siddiqi, 2006), pripažįstama, kad statistiniai kredito rizikos vertinimo modeliai atskiria patikimus ir nepatikimus skolininkus tiksliau, nei ekspertiniai modeliai. Kredito įstaigos, taikydamos tikslesnius modelius, veikia efektyviau: pirma, suteikiama mažiau paskolų nepatikimiems klientams (pirmo tipo klaida), antra, tikslesnis vertinimas leidžia suteikti daugiau paskolų patikimiems klientams (išvengiant antro tipo klaidos) ir taip didinti kredito įstaigos pajamas iš palūkanų. Statistinius metodus rekomenduojama taikyti ir Bazelio bankų priežiūros komiteto rekomendaciniuose dokumentuose (BCBS, 2004).

Statistinio modelio tinkamumas naudoti kredito įstaigos veikloje daugiausiai priklauso nuo dviejų veiksnių tipų: pirma – tikslumo, kuris ženklia dalimi priklauso nuo naudojamos statistinės imties kokybės ir atitikimo kredito įstaigos tikslinio kreditavimo segmentui ir antra – atitikimo kredito įstaigos verslo poreikiams. Mokslinėje literatūroje pripažįstama, kad kredito unijų veiklos modelis skiriasi nuo komercinių bankų ar kitų finansinių institucijų veiklos modelių (Fonteyne 2007). Todėl galima teigti, kad kredito rizikos vertinimo modeliai, siūlomi šiuolaikinėje mokslinėje literatūroje, nėra tinkami taikyti Lietuvos kredito unijų sektoriuje dėl skirtumų šių kredito įstaigų verslo poreikiuose ir naudotų statistinių imčių neatitikimo kredito unijų tiksliniam kreditavimo segmentui. Teoriniu požiūriu, su kredito rizika susijusiomis problemomis dažniausiai turėtų susidurti kredito unijos, esančios tranzitiniame ir brandžiame išsivystymo etape, tačiau šis klausimas iki šiol nebuvo nagrinėtas nei Lietuvos, nei užsienio tyrėjų.

Mokslinės problemos ištyrimo lygis. Visuotinai teigiama, kad šiuolaikinio statistinio kredito rizikos vertinimo pradininkas yra Altman, 1968 metais pasiūlęs diskriminantinį kredito rizikos vertinimo modelį įmonėms[9] (Altman, 1968). Po Altmano diskriminantinius modelius taip pat siūlė Martin (1977), Tafler ir Tisshaw (1977), Springate (1978), Lis (1982), Fulmer (1984) ir kiti (Mackevičius, 2007; Altman, 2000; Altman, Saunders, 1998). Logistinės regresijos modelį kredito rizikos vertinimui pirmasis 1974 metais pasiūlė Chesser, po jo vieni pirmųjų šiam tikslui logistinę regresiją taikė: Martin (1997), Ohlson (1980), Zmijewski (1984), West (1985), Koh (1991), Platt ir kiti (1991), Hopwood ir kiti (1994) (Dzidzevičiūtė, 2010; Mackevičius, Silvanavičiūtė, 2006; Lennox, 1999; Altman, Saunders, 1998). Statistiniai metodai vertinant kredito riziką yra plačiai taikomi ir naujausiuose moksliniuose tyrimuose (Fernandes, Artes, 2016; Sousa ir kiti, 2016; Petropoulos ir kiti, 2016; Sohn ir kiti, 2016; Xiao ir kiti, 2016; Lessmann ir kiti, 2015; Danėnas, Garšva, 2015; Manab ir kiti, 2015; Fei ir kiti, 2015; Florez-Lopez, Ramon-Jeronimo, 2015; Tomczak, Zięba, 2015; Harris, 2015; Van Vlasselaer ir kiti, 2015; Wang ir kiti, 2015; Bekhet, Eletter, 2014; Gupta ir kiti, 2014; Niklis ir kiti, 2014; Ju, Sohn, 2014; Verbraken ir kiti, 2014).

Dirbtinio intelekto metodus, skirtus prognozuoti nemokumą, vienas pirmųjų taikė Tam (1991). Jis sudarė neuronų tinklo modelį, skirtą prognozuoti komercinių bankų nemokumą. Be neuronų tinklų, vertinant kredito riziką plačiai taikomi ir kiti dirbtinio intelekto metodai, populiariausi yra sprendimų medžiai (Florez-Lopez, Ramon-Jeronimo, 2015; Tomczak, Zięba, 2015) ir atraminių vektorių mašinos (Cardoso ir kiti, 2016; Petropoulos ir kiti, 2016; Xiao ir kiti, 2016). Dirbtinio intelekto metodai sparčiai populiarėja, tačiau jų praktinis naudojimas kredito įstaigų veikloje yra ribotas dėl žemo rezultatų paaiškinamumo ir to nulemto nesuderinamumo su Bazelio bankų priežiūros komiteto rekomendacijomis. Dirbtinio intelekto metodų populiarumą lemia jų aukštas tikslumas ir praktinio taikymo galimybės tose finansų įstaigose, kurioms galioja kitoks teisinis reguliavimas, nei rekomenduojama Bazelio dokumentuose. Įprastai šios finansų

[9] Dėl Altman modelių pritaikymo paprastumo, nesudėtingo interpretavimo ir universalumo, autoriaus pasiūlyti modeliai sparčiai populiarėjo ir buvo plačiai taikomi moksliniuose tyrimuose. Šios disertacijos rengimo metu, anot Prado ir kiti (2016), Altman buvo labiausiai cituotajamas autorius kredito rizikos vertinimo srityje.

įstaigos nepriima valstybės draustų indėlių, pvz., sutelktinio finansavimo ir tarpusavio skolinimo bendrovės, greitųjų kreditų ir lizingo paslaugų įmonės.

Vienas pirmųjų Lietuvos tyrėjų, analizavusių kredito rizikos vertinimo metodus bankroto prognozavimo kontekste, buvo Grigaravičius (2003; 2003a), taikęs logistinės regresijos modelį prognozuoti įmonių bankrotą. Pažymėtinas Valvonio (Valvonis 2004, 2006, 2006a, 2008a, 2009; Savickaitė, Valvonis, 2007; Kamienas, Valvonis, 2004; Jasevičienė, Valvonis, 2003) mokslinis įdirbis analizuojant kredito rizikos vertinimo metodų aspektus Lietuvos komercinių bankų kontekste. Disertacijoje (Valvonis, 2008) mokslininkas pateikė apibendrintą kredito rizikos vertinimo modelį, taikomą Lietuvos komerciniuose bankuose. Dzidzevičiūtė (2010; 2010a; 2013) išsamiai analizavo statistinių kredito rizikos vertinimo modelių sudarymo ir taikymo komerciniuose bankuose metodiką. Disertacijoje (Dzidzevičiūtė, 2013) ji pasiūlė Lietuvos įmonių statistinį kredito rizikos vertinimo modelį, sudarytą logistinės regresijos pagrindu. Danėnas ir Garšva (2015; 2012; 2011; 2010; 2009) bei Danėnas ir kiti (2011) kredito rizikos vertinimui taikė atraminių vektorių mašinas ir tyrė jų veikimo tikslumą. Publikacijas kredito rizikos vertinimo tematika pastaruoju metu paskelbė šie Lietuvos tyrėjai: Butkus ir kiti (2014); Mileris (2014; 2012; 2009); Budrikienė, Paliulytė (2012); Bivainis, Garškaitė (2010); Mackevičius (2010); Vasiliauskaitė, Cvilikas (2008); Garškaitė (2008); Mackevičius, Silvanavičiūtė (2006); Merkevičius ir kiti (2004); Jasevičienė, Valvonis (2003). Lietuvoje pastaruoju metu buvo apginta nemažai disertacijų, kuriose analizuoti kredito rizikos vertinimo klausimai: Danėnas (2013), Dzidzevičiūtė (2013), Stulpinienė (2013), Mileris (2011), Pridotkienė (2009), Merkevičius (2008), Valvonis (2008), Valužis (2007), Grigaravičius (2003). Pažymėtina, kad kredito rizikos vertinimo klausimai dažniau analizuojami matematikos ir informatikos, nei ekonomikos ar vadybos mokslo krypčių disertacijose.

Kredito rizikos vertinimo klausimai mokslinėje literatūroje tapo ženkliai populiaresni nuo 2009 metų. Tai gali būti susiję su globalia finansine krize, turinčia ryšį su prastu kredito rizikos vertinimu (Prado ir kiti, 2016). Nors kredito rizikos vertinimo klausimai yra plačiai analizuoti praeityje, tačiau ir šiuo metu jie išlieka aktualūs tyrėjams. Kredito rizikos vertinimas kooperatinėje bankininkystėje buvo tirtas tik fragmentiškai. Lietuvoje kredito unijų veiklos ypatybes ir su jomis susijusias rizikas analizavo Kėdaitis, Žilinskas (2013), Kaupelytė, McCarthy (2006). Bendrai kredito unijų veiklą pastaruoju metu tyrė Jasevičienė ir kt. (2015, 2015a, 2014); Jasevičienė (2014); Dubauskas (2012); Igarytė, Ramanauskas (2011); Lukoševičius (2005); Bubnys, Kaupelytė (2004); Levišauskaitė, Kaupelytė (2003). Tačiau šiuose tyrimuose nebuvo analizuojamos įmonių kredito rizikos vertinimo problemos kredito unijose.

Užsienyje atraminių vektorių mašinų pagrindu suformuotą kredito rizikos vertinimo modelį Barbadoso kredito unijoms siūlė Harris (2013), neuronų tinklų pagrindu kredito rizikos vertinimo modelį kredito unijų veiklai siūlė Desai ir kiti (1996). Pažymėtina, kad nors šie autoriai ir naudojo kredito unijų tikslinius segmentus atitinkančias duomenų imtis, tačiau sudarant minėtus kredito rizikos vertinimo modelius, nebuvo analizuotos kredito unijų veiklos ypatybės, problematika, išorinė aplinka bei kredito unijų verslo poreikiai ir reikalavimai kuriamiems modeliams. Be to, šie modeliai nėra tinkami naudoti Lietuvos kredito unijų sektoriuje dėl reguliacinių ir tikslinio kreditavimo segmento neatitikimų. Pažymėtina ir tai, kad Lietuvoje kredito unijų asocijuotais nariais gali būti juridiniai asmenys, atitinkantys mažų ir labai mažų įmonių apibrėžimą (Žin., 2016, XII-2567), kaip apibrėžta LR Smulkiojo ir vidutinio verslo plėtros įstatyme (Žin., 1998, 105-4689). Iki šiol šiam įmonių segmentui Lietuvoje kredito rizikos vertinimo modeliai kurti nebuvo, taip pat šio segmento kontekste nebuvo analizuoti ir kiti su kredito rizikos vertinimu susiję klausimai.

Apibendrinant galima teigti, kad apskritai mokslinėje literatūroje pasigendama tyrimų, analizuojančių kredito rizikos vertinimo klausimus kredito unijose ir kooperatinėje bankininkystėje. Iki šiol tyrėjai nėra analizavę kredito unijų verslo poreikių kredito rizikos vertinimo modeliams, nėra sudaryta ir modelių, atitinkančių kredito unijų tikslinį kreditavimo segmentą – mažas ir labai mažas įmones. Tyrėjų dėmesio pasigendama ne tik kredito rizikos analizės srityje – iki šiol kooperatinės bankininkystės kontekste buvo mažai analizuoti ir kiti bankinės rizikos tipai, pvz., operacinė, rinkos, likvidumo rizika, kt.

Mokslinis problemos apibrėžimas. Kredito unijų evoliucijos procese, joms plečiant veiklą už bendruomenės ribų, socialinės kontrolės elementas iš dalies arba pilnai nustoja veikti, todėl kredito unijos susiduria su sunkumais vertindamos kredito riziką. Atsižvelgus į tai, šiame disertaciniame tyrime sprendžiama problema yra statistinių kredito rizikos vertinimo modelių kūrimas ir taikymas kredito unijose, atsižvelgus į jų veiklos specifiškumą, verslo poreikius bei išorinę aplinką, kurioje jos veikia.

Disertacijos objektas yra įmonių kredito rizikos vertinimas kredito unijose taikant statistinius kredito rizikos vertinimo modelius.

Disertacijos tikslas – išanalizavus kredito unijų kredito rizikos vertinimo problematiką, poreikius ir reikalavimus, sukurti statistinį įmonių kredito rizikos vertinimo modelį Lietuvos kredito unijoms.

Disertacijos uždaviniai:

1. Apibrėžti rizikos sampratą ir rūšis bei teoriškai išanalizuoti skirtingų rizikos rūšių raišką kredito unijų veikloje.
2. Teoriškai išanalizuoti kredito rizikos vertinimo aspektus skirtingais kredito unijų raidos etapais.
3. Apibrėžti ir teoriškai išanalizuoti pagrindinius statistinio kredito rizikos vertinimo modelio sudarymo etapus, metodus bei veiksnius, veikiančius modelio sudarymo metodų ir naudojamų duomenų pasirinkimą.
4. Išanalizavus Lietuvos kredito unijų veiklos problematiką, nustatyti kredito unijų poreikius, lūkesčius ir reikalavimus statistiniam kredito rizikos vertinimo modeliui.
5. Atsižvelgus į nustatytus kredito unijų verslo poreikius, lūkesčius ir reikalavimus kredito rizikos vertinimo modeliui, suformuoti modelio kūrimo imtį ir parinkti tinkamus modelio sudarymo metodus.
6. Sukurti statistinį kredito rizikos vertinimo modelį Lietuvos kredito unijoms.
7. Pritaikyti sukurtą modelį analizuojant Lietuvos kredito unijų verslo paskolų portfelį bei atlikti grįžtamąjį modelio įvertinimą.

Tyrimo metodai. Rengiant šį darbą analizuota mokslinė literatūra, teisės aktai, dokumentai, juose esanti informacija abstrahuota, sisteminta bei kritiškai nagrinėta. Taikyti ir kiti bendramoksliniai tyrimo metodai.

Tiriant Lietuvos kredito unijų sektorių buvo taikomi kiekybiniai tyrimo metodai: apklausa (interviu) bei apklausa telefonu. Apklausų duomenys apibendrinti ir susisteminti suformuojant statistinę imtį. Apdorojant statistinius duomenis naudotasi MS Excel, bei R programiniais paketais. Tyrimo rezultatai pavaizduoti vizualiai pasitelkus MS Excel, R ir Circos programinius paketus.

Sudarant statistinį kredito rizikos vertinimo modelį, taikyti matematiniai ir statistiniai metodai: Markovo grandinės, duomenų vizualinio atvaizdavimo metodai, entropijos matu paremti metodai, regresinė analizė. Modelio patikimumas pamatuotas taikant binarinio klasifikavimo modelių įvertinimo metodus: gavėjų charakteristikų kreivę ir matą, parodantį plotą po šia kreive (AUC), Gini indeksą, prognozuotų tikimybių grafiką. Siekiant nustatyti optimalų lūžio tašką, taikytas Tikėtino maksimalaus pelno (EMP) apskaičiavimo metodas.

Mokslinis naujumas. Atsižvelgus į jau atliktus mokslinius tyrimus ir nustatytas fragmentiškai tirtas sritis, šios disertacijos mokslinis naujumas apibrėžiamas taip:

1. Išskirti kredito unijų veiklos bruožai bei jų priežasties ir pasekmės ryšys su specifinėmis kredito unijų veiklos rizikomis.
2. Išanalizuoti kredito rizikos vertinimo ypatumai skirtingais kredito unijų raidos etapais.
3. Nustatyti veiksniai, lemiantys kredito rizikos vertinimo metodų ir duomenų pasirinkimą kuriant kredito rizikos vertinimo modelius.
4. Atlikus išsamų Lietuvos kredito unijų sektoriaus tyrimą, nustatyti probleminiai Lietuvos kredito unijų veiklos aspektai, tiksliniai kreditavimo segmentai bei reikalavimai statistiniam kredito rizikos vertinimo modeliui.
5. Sukurta ir detaliai pristatyta nauja „gerų“ ir „blogų“ įmonių apibrėžimų formavimo metodika mažų ir labai mažų įmonių segmentui.
6. Sudarytas statistinis mažų ir labai mažų įmonių kredito rizikos vertinimo modelis naudojant statistinę imtį, atitinkančią Lietuvos kredito unijų tikslinį kreditavimo segmentą bei atsižvelgus į kredito unijų reikalavimus ir poreikius.
7. Pateiktos modelio integravimo į kredito unijų sprendimų priėmimo paramos sistemą rekomendacijos leidžia į kreditavimo sprendimų priėmimo procesą įtraukti Centrinę kredito uniją. Pasiūlytas integracijos metodas taip pat suteikia galimybę efektyviau išnaudoti plataus kredito unijų tinklo galimybes dalijantis atmestomis praraiškomis.

Pagrindiniai ginamieji teiginiai:

1. Ekspertinis kredito rizikos vertinimas kredito unijų veikloje gali būti efektyvus tik tol, kol kredito unija yra pradiniame raidos etape ir turi galimybę naudoti socialinės kontrolės elementą informacijos asimetrijai mažinti.
2. Šiuolaikiniai kredito rizikos vertinimo modeliai (taip pat sudaryti ir taikomi kitų rūšių kredito įstaigose bei kredito biuruose) nėra tinkami naudoti Lietuvos kredito

unijų veikloje, kadangi juos kuriant neatliekama analizė iš trijų perspektyvų: kredito įstaigos, išorės veiksnių bei homogeninės rizikos grupės.

3. Sukurtas statistinis mažų ir labai mažų įmonių kredito rizikos vertinimo modelis yra efektyvus įrankis vertinti kredito riziką kredito unijoms esant tranzitiniame ir brandos raidos etapuose.

Praktinis darbo reikšmingumas. Šio darbo tyrimų rezultatai autoriui padėjo sukurti interaktyvią kredito rizikos vertinimo modeliavimo sistemą, kuri sėkmingai įdiegta skirtingų tipų kredito įstaigose Lietuvoje ir užsienyje. Šiuo metu sistema adaptuojama centrinių kredito unijų veiklai siekiant vertinti ir valdyti kredito riziką sisteminiu lygmeniu.

Pagrindinės tolimesnių tyrimų kryptys:

Sukurtą modelį pritaikyti dichotominei kredito unijų prigimčiai, įtraukiant sukuriamos socialinės vertės veiksnį.

Svarbiausios tyrimo prielaidos ir apribojimai:

1. Atliekant kredito unijų apklausą šalyje veikė 72 kredito unijos, sudariusios tyrimo populiaciją. Dėl tyrimo tikslumo buvo siekiama apklausti visą populiaciją, tačiau tyrime dalyvauti sutiko ir buvo apklaustos 56 kredito unijos.
2. Vienas iš kredito unijų nehomogeniškumo požymių yra tas, kad jos turi skirtingus tikslinius kreditavimo segmentus. Nepaisant to, apklausos duomenys generalizuoti visai populiacijai, sudarytas apibendrintas kredito unijų verslo poreikių sąvadas, kuris panaudotas kuriant ***įmonių*** kredito rizikos vertinimo modelį. (Ignoruojant tai, jog kai kurie respondentai nekreditavo juridinių asmenų).
3. Kredito unijų veikla yra ribojama teritoriniu principu (Žin. 1995). Kuriant įmonių kredito rizikos vertinimo modelį, naudotasi įmonių statistine imtimi, apimančia bendroves iš skirtingų Lietuvos geografinių vietovių. Taigi buvo daroma prielaida, kad skirtingose geografinėse vietovėse veikiančios mažos ir labai mažos įmonės sudaro vieną homogeninį rizikos segmentą.
4. Sudarant modelį naudota maksimali, pagal faktines galimybes, imtis – 1252 įmonės.
5. Kadangi turimoje statistinėje imtyje nebuvo atmestų paraiškų duomenų, atitinkamai, kuriant modelį atmestų paraiškų įtraukimo problema nebuvo analizuota.

Darbo struktūra. Darbas susideda iš įvado, trijų dalių, išvadų, literatūros sąrašo ir priedų (1 pav.).

Pirmoje darbo dalyje vystoma teorinė diskusija. Šioje dalyje apibrėžiama rizikos samprata, išskiriami tipiniai kredito unijų veiklos bruožai, nurodomi jų priežasties ir pasekmės ryšiai su kredito unijų veiklos rizikomis, išanalizuoti kredito rizikos vertinimo ypatumai skirtingais kredito unijų raidos etapais. Išskirtas ekspertinių kredito rizikos vertinimo metodų ribotumas, išnagrinėti kredito rizikos vertinimo modelio sudarymo etapai ir metodai. Išanalizuota statistinio kredito rizikos vertinimo modelio sudarymo eiga bei nustatyti veiksniai, lemiantys modelio sudarymo metodus ir naudojamus duomenis. Pirmoje dalyje taip pat analizuojami pagrindiniai modelio formavimo metodai, išskiriami jų privalumai, trūkumai ir taikymo apribojimai.

Antroje darbo dalyje pateikiama modelio sudarymo metodika. Šioje dalyje formuojama kredito unijų sektoriaus tyrimo metodologija, kurią sudaro kredito unijų klasterizavimas, verslo paskolų portfelio tyrimas ir kredito unijų apklausa. Šioje dalyje taip pat pateikiama statistinio modelio sudarymo metodika ir iškeliamos tyrimo hipotezės.

Trečioje, empirinėje darbo dalyje, pateikiami tyrimo rezultatai. Pirma, pristatomi kredito unijų sektoriaus rezultatai, suteikę galimybę parinkti kredito unijoms tinkamus modelio sudarymo metodus ir duomenis. Antra, sudarytas logistinės regresijos modelis ir atliktas jo išankstinis įvertinimas. Trečia, modelis pritaikytas vertinant kredito unijų verslo paskolų portfelį bei atliktas grįžtamasis modelio įvertinimas. Ketvirta, pateikiamos modelio taikymo rekomendacijos ir pasiūlytas modelio integravimo į kredito unijų sprendimų priėmimo paramos sistemą būdas.

IŠVADOS

1. Šiame disertaciniame tyrime rizika apibrėžiama kaip tikimybė, kad ateityje faktiniai kredito įstaigos veiklos rezultatai skirsis nuo planinių. Rizika gali būti statistiškai išmatuojama ją išreiškiant tikimybės išraiška, kuri gali būti nustatyta analizuojant veiksnius, sukeliamus kredito įstaigos veiklos ir lemiančius rizikos atsiradimą. Kredito unijų veikloje, kaip ir komercinėje bankininkystėje, išskirtinos keturios pagrindinės rizikos rūšys: operacinė, kredito, rinkos ir likvidumo.

   Kooperatinėje bankininkystėje, kitaip nei tradicinėje, pasireiškia nepalankaus pasirinkimo, moralinė, nuosavo kapitalo prisitraukimo rizikos, kurios būdingos ir kitoms bankininkystės rūšims, tačiau kooperatinėje bankininkystėje jų raiška susijusi su šios bankininkystės rūšies bruožų ypatumais. Išskirtini ir specifiniai rizikos veiksniai: interesų persidengimas, mažas rinkos gylis, ekspertinių kredito rizikos vertinimo modelių taikymas, ribotos skolinto kapitalo pritraukimo galimybės ir aukšta skolinto kapitalo kaina. Visos rizikos rūšys ir veiksniai yra susiję tarpusavyje priežasties ir pasekmės ryšiais bei daro įtaką bendrai kredito unijų veiklos rizikai.

2. Atlikus mokslinės literatūros analizę, nustatyta, kad veikiant pagal naująjį veiklos modelį, siekiant veiklos efektyvumo ir masto ekonomijos, kredito unijos privalo vystytis ir jų raida iš esmės atitiks Sibbald ir kiti (2002) apibrėžtus raidos etapus. Skirtinguose unijų raidos etapuose, priklausomai nuo kredito unijų gaunamos analitinės informacijos, turimų žmogiškųjų, technologinių ir finansinių resursų, unijos turėtų taikyti skirtingus kredito rizikos vertinimo metodus, siekdamos kuo tiksliau įvertinti potencialių paskolos gavėjų kredito riziką.

   Ankstyvajame raidos etape kredito unijos gali gana efektyviai vertinti kredito riziką ekspertiniais kredito rizikos vertinimo metodais, pasitelkdamos socialinės kontrolės elementą. *Tranzitiniame* etape unijų veikla plečiama už bendruomenės ribų, socialinis kontrolės elementas silpsta, todėl kredito unijos turėtų taikyti kiekybinius metodus, pasitelkdamos objektyvią analitinę informaciją. Įprastai šiame raidos etape kredito unijos dar nebūna sukaupusios pakankamo duomenų kiekio kurti statistinius modelius, todėl pereinamuoju laikotarpiu gali būti taikomi taisyklių pagrindu ekspertiškai suformuoti vertinimo modeliai. Tačiau norėdamos kuo tiksliau įvertinti potencialių paskolos gavėjų kredito riziką, unijos turėtų pradėti taikyti statistinius kredito rizikos vertinimo modelius per kuo trumpesnį laiką.

Brandos etape socialinis kontrolės elementas būna dingęs arba itin nereikšmingas, tad turėtų būti taikomi statistiniai kredito rizikos vertinimo metodai.

3. Statistinio kredito rizikos vertinimo modelio sudarymas yra kompleksinis procesas, kuris gali būti suskirstytas į šešis žingsnius: 1) modelio sudarymo poreikio ir galimybių analizė, 2) statistinės imties formavimas, 3) priklausomo kintamojo apibrėžimas, 4) nepriklausomų kintamųjų apibrėžimas, 5) modelio sudarymas, 6) modelio kiekybinių ir kokybinių savybių įvertinimas.
   a. Disertacijoje praplėstas pirmas modelio kūrimo žingsnis ir pasiūlyta *teorinė modelio kūrimo koncepcija*, leidžianti įvertinti statistinio modelio sudarymo galimybes, parinkti modelio kūrimo metodus ir modeliui kurti naudojamus duomenis atliekant analizę iš trijų perspektyvų: kreditoriaus, išorinių veiksnių ir prognozuojamo segmento. Atliekant analizę *iš kreditoriaus perspektyvos*, nustatomas kreditoriaus tikslinis kreditavimo segmentas, įvertinama vidinė informacinė infrastruktūra bei turimi ŽTF ištekliai, nagrinėjama kreditavimo politika bei tiriamas paskolų portfelis. Atliekant analizę *iš išorės veiksnių perspektyvos*, tiriama išorinė informacinė infrastruktūra, reguliaciniai reikalavimai bei įvertinama konkurencinė aplinka. Atliekant analizę *iš prognozuojamo segmento perspektyvos*, nagrinėjamo binarinio įvykio kontekste nustatomi galimi diskriminuojantys kintamieji bei įvertnama būdinga elgsena. Disertacijoje parodyta, kad taikomi metodai ir naudojami duomenys lemia pagrindines sudaromo modelio charakteristikas: diskriminacinę galią analizuojamo segmento atžvilgiu, modelio rezultatų paaiškinamumą, rizikos tolerancijos lygį, atitikimą kreditoriui galiojantiems reguliaciniams reikalavimams bei kitiems kreditoriaus verslo poreikiams.
   b. *Priklausomo kintamojo apibrėžimas* kredito rizikos vertinimo kontekste yra vadinamas „blogos“ paskolos apibrėžimu. Apibrėžiant „blogą“ paskolą, atsakoma į du klausimus: *pirma*, koks požymis ar požymių rinkinys galėtų charakterizuoti analizuojamą paskolą kaip „blogą“; *antra*, koks yra optimalus paskolos stebėjimo laikotarpis. Dažniausiai pagrindiniu „blogos“ paskolos požymiu pasirenkami įvairūs paskolos sutarties nevykdymo požymiai: bankrotas, nemokumas ar užsitęsęs mokėjimo vėlavimas. Darbe atliktos mokslinės literatūros analizė parodė, kad

dažniausiai taikomas „blogos“ paskolos apibrėžimas yra mokėjimo vėlavimas 90 dienų. Toks maksimalus mokėjimo vėlavimo toleravimo terminas yra nurodomas ir Bazelio bankų priežiūros dokumentuose. Dažniausiai taikomas statistinis „blogos“ paskolos apibrėžimo metodas – Markovo migracijų matrica. Optimalaus paskolos stebėjimo laikotarpio nustatymo tikslas – nustatyti tokį stebėjimo laikotarpį, per kurį vidutinis pasirinkto paskolų segmento vidutinis vėlavimo dienų skaičius sparčiai auga. Dažniausiai norint pasiekti šį tikslą, taikoma kohortų analizė.

c. *Nepriklausomų kintamųjų atrinkimas* atliekamas trim etapais. *Pirma*, sudaromas galimų naudoti kintamųjų sąvadas. Šiame etape dažniausiai taikomi bendramoksliniai tyrimo metodai. *Antra*, atliekama rodiklių analizė, kurios metu pašalinami žemos diskriminacinės galios ir tarpusavyje susiję kintamieji. Šiame etape plačiausiai naudojami filtrų metodai, leidžiantys įvertinti kintamųjų individualią diskriminacinę galią bei tarpusavio priklausomybę. *Trečia*, sudaromas optimalus nepriklausomų rodiklių rinkinys, kuris įtraukiamas į galutinį modelį. Šiame etape daugiausiai naudojama šalinamoji arba įtraukiančioji regresija.

d. *Sudarant modelį* pasirenkamas ir taikomas klasifikavimo metodas. Mokslinėje literatūroje *klasifikavimo metodai* dažniausiai grupuojami į statistinius ir dirbtinio intelekto. Darbe nustatyta, kad dažniausiai taikomi klasifikavimo metodai yra diskriminantinė analizė, logistinė regresija, neuronų tinklai ir sprendimų medžiai. Darbe aptartos šių metodų teorinės prieigos.

e. *Modelio diskriminacinės galios įvertinimo metodai* gali būti išskiriami į dvi rūšis: *įvertinimo atsižvelgiant į lūžio tašką* ir *įvertinimo neatsižvelgiant į lūžio tašką*. Pirmai metodų rūšiai priskiriami grafiniai metodai: gavėjų charakteristikų kreivė (ROC), kaupiamojo tikslumo kreivė (CAP). Su šiais grafiniais metodais susiję rodikliai: plotas po gavėjų charakteristikų kreive (AUC), teisingo klasifikavimo rodiklis (AR), Gini indeksas, Pietra indeksas. Darbe atskleista, kad šie įvertinimo metodai yra susiję tiesiniais ryšiais. Prie *įvertinimo metodų pasirinkus lūžio tašką* priskirtini įvairūs klasifikavimo tikslumo įvertinimo rodikliai, kurie apskaičiuojami pagal klasifikavimo matricos duomenis. Šie modelio įvertinimo metodai taikomi atliekant išankstinį ir grįžtamąjį modelio įvertinimą.

f. Siekiant *nustatyti optimalų lūžio tašką,* mokslinėje literatūroje išskiriamos dvi metodų rūšys: pagrįstieji klasifikavimo tikslumo analize ir pagristieji ekonominės naudos optimizavimo analize. Dėl nuostolių dydžio skirtumo dėl pirmo ir antro tipo klasifikavimo klaidų, kredito rizikos vertinimo atveju ekonominės naudos maksimizavimo metodai yra tinkamesni.

4. Siekiant sukurti kredito rizikos vertinimo modelį, atitinkantį Lietuvos kredito unijų poreikius, atlikta išsami Lietuvos kredito unijų sektoriaus analizė. *Pirmiausia* išanalizuotas Lietuvos kredito unijų sektorius, jo struktūra bei kredito unijų verslo paskolų portfelis, identifikuotos problemos, su kuriomis susiduria kredito unijos vertindamos juridinių asmenų kredito riziką. *Antra*, atlikta kredito unijų apklausa. Apklausos metu nustatyti kredito unijų reikalavimai bendroms kredito rizikos vertinimo modelio savybėms bei išanalizuoti sunkumai tobulinant esamą ir / ar kuriant naują kredito rizikos vertinimo modelį.
    a. Atlikta *sektoriaus struktūros analizė* leido padaryti dvi išvadas. *Pirma*: kredito unijos yra nehomogeniškos, matyti ženklūs skirtumai – jos veikia skirtingų dydžių rinkose, turi skirtingą turto struktūrą, laikosi skirtingų turto valdymo strategijų bei reikšmingai skiriasi jų dydžiai – tiek paskolų portfelių, tiek ir turto apskritai. *Antra*, dauguma Lietuvos kredito unijų yra mažos pagal savo valdomo turto ir paskolų portfelio dydžius. Nors didžioji dalis kredito unijų veikia mažose rinkose, o kredito unijos Lietuvoje veikia pagal teritorinį principą, matyti, kad tai nėra pagrindinis veiksnys, trukdantis kredito unijų vystymuisi, nes nemaža dalis vidutinio dydžio ir didelėse rinkose veikiančių kredito unijų taip pat yra mažos (tiek turto, tiek valdomų paskolų portfelio požiūriu). Tokia situacija Lietuvos kredito unijų sektoriuje leidžia daryti prielaidą, kad kredito unijos susiduria su sunkumais pereidamos nuo socialiai orientuoto prie verslo veiklos modelio.
    b. Kredito unijų *verslo paskolų portfelio analizė* parodė, kad mažose rinkose veikiančių kredito unijų paskolų portfeliai yra ženkliai kokybiškesni, nei vidutinėse ir didelėse rinkose. Šie rezultatai leidžia teigti, kad mažose rinkose socialinis kontrolės elementas veikia efektyviau, o veiklai plečiantis už bendruomenės ribų, jis silpsta. Tai patvirtina statistinių kredito rizikos vertinimo modelių poreikį kredito unijoms plečiant veiklą už bendruomenės ribų. Šios analizės rezultatas leidžia apibrėžti kredito unijų naudojamo kredito rizikos vertinimo modelio ribotumą – modelis nėra tinkamas naudoti vidutinio ir didelio dydžio rinkose veikiančių kredito unijų veikloje.

Pažymėtina ir tai, kad kredito unijų naudojamas modelis neatitinka Bazelio bankų priežiūros komiteto rekomendacijų dėl išskirtino rangų kiekio skalėje.

c. Atlikta kredito unijų *tikslinių kreditavimo segmentų bei jų problemiškumo analizė* atskleidė, kad daugiausiai sunkumų vertindamos kredito riziką kredito unijos patiria analizuodamos fizinių asmenų bei verslo subjektų paskolų paraiškas. Šie rezultatai leidžia preziumuoti, kad statistinio kredito rizikos vertinimo modelio naudojimas kredito unijų veikloje supaprastintų paraiškų analizės procesą bei darytų teigiamą įtaką kredito unijų veiklos efektyvumui. Kredito unijų tikslinių kreditavimo segmentų analizės rezultatai leidžia motyvuotai apibrėžti tikslinį modeliavimo segmentą – mažas ir labai mažas įmones, taip, kaip jos apibrėžiamos LT Smulkiojo ir vidutinio verslo plėtros įstatyme (1998, Nr. 109-2993).

d. Atlikus kredito unijų *verslo poreikių ir reikalavimų kuriamam modeliui tyrimą*, nustatyta, kad tobulindamos naudojamą ir / ar kurdamos naują modelį, kredito unijos patiria daugiausiai sunkumų dėl ribotų ŽTF išteklių ir valdymo organų politinės valios stokos. Buvo nustatyti kredito unijų reikalavimai kuriamam modeliui: aukšta diskriminacinė galia, modelio rezultatų paaiškinamumas ir prieinamos išorinės informacijos įtraukimas (nepriklausomų kintamųjų forma) į modelio sudarymą, įskaitant finansinę ir nefinansinę informaciją.

5. Atsižvelgus į kredito unijų veiklos problematiką ir nustatytus kredito unijų poreikius bei reikalavimus kredito rizikos vertinimo modeliui, parinkti modelio sudarymo metodai ir suformuota modelio kūrimo imtis.

   a. Remiantis LR Kredito unijų įstatymu, atlikta Lietuvos kredito unijų apklausa. Atsižvelgus į maksimalią galimą vienos paskolos sumą, kurią kredito unijos gali suteikti vienam nariui, modeliui kurti pasitelkta mažų ir labai mažų įmonių imtis.

   b. *Priklausomas kintamasis* apibrėžtas pagal nustatytą blogos paskolos apibrėžimą kredito unijų sektoriuje. Lietuvos kredito unijų sektoriaus apklausa atskleidė, kad „blogos“ paskolos apibrėžimui dažniausiai taikomas bruožas yra paskolos įmokos vėlavimas (DPD). Apibendrinant atliktą analizę, galima teigti, kad didžiausia dalis respondentų kaip pagrindinį „blogos“ paskolos požymį traktuoja 90 arba 60 dienų mokėjimo vėlavimą. Atsižvelgus į tai, kad tiriamas kredito unijų segmentas pasirodė esąs nehomogeniškas „blogos“ paskolos apibrėžimo atžvilgiu, nustatant „blogos“ paskolos apibrėžimą pasitelkti statistiniai metodai: Markovo grandinės ir kohortos.

Statistinė analizė atlikta LCKU verslo paskolų portfelio imtyje. Nustatyta, kad „blogu“ skolininku tikslinga laikyti įmonę, kuri per 24 mėnesių stebėjimo laikotarpį bankrutavo arba kuriam nors kreditoriui (pagal turimus duomenis) vėlavo sumokėti ilgiau, nei 90 kalendorinių dienų, o bendra vėluojama sumokėti suma sudarė 2000 ar daugiau eurų, atitinkamai bendras vėluojamų sumokėti skolų kiekis sudarė dvi arba daugiau skolų.

c. Atlikus papildomą „gerų“ įmonių imties patikrą autoriaus pasiūlytu metodu, nustatyta, kad dauguma „gerų“ įmonių imties neturėtų būti laikoma tokia. Šie tyrimo rezultatai leidžia teigti, kad reikšminga dalis įmonių, kurioms kredito unijų suteiktos paskolos tampa neveiksniomis, nebankrutuoja. Šie rezultatai taip pat leidžia teigti, kad mažų ir labai mažų įmonių segmentas sudaro atskirą homogeninę rizikos grupę, kurią įvertinti būtini kiti specifiniai kredito rizikos įvertinimo metodai, nei iki šiol siūlyti mokslinėje ir profesinėje literatūroje.

d. Papildomos „gerų“ įmonių imties patikros rezultatų pagrindu *formuojant modelio kūrimo imtį* taikytas modifikuotas „geros“ įmonės apibrėžimas. Iš modelio kūrimo imties pašalintos tos įmonės, kurios neatitiko nustatytų „gerų“ ir „blogų“ įmonių apibrėžimų. Apskaičiuota, kad suformuota modelio sudarymo imtis leidžia prognozuoti PD su 95 % tikimybe bei 7 % paklaida.

e. Galimų naudoti *neriklausomų kintamųjų* sąvadas suformuotas iš dviejų dalių. Pirma, atlikus išsamią mokslinės ir profesinės literatūros analizę, suformuotas galimų naudoti finansinių nepriklausomų kintamųjų rinkinys. Antra, išanalizavus kredito unijų išorinę informacinę infrastruktūrą, parinkti nefinansiniai kintamieji. Sujungus nustatytus finansinius ir nefinansinius rodiklius, suformuotas galimų naudoti nepriklausomų kintamųjų sąvadas.

f. Atsižvelgus į tikėtiną *klasifikatorių* tikslumą, taikymo dažnumą, modelio rezultato paaiškinamumo galimybes bei galiojančius teisės aktus, sudarant statistinį įmonių kredito rizikos vertinimo modelį pasirinktas logistinės regresijos metodas.

g. Atsižvelgus į veiklos pelningumo svarbą kredito unijų veikloje, lūžio taško nustatymui pasirinktas Maksimalaus tikėtino pelno metodas (EMP). Rangų skalė pasirinkta formuoti atsižvelgus į nustatytą lūžio tašką ir laikantis Bazelio bankų priežiūros komiteto rekomendacijų.

   h. Atliekant modelio įvertinimą, daugiausiai dėmesio skirta toms modelio savybėms, kurios kredito unijų įvardytos kaip svarbiausios. Išsamiai įvertinta modelio ekonominė veikimo logika, diskriminacinė galia, rezultatų paaiškinamumas bei galimybė modelį taikyti automatiniu ar pusiau automatiniu režimu.

6. Logistinės regresijos pagrindu sukurtas įmonių kredito rizikos vertinimo modelis, skirtas Lietuvos kredito unijoms. Išankstinis modelio įvertinimas parodė, kad į modelio sudarymą įtraukti kintamieji pasižymi stipria diskrinimacine galia ir yra statistiškai reikšmingi. Ekonominės logikos prasme pasirinkti kintamieji laikytini reikšmingais, nes analizuoja svarbiausias įmonių veiklos sritis bei apima tiek finansinius, tiek ir nefinansinius rodiklius.
   a. Nustatyta, kad Lietuvos kredito unijos, taikydamos sukurtą modelį, tikėtina, maksimizuotų įmonių kreditavimo veiklos pelną nustačiusios lūžio tašką T=0,48.
   b. Modelio rangų skalė suformuota iš 10 rangų, 6, tikėtina, įsipareigojimus vykdysiančioms įmonėms, 3, tikėtina, nevykdysiančioms ir 1 (10-as) – faktiškai nemokioms įmonėms. Tokia rangų skalės sudarymo metodika atitinka Bazelio bankų priežiūros komiteto rekomendacijas.
7. Apibendrinus sudaryto modelio taikymo ir grįžtamojo įvertinimo rezultatus, galima tvirtinti, kad modelio diskriminacinė galia vertintina kaip puiki. Atlikus modelio tinkamumo naudoti kredito unijų veikloje analizę, matyti, jog modelis sukurtas atlikus išsamų kompleksinį kredito unijų sektoriaus tyrimą. Modelio kūrimo metodai parinkti įvertinus kreditoriaus veiklos specifiškumą, rizikos toleranciją bei taikomus reguliacinius reikalavimus. Modelio kūrimo imtis suformuota atsžvelgus į kreditoriaus tikslinį kreditavimo segmentą bei atitinka modeliuojamą homogeninę grupę. Modelio kintamieji parinkti atlikus išsamią mokslinės ir profesinės literatūros analizę bei įvertinus jų praktinio taikymo galimybes tiriant kredito unijų išorinę informacinę infrastruktūrą. Modelio diskriminacinė galia įvertinta statistiškai bei palyginta su naujausių mokslinių tyrimų rezultatais. Kaip papildomas tyrimo rezultatas, darbe pateikta sukurto modelio taikymo metodika.

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