Risk management of the leasing company

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Abstract. The number of leasing clients in Slovakia is constantly growing and this sector is becoming an increasingly important part of the local economy. Leasing as such ensures its financial stability, and the leasing companies themselves have changed from medium-sized companies to strong institutional investors who accumulate temporary free funds and place them on the financial markets. The management of potential risks that could jeopardize economic performance and stability must therefore be an essential part of their internal processes and must be given adequate attention. Under the pressure of competition and with the aim of profit, leasing companies also involve modern optimization methods in decision-making, and these become an integral part of business analysis. This work focuses on the potential use of one of the most widely used computational techniques in examining the risk of payment failure of their clients. By discriminatory analysis, we will verify the solvency of clients on the examined sample and then predict the probability of their future non-payment.

Keywords: credit scoring, discriminant analysis, leasing, risk management

JEL classification: *G11, G32*

1 Introduction

The leasing industry as a part of the financial sector represents a wide space for the application of heuristic methods and computer technology. Some of the areas, e.g. damage studies or estimates of interest rate developments have unique features in the industry, while customer classification, insolvency prediction or specific risk modeling are common research subjects for all firms, regardless of business. The considerable potential and achievements of these methods cannot be ignored, and for this reason we focus in this work on the use in the prediction of a relatively neglected, yet one of the most important factors in providing leasing, the risk of non-payment by clients. Many innovative methods have been developed in recent decades, which have found application, for example, in business (eg Alon et al. 2001; Kaefer et al. 2005), financial markets (eg Bildirici and Ersin, 2009; Enke and Thawornwong, 2005; Eakins and Stansell, 2003) or banking (eg Celik and Karatepe, 2007; Abdou et al. 2008; Mostafa, 2009).

The original idea in the development of credit risk analysis was to use statistical tools on a sample of historical data in order to facilitate the decision-making process in selecting a suitable business partner and customer. In particular, banks have long had screenings of their loan applicants and lengthy data reviews. However, the massive rise of artificial intelligence and the availability of advanced computing in the 1980s marked the rise of sophisticated risk management techniques in general, including credit risk. Improvements in this area have enabled financial institutions to allocate capital more efficiently and to create new means of preventing, sharing and trading in this type of risk, such as credit derivatives.

Trinkle and Baldwin (2008) focused on creating an easy-to-interpret credit model, while Khasman (2010) tested several types of networks and learning algorithms to achieve the best possible predictions. Atiya (2001), Piramuthu (1999) and Tsai and Wu (2008) used the classification ability to develop effective methods for corporate credit ratings. The last group of authors tried to solve some shortcomings by presenting a combined system that integrates networks and fuzzy logic. Wu and Wang (2000) focused their attention on small American companies and deciding on their loan applications. They separated individual applicants according to set criteria and then compared their results with information from regional banks on loans granted and rejected. The authors came to the final conclusion that the new methods surpassed conventional types of credit risk analysis in the form of classical regression and logistic models. On the other hand, Bensic et al. (2005) successfully investigated small business loans in transition countries with the help of networks and decision trees.

One of the main economic areas where the risk of default plays a significant role is consumer loans. West (2000), Malhotra and Malhotra (2003), Xiao et al. (2006) or Šušteršič et al. (2009). Using artificial intelligence algorithms, Khandani et al. (2010) several nonlinear nonparametric models for predicting consumer credit risk. The calculations were based on data from US commercial banks on small loans provided from January 2005 to April 2009. By applying these techniques, the authors report a reduction in losses from intentional and unintentional payment default of up to 25%.

An inseparable part of understanding credit risk are its indicators published by international agencies, the so-called credit ratings. In an effort to contribute to the transparency and efficiency of financial markets, Bennel et al. (2006) their explanatory value and compared the results obtained by neural networks with the probit model. Huang et al. (2004) and Jiao et al. (2007) combined traditional types of networks with known heuristic procedures when examining credit ratings, while Hájek (2011) assessed the creditworthiness of smaller US municipalities. Other applications of heuristic methods and artificial intelligence in credit risk analysis can be found in Yu et al. (2008).

However, in addition to industry-specific risks, leasing companies, as businesses, are exposed to another group of risks, typical of all companies in a market environment. Among others, these are mainly strategic risk, market risk, operational risk and legal environment risk. These concepts are common in business practice and are precisely defined, for example, by Alexander and Sheedy (2005). However, as already mentioned, the subject of research of this work is the risk that the other party to the contractual relationship will not meet its obligations and will not make a pre-agreed payment, i. credit risk. There are several definitions of credit risk, including from Colquitt (2007) which states that, "... credit risk arises when a creditor is exposed to a possible loss from a counterparty ...". Nason (2010) describes credit risk as "a potential gain or loss due to a change in the debtworthiness of a customer or counterparty ..." and Wu and Olson (2008) define it as "... risk of loss due to default on a debtor ...". All the mentioned definitions point to one fact, namely the necessity of appropriate selection and correct evaluation of the contractual partner, the client. Financial institutions are trying to address this issue by using a number of tools, e.g. credit scoring, ratings, or credit commissions for partner assessment and the like. The client is assessed from the point of view of the risk of collection of performance rather than solvency. In these established processes, leasing companies use all available information by default to compensate for information asymmetry and reduce the likelihood of adverse selection.

The economic phenomenon of unfavorable choice could be briefly described as the fact that an individual's demand for service grows in proportion to his exposure to risk. However, as its exact risk factor is unknown to the institution itself, it must resort to the above procedures and differentiate clients according to certain factors and criteria. The analysis of the provision of information and transactions at this level from the point of view of game theory has already been dealt with by several authors, e.g. Rasmusen (2006). In the classic principal-agent leasing game, the game begins by assigning characteristic features to each agent (client) that are known to him but not to the principal. There are usually higher and lower risk agents. The game continues by offering the principal an agent to conclude a contract and the opportunity to classify him according to the information obtained. The resulting contract with the individual agents reflects the relative level of expectations.

For example, for banks, their product portfolio is primarily based on keeping the savings of a large number of retail depositors, and in a stable market situation, it is unlikely that all clients will come to withdraw their deposits at the same time. At the same time, they have high revenues from various administrative and brokerage fees, and thus they can expand their activities to provide other products that already involve risk and, of course, return for the business. However, for leasing companies, it is necessary to integrate the insolvency risk management of clients with the management of other corporate risks.)

2 Methodology

This section is intended to present a technique that is often used in practice to analyze problems with a dichotomous dependent variable. Discriminant analysis (DA) as a whole deals with the relationships between a categorized and a set of variables related to it (McLachlan, 2004). This method is currently used quite often for research in the economic sphere, for example in the field of banking (Pasiouras and Tanna, 2010) or finance (Sueyoshi and Goto, 2009). The main task of DA is to predict the affiliation of a dependent (group) variable to a certain group, type or category based on a set of independent (predictive) variables. In this respect, it recalls multiple regression, although it is most often used when there are several categorization groups of the dependent variable, its application is of course also possible in the dichotomous problem. The course of DA could be described as:

1) Verification of whether it is possible to explain group membership by independent variables,
2) Finding the independent variables with the highest explanatory value,
3) Selection of a suitable classification function.

Assignment to an appropriate group is performed by predictive discriminant analysis based on a set of observations that are known to individual groups. This set is called a test set. The result is then the so-called discriminant function, for example in linear form:

$$D = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n \tag{1}$$

in which *x* is a vector of prediction variables, *b* is a vector of discrimination coefficients and b_0 is a constant. The division itself takes place using a certain classification rule, the criteria of which may take the form of a minimum distance between two points Δ or a combination of predictive variables and the estimated probability of belonging to a particular category (Huberty and Olejnik, 2006). The classification rule follows one of these criteria and determines the required group affiliation. For example, Δ is used as an index of the distance between two points in p dimensional vector space. In this case, the basic requirement for comparing the distances of several variables is the same metric when calculating the individual distances. One way to achieve this is to take into account the different variances and the correlation of the variables. The most commonly used Mahalanobis distance (1936) is a measure of the distance between two points in space of correlated variables with different variances and is expressed as:

$$\Delta_{AB}^2 = (x_A - x_B)^T \Sigma^{-1} (x_A - x_B) \tag{2}$$

Discriminant analysis covers a wide range of classification rules and their criteria, and this brief mention for the purposes of our research is far from providing a sufficient overview.

3 Results

When modeling the payment default, a sample of 6,000 clients of an unnamed leasing company for 2020 was examined. 4,255 (70.9%) of the clients in the sample were standard and 1,745 (29.1%) were non-payers. The individual variables that were originally expected to affect the riskiness of the client were gender, marital status, number of children, region of residence, frequency of payment (monthly / yearly), amount and number of years of payment. Discriminant analysis was calculated in IBM SPSS Statistics.

The discriminant analysis was designed to solve problems with a limited dependent variable, and therefore it should cope with this categorization task. In the following tables we see the output of the performed DA in the statistical software SPSS. Table 1 shows the eigenvalue of the discriminant function. Eigenvalues describe the discriminant power of the respective eigenvectors. In DA, the maximum number of discriminant functions is the number of categories minus 1, which in our case represents a single function. Each of the functions has exactly one eigenvalue, which indicates the part of the explained variance, and for the purposes of our research it will represent the equivalent of the determination coefficient R2. A high eigenvalue represents a strong discriminant function. The canonical correlation represents the correlation between the achieved discriminant value and the values of the prediction variables. In the case of a single function, it provides an index of the overall quality of the model, and its high level again means good function.

Table 13. Eigenvalue.

Function	Eigenvalue	% of variability	Cumulative %	Canonical correlation
1	0,187	100	100	

We see that the size of the eigenvalue indicates approximately 5% better explanatory power of the model than in the previous methods, but 18.7% is still not a high value. When calculating the answer, we get an even lower figure in the form of 18.6%. The canonical correlation is already showing some improvement, as almost 40% is a commonly achieved indicator. The coefficients of the canonical discriminant function in Table 2 have a similar role as the coefficients in the common regression equation. The discriminant score of each subject is calculated by entering the magnitudes of its true independent variables into the discriminant equation.

Table 2. Coefficients of the canonical discriminant function.

Input	Coefficient
Const	-2,437
Sex	0,125
Age	-0,016
State	0,293
Children	0,293
Region	0,050
Payment	0,083
Amount	0,088
Period	0,151

In Figure 1, for better clarity, the distributions of the achieved discriminant score for both categories are presented, i. e. payers and non-payers. The more different the observed values and the histograms in other places, the better the discriminant analysis achieved the classification ability. We can see that the charts for the group of borrowers and regular clients almost overlap, which indicates poor results.

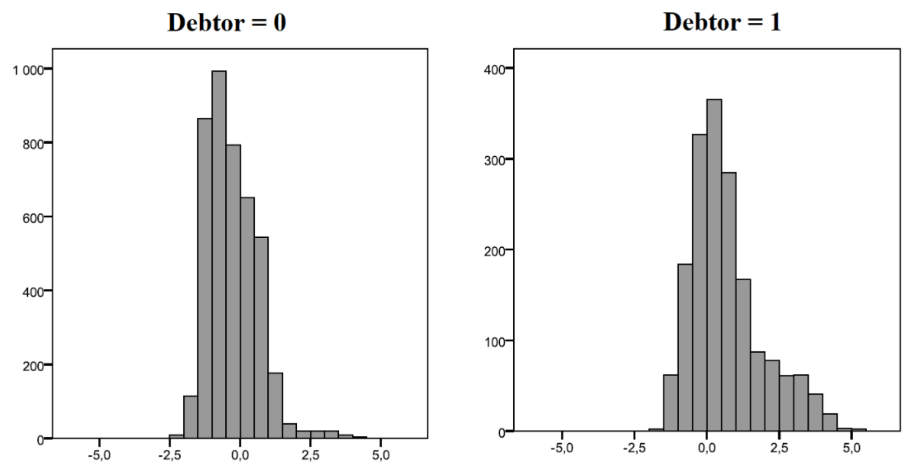

Fig. 14. Discrimination score

The last indicator, which, as in the case, we will involve in the evaluation of this model, is the number of correctly classified samples. 68% of the legal predictions in Table 3 represent a relatively applicable model. In the above context, it is necessary to note that, unlike in technical problems, socio-economic issues are often a result of a complex interaction of many parameters. Therefore, it is possible to consider the informative value of the model in the vicinity of 70% as acceptable and in business practice as relatively usable. To enhance the significance of the model, it is possible to focus on exploring other robust methods in the field of risk assessment to increase the accuracy of prediction and applicability in real business.

Table 3. Number of correctly classified examples.

Reality		Predicted	
		0	1
	0	3073	1182
	1	717	1028
Successful		68%	

4 Conclusion

Although a leasing company is, by its nature, exposed to the phenomenon of information asymmetry and adverse selection, by default, knowledge about the client's condition is the subject of its examination before concluding a new contract. The main goal of the presented work was to point out these large amounts and to predict the risk of payment failure of clients using discriminant analysis. The model was tested on a sample of 6,000 clients of an unnamed Slovak leasing company, which contained information on their gender, marital status, number of children, region of residence, frequency of payment and the amount and number of years of payment.

At present, discriminatory analysis is a frequently applied method in a wide range of corporate finance and management issues. Although it requires certain assumptions and conditions to be met, it can often provide better results than other conventional statistical and econometric models. In the interests of efficiency and better management, it would therefore be advantageous to integrate these mechanisms into the decision-making processes and insolvency risk management of leasing companies' clients.

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