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The effectiveness of the use of statistical data of credit histories bureaus in risk management systems

Keywords: credit bureau, credit risk management, reject analysis.

Abstract

The article is devoted to analysis of application the statistical potential of credit bureaus. Credit bureaus became an inherent part of modern credit market, especially at the segment of consumer lending. At the same time, possibilities of bureau`s statistics are not used effectively. The article suggests approaches to increasing effectiveness of risk management in consumer lending segment based on the study of data amassed by credit bureaus. In particular, the analysis of rejected applications, the analysis of statistical distribution of scoring inflows and bureau benchmarking are considered. The reject analysis gives the possibilities to improve rules for discrimination good and bad borrowers. The statistical analysis of market inflow is a good indicator for understanding risk environment. Bureau benchmarking which based on market statistics provides good comparison for understanding effectiveness separate creditors.

1 Introduction

The system of credit bureaus is one of the most important components of modern credit relations and an important infrastructural element of the credit market. Credit bureaus engage in collection and exchange of credit reports, thus reducing the information asymmetry between lenders and borrowers. Effectiveness of this system contributes to greater reliability of lending, strengthens and improves stability of the financial sector.

Effective performance of credit bureaus reduces credit risks and makes loans more affordable to responsible borrowers. In the corporate segment, credit bureaus help increase competitiveness of organizations.

Credit bureaus have existed and accumulated experience in the credit markets of some developed countries for more than 150 years. The first bureaus appeared

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in the second half of the 19th century in Austria (1860), Sweden (1890), Finland (1890) and, later on, in other countries of Western Europe. Today, credit bureaus operate in the credit markets at almost all countries. Credit information exchange systems have integrated into the institutional architecture of a developed market economy, both in Europe and in the world. In Europe, in the vast majority of countries (17 against 6), provision of credit information is optional. Genesis of credit bureaus and cross-country evidence are presented in [7,10,11,17].

The organization of the bureau system, its structure and functions differ from one market to another. In a number of countries, the bureau system is organized as a competitive environment of private institutions. A typical example is the system of credit bureaus in the United States of America, where there are three basic bureaus (TransUnion, Experian and Equifax) and a number of smaller bureaus serving individual regions or industries. Bureaus there share both positive and negative credit information. In Germany, the bureau of credit histories is a union of eight regional, legally and economically independent entities (SCHUFA). In France, this system is represented by a state register. In Denmark, Belgium, Spain, Australia, Mexico, Brazil and several other countries provide only negative credit information.

In 1997, a Credit Information Bureau (BIK) was established in Poland. The main task of BIK was to provide information on clients' creditworthiness. At present, more than 680 institutions participate in BIK information exchange systems. Information resources BIK cover over 137 million credit accounts owned by 23 million Poles ([21]). According to experts from the World Bank in 2013, Poland was one of the leaders in the region and globally in terms of the quality of the credit information.

Credit bureaus as inherent element of the consumer loans market were established in Ukraine at 2005. There are 7 credit bureaus in Ukraine in current period, though three largest bureaus cover 99% of individual borrowers ([22,23,24]). The market of personal loans uses bureaus very intensively. The market of corporative credits interacts with bureaus non-actively.

There are about 30 credit bureaus in Russia (the main five of them hold information about 95% of borrowers). Moreover, the Central Bank of Russia created a central catalogue of credit histories containing information on bureaus holding particular borrower's credit history.

It is necessary to note that some countries use approach based on establish state credit register. Bosnia and Herzegovina is an example.

Credit bureaus are focused on the collection and provision of credit information to participants in the credit market. At the same time, they accumulate enormous statistical information, and its use presents significant potential in improving the efficiency of risk management systems. This article suggests approaches for using the data of credit bureaus in order to raise the efficiency of credit risk management systems in consumer lending segment.

2 Functions of credit bureaus

Economic literature comprises a number theoretical and empirical studies devoted to the analysis of the functions of credit bureaus, credit reporting systems, and their role. Important contributions to the study of credit reporting were made by M. Miller, D. Rudmen, T. Jappelli, M. Pagano, S. Djankov, V.Simovic, M.Rothemund, M.Gerhardt and many others.

The system of credit information exchange through credit bureaus consists of economic, technical, and legal components. This article focuses on the economic one. Existing research (for example, [5]) has defined a number of credit bureaus' economic functions, including the following:

Reduction of information asymmetry risk. The risk of information asymmetry is inherent to credit relations, as lenders and borrowers often have different information at their disposal. When credit bureaus system is not existent, lenders can not properly assess the borrowers' creditworthiness. Borrowers may hide information about some negative aspects of their past and, vice versa, assign greater importance to the positive aspects. Taken together, this may lead to a potentially misguided decision made by lender and increases the credit risk. Moreover, borrowers may be over-credited and hide this information from the lender, applying for a new loan. Reduction in the information asymmetry with the help of credit bureaus decreases lenders' risk, helps reject adverse borrowers and ensures more favourable terms for responsible and trustworthy borrowers.

1) Reduction in costs on information collection and data analysis. In the absence of credit bureaus, creditors need to spend a lot of time searching for information about borrowers in different sources. As an alternative to bureaus, they may use the so-called 'blacklists', but their legitimacy is under big question. When credit bureaus are present on the market, they store information on all credit transactions, and when a credit institution makes a query to the bureau, the required information is promptly provided. Modern information technologies enable collection, systematization and provision of credit information in a highly efficient manner. The duration of the query to the bureau and receipt of the answer takes only a few seconds.
2) Reduction of moral hazard to borrowers. Failure to repay a loan may result from the economic to do so or from the borrower's reluctance to make the necessary payment. In the latter case, credit bureaus stimulate borrowers to develop more responsible attitude to fulfilling their obligations. Information about credit transactions is stored for a long period (e.g., in Ukraine it is stored for ten years), during which a borrower with a negative credit history will not be able to get a loan from banks working with the bureau.

The abovementioned functions have a significant impact on the credit market. In particular, reductions in information asymmetry and moral hazard allow lenders reduce interest rates on loans. Generally, lenders include risk premium into the interest rate, which naturally affects the lending economy: with an increase of risk premium, the demand for loans falls.

There may be differences in the implementation of credit bureau functions in specific markets and they are usually reflected in the principles of bureau system organization and in market structure. Main differences in the organization of bureau systems are as follows:

1) obligation to provide information to the bureau by all lenders;
2) participation of the state in the credit bureau system;
3) information provided to bureau users (only negative, or both negative and positive);
4) need of agreement with the borrower on processing and transferring of his/her personal information to the bureau.

3 Implementation of credit bureaus into the risk management system

The information significance of credit bureaus is growing. The first reason of this is that the databases have currently accumulated enough statistics about borrowers to provide lenders with increasingly comprehensive information reports. The second reason is that the content of information available to the bureau is also growing. For example, currently, borrowers' photos are collected and stored in their credit history files helping to reduce potential risk of fraud. Yet, in such circumstances, the issue of effective implementation of the lender's interaction with the bureau into the general system of risk management is becoming increasingly important. Consequently, it calls for exploring the logic of interaction with other structural elements of risk management and defining its most effective option. General logic of risk management system is presented in [2,18]. The interaction credit bureaus with other components were considered for consumer lending in [12] and [15].

In our study, we analysed several conceptual approaches to the implementation of credit bureau services to the credit risk management system of consumer lending. As an assumption, we consider the situation when several credit bureaus operate in the market, as it represents the most common model in modern credit markets. Therefore, the model of work with bureaus involves the need to interact with several bureaus, as information provided by different bureaus may not overlap. However, an opposite argument in this case is that the higher cost of working with several bureaus will affect the economy of lending.

To illustrate the case, we assume that lenders interact with three major bureaus (for instance, this is a true case in Ukraine, where most lenders work with three credit bureaus). We distinguish two main models of the organization of interaction between the lender and the credit bureau:

- a model of sequential queries to different bureaus;
- a model of simultaneous queries to all bureaus.

The model of sequential queries is illustrated in Figure 1, and the model of parallel queries is presented in Figure 2.

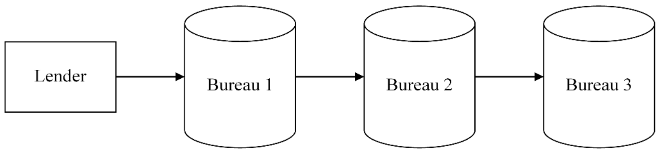

Figure 1. Model of sequential queries to credit bureaus.

Source: own elaboration.

The advantage of the first model is the reduction of risk management costs for the use of bureau services. If negative credit history is revealed in the first query to the Bureau 1, subsequent queries may be avoided. At the same time, it makes sense to make queries to the bureau on the basis of Hit Rate, i.e. the effectiveness of finding a credit history with the bureau. A disadvantage of this model is that fragmentary credit history is obtained, which does not allow to fully assess the risks. This refers to the situation when a query to Bureau 1 yields negative history, while Bureau 2 and Bureau 3 may hold positive credit history on other loans. For example, the negative credit history in the Bureau 1 may have been due to outstanding payments during the crisis period on the market.

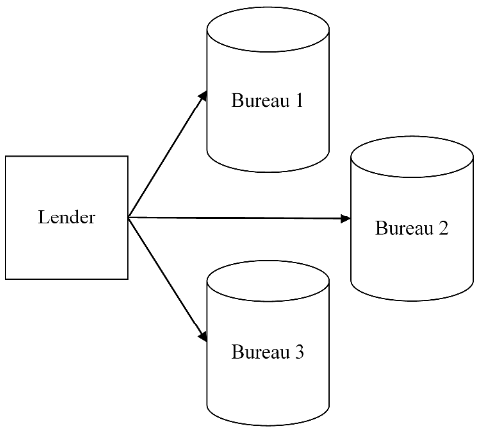

Figure 2. Model of simultaneous queries to credit bureaus.

Source: own elaboration.

The advantage of the second model is that it provides lenders with a comprehensive picture of the borrower's entire credit history. This allows making an informed credit decision taking into account not only the negative aspects of credit history, but also the positive ones.

We studied the models of organization of the credit risk management system in the framework of interaction of queries to credit bureaus and other components of risk management, in particular, the 'black lists' and the internal application credit scoring. We distinguish between two main models of credit risk management in consumer lending. Their rationale is presented in Figure 3.

The first model involves initial check of the borrower against the internal 'black-lists' as well as other lender's procedures of identification and verification. A certain percentage of applications (e.g., according to statistical data in Ukraine, we estimate this level at 10%-15%) is rejected at this stage. Others potential borrowers are subjected to internal application scoring and creditworthiness check procedures. Here, the rejection rate is a little higher (we estimate it to reach 10%-20%). Following first two stages, 65%-80% of the potential borrowers from the incoming flow get checked through a query sent to the credit bureau. Based on information from the bureau, approximately 30% of borrowers with a negative credit history are rejected. Finally, the remaining 35%-50% of loan applications are approved.

In terms of scoring methodology, Figure 4 illustrates the borrower's assessment in the framework of the model. Area B represents the part of applicants' incoming flow rejected at the internal 'black lists' check. At the stage of scoring assessment, applications with a score below the cut-off point are rejected (darker area A on the left). Finally, at the third stage, rejection decisions are made on the basis of information received from credit bureaus, (area C in Fig. 4). Area D represents approved applications (potentially issued loans).

Using the second model of using credit bureaus as part of risk management system, credit bureau information, applications are initially checked with the bureau (and an area similar to C is rejected), then against the 'black lists' (area B), and eventually, another part of borrowers' applications are rejected following internal scoring (area A).

Both models described above have a number of advantages. The first model's advantage is that the costs it involves are lower. The queries to the credit bureaus are made only for those applicants who have successfully passed stages 1 and 2. Taking into account that 20% to 35% applications are rejected at these stages, it means the costs are reduced by similar values. For instance, a bank with an incoming inflow of 10,000 potential customers per month and paying a fee of $1 per query, may achieve cost savings in the amount of $2000-$3500 per month. One disadvantage of this model is the amount of time spent by banking personnel on the first two stages for clients with negative credit history. Thus, if processing of each application takes about one hour during the first two stages (filling in the application form, etc.), and then 30% of them are rejected following negative information from the credit bureau, then, additional expenses may reach up to 3600 hours per month.

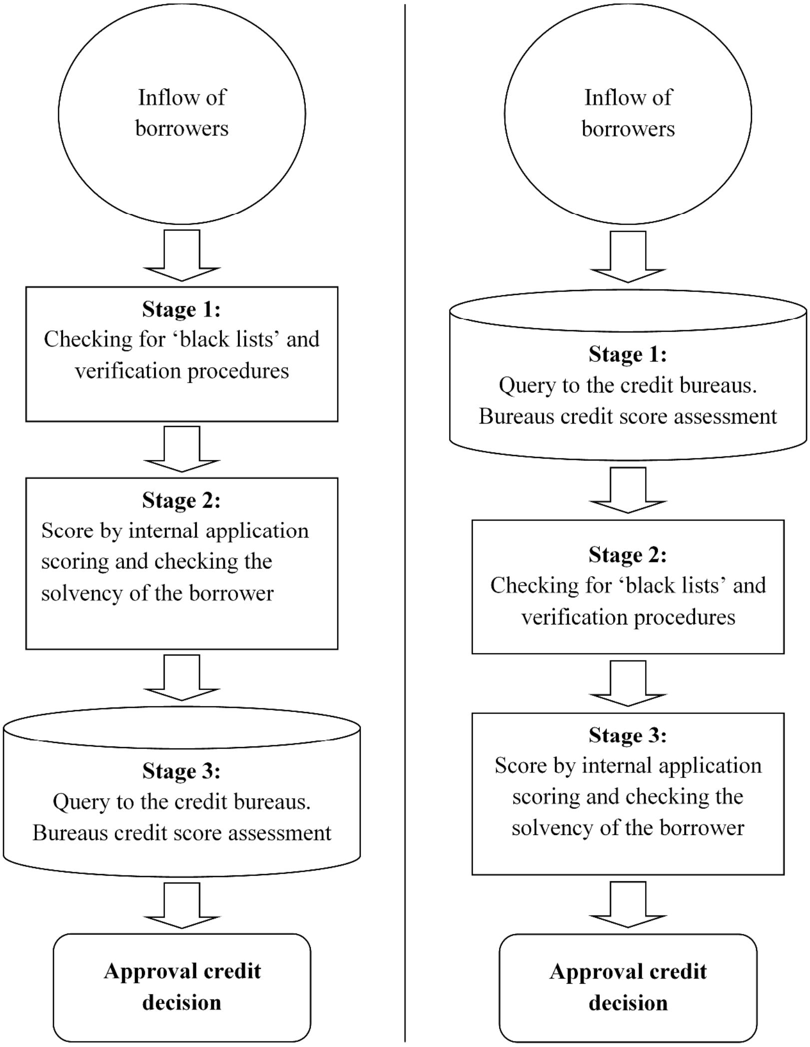

Fig. 3. Models of implementation of the credit bureau services in the system of credit risk management

Source: own elaboration.

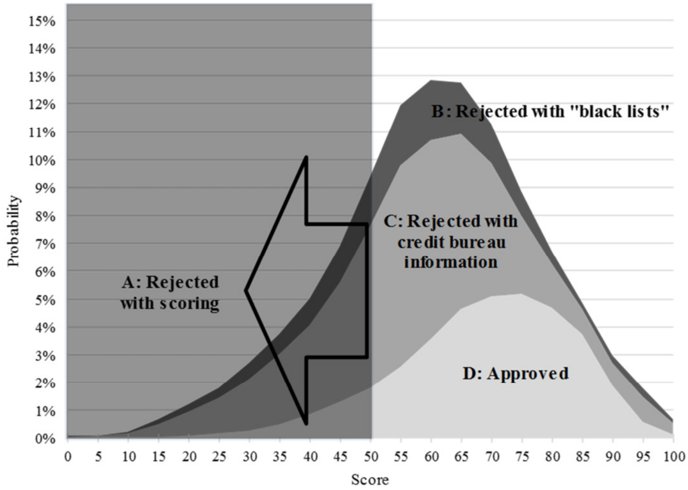

Figure. 4. Graphic illustration of processing borrower`s application

Source: own elaboration.

The second model, on the other hand, allows lender to save time spent on application processing. Having made query to the credit bureau and received negative information, lender can immediately stop application process and move to serving the next client. Operating efficiency in this case grows together with costs for credit bureau services.

The efficiency of these models may be defined by the state of the market. The first model would be preferable for lenders with a small application inflow. The second model can be effectively used in a dynamic market with large number of customers, in particular, with express loans and store loans. In order to evaluate the effectiveness of the models, we recommend comparing the cost of bureau services and the cost of applications processing for stages 1 and 2 of the first model.

Increasing effectiveness of risk management based on the use of credit bureau information

Nowadays, credit bureaus store huge amounts of market data. The idea of using bureaus' statistics for the study of economic problems was first proposed by David Burch in the 1970s. Burch used information from Dun's Market Identifiers (DMI), a private credit bureau, to find out the dependency of employment rates on firm relocations between US states ([3]).

There is a variety of ways how credit bureaus' data can be used to improve the effectiveness of risk management systems. Our study focuses on three aspects:

- reject service;
- statistical analysis of the incoming flow of applications; and
- benchmarking the lender's performance.

Reject service. In order to improve the efficiency of credit risk management system, we suggest using the statistical potential of credit bureaus for assessing loan applications that were rejected by lender at the verification stage (step 1) and at the application scoring stage (step 2). Analysis of rejection decisions by further monitoring the borrower's risks is called the analysis of rejected applications or the reject service. Feelders in [8] studied this phenomenon for commercial loans. Also, reject inference was analysed in [9].

To improve the effectiveness of verification process, it makes sense to first classify the rules making part of this process and being used to take the rejection decisions. Assume that rejections are based on k rules:P_1 ,…, P_k. Then, when lenders make queries to bureaus to receive additional information on borrowers whose applications were rejected in accordance with k rules, they can get information on whether other loans were granted after the rejection, and if they did, then whether they were paid back on time ("Good" loan status) or not ("Bad" loan status). A matrix of rejected applications can then be created shows at Table 1.

Table 1. Reject analysis for verification rules.

Verification rule	No loans received after rejection	Loan received after rejection and paid back on time	Loan received after rejection and not paid back on time
P_1	ND_1	G_1	B_1
…	…	…	…
P_k	ND_k	G_k	B_k

Source: own elaboration.

Economic analysis of rejected applications by certain rule helps compare and evaluate interest income from "good" and losses from "bad" cases. If the interest income from "good" exceeds the loss from "bad", verification should be changed by removing this rule.

Information provided by credit bureaus can be used for analysis of rejected applications based on application scoring values. Its logic is presented is Figure 5 and is based on consideration of "good" and "bad" results for rejected applications.

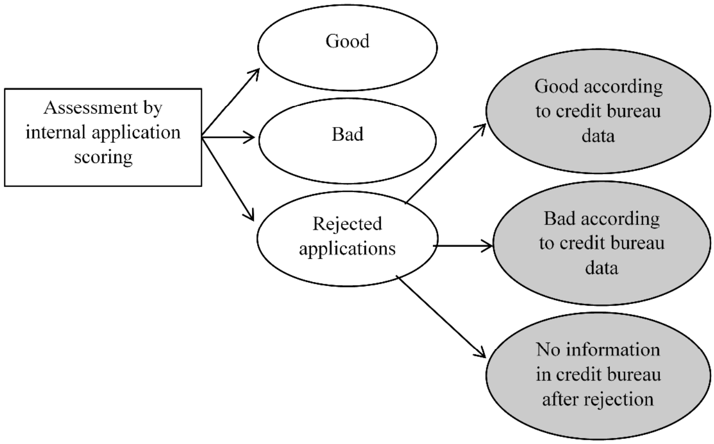

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Figure 5. Rationale for analysis of reject service based on application scoring.

Source: own elaboration.

In the simplest application scoring model, applications go through one stage only where at a pre-defined cut-off point the decision is made on loan approval or rejection. Reject service analysis provides lenders with more detailed information on applicants whose loan applications had been rejected. Using this information, lenders can adjust decision-making rules in order to issue more loans in the future. It also allows improving the discriminatory power of application scoring by including additional information on good and bad statuses of borrowers' existing loans from credit bureau into classification of good and bad loans at the stage of scoring system development or upgrading.

Thus, information from the credit bureau allows additional statistical calculations to optimize the risk management system, in particular through the improvement of the verification and application scoring stages. Analysis of rejected applications (reject service) can improve the effectiveness of discriminating between good and bad applications at the first and second stages.

Let us consider example of application reject service procedure. Authors have applied described reject service logic for one Ukrainian financial company, which issued consumer loans in 2013-2017. During this period 33210 applications were rejected in credit granting. The rejected procedures were based on the model which present at the left part of Fig.3 ("black lists" and internal application scoring). The statistics from three basic Ukrainian bureaus which were analysed by authors indicate that 18421 (55,59%) rejected applicants have received loans in other financial institutions after rejections. The information in credit bureaus about other 14789 (=33210-18421) is absent after rejections. To all appearance, these rejected applicants were really “Bad” and any creditor did not want to grant loans for them.

18421 rejected applicants on the base of bureaus information were divided to 11347 (“Goods”) and 7074 (“Bads”). “Goods” repaid loans successfully without delinquency more than 91 days. “Bads” had delinquency more 91 days and 93% of them did not go out from delinquency during one year after it begun.

We used statistical analysis for reject factors. Here we present factors which were included in internal application scoring. There were 13 basic application factors. First group of factors included socio-demographic factors: age, borrower gender, marital status, number of children, education level. Second group included professional factors: job position and time at employment. Third group of factors was devoted to welfare indicators: applicant`s monthly income, ownership indicators, time of car using. Fourth group was focused on loan characteristics: required amount of loan, duration of loan, recurring loan. Abovementioned characteristics formed core of internal application score, but did not exhaust all indicators for estimation.

We analysed Information Value (IV) statistic which is good screener for predictor variables of application scoring. Calculation of IV (see, for example [1], [20]) was done by formula (1):

$$IV = \sum_{i=1}^{n} (Good\_odds_i - Bad\_odds_i) \cdot \ln(\frac{Good\_odds_i}{Bad\_odds_i}) \cdot 100\% \qquad (1)$$

$Good\_odds_i$ is a share of “Good” applications for attribute i among all “Good” cases and Bad_odds_i is a share of “Bad” ones for attribute i amoung all “Bad” cases. According to IV methodology, its statistic values interpretation is:

- $IV < 0{,}02$ – factor has no predictive influence;
- $0{,}02 \leq IV < 0{,}1$ – low influence power;
- $0{,}1 \leq IV < 0{,}3$ – average influence power;
- $0{,}3 \leq IV < 0{,}5$ – statistically high predictive influence;
- $IV \geq 0{,}5$ – influence should be checked because of suspicious high influence power of factor.

Statistic IV is using in application scoring by signing higher weights to those predictors which have higher IV.

Firstly, we analysed statistics IV for Goods and Bads from creditor portfolio of loans. Then we expanded pool for analyses according to Fig.5. The results are presented at the Table 2 below.

Table 2. IV statistics for creditor`s data and for expanded data through reject service.

Factors, which included into application scoring	IV statistic for the data from creditor loans portfolio	IV statistic for the expanded data, which include rejective queries
Age	0.056120	0.054181
Borrower gender	0.001998	0.002449
Marital status	0.028445	0.027949
Number of children	0.020031	0.032251
Education level	0.017229	0.014506
Job position	0.019830	0.005123
Time at employment.	0.000212	0.002403
Applicant`s monthly income	0.123439	0.257549
Ownership indicators,	0.006214	0.007006
Time of car using	0.001763	0.001906
Required amount of loan	0.005119	0.088092
Duration of loan	0.000114	0.011906
Recurring loan	0.159000	0.297540

Source: authors` calculation.

IV statistics are similar for some predictors and differs for other. The differences in our case are concerned with “applicant`s monthly income”, “required amount of loan”, “duration of loan” and “recurring loan”. It means, that comparing this information values with ones, used for internal credit scoring development, lender can improve its scorecard, for example by correcting weights of risk factors or including additional factors, or change decision rules based on the results of the analysis.

Thus, information from the credit bureau allows for additional statistical calculations to optimize the risk management system, in particular through the improvement of the verification steps and application scoring decisions step.

Analysis of rejected applications (reject service) can improve the effectiveness of discrimination between goods and bads applications at the first and second stages.

4 Statistical analysis of applications inflow

The statistical potential of the credit bureau provides an opportunity to calculate the average market values of certain parameters of the borrower incoming flow. As example, at the Table 3 we illustrate market inflow at the form of risk distribution. Data reflect Ukrainian consumer credit market inflow for January-

September of 2017 year. R1-R15 are risk classes of International Bureau of Credit Histories (R1 indicate low risk, R15 indicate high risk).

Table 3. Inflow risk distribution in Ukrainian consumer credit market (%).

R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15
1.6	3.3	3.7	5.7	7.3	6.5	7.7	8.4	9.7	8.8	7.8	8.3	6.6	6.9	7.7

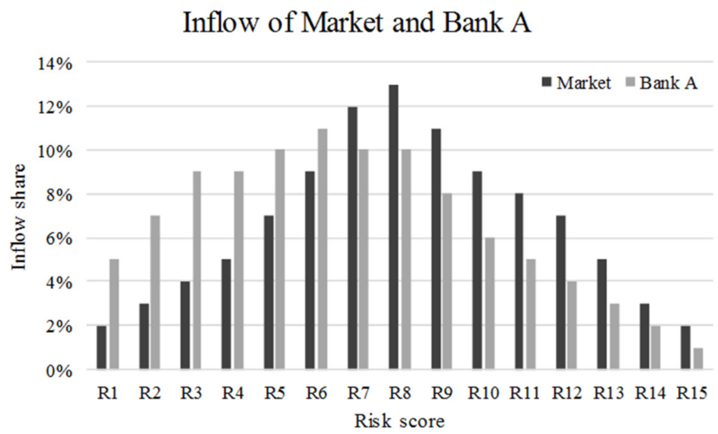
Source: authors` calculation on the base of [24].

They can be used to compare the level of inflow risk to market risk for each individual lender. Identifying this difference is directly related to the effectiveness of lender's risk management. Therefore, if the incoming flow of applications is riskier than market, risk management should be 'tougher'. Conversely, if the incoming flow is better compared to market average, then the risk management system may be 'softened'. Graphs in Figure 6 illustrate this approach. They show a comparison of the inflows of the entire market (in dark grey) against banks A and B (in light gray). Incoming flows are shown by the distribution functions of scores of potential borrowers applying separately to these banks, and in general on the market. R1-R15 are scoring classes (a total of 15 classes), each characterized by borrowers' default probability. Class R1 corresponds to almost zero probability of default, and R15 to 100%, other classes have interim default probability values between R1 and R15.

The upper graph shows that the inflow of borrowers to Bank A is characterized by a higher number of borrowers with lower credit risk than average on the market. Bank B's inflow, by contrast, is worse than the market average. This assessment is a unique tool provided by the bureau and raising the question: why is the flow of borrowers to the bank is worse than the market average? If lender's inflow can be improved by changes in marketing policies, then it will have impact on risk management.

5 Benchmarking effectiveness of the risk management system

Assessing effectiveness of credit risk management is a rather challenging task. Traditional indicators for such assessment include different types of overdue rates, rate of approved applications, rate of return on arrears, etc. However, these indicators, considered for an individual lender, do not reflect the impact of entire market conditions. A sound approach to evaluate lender performance is to use specific benchmarking that would reflect market average values. Then, comparison of individual lender's values to average market values gives an opportunity to assess their effectiveness properly. Among others this problems investigated in [14].



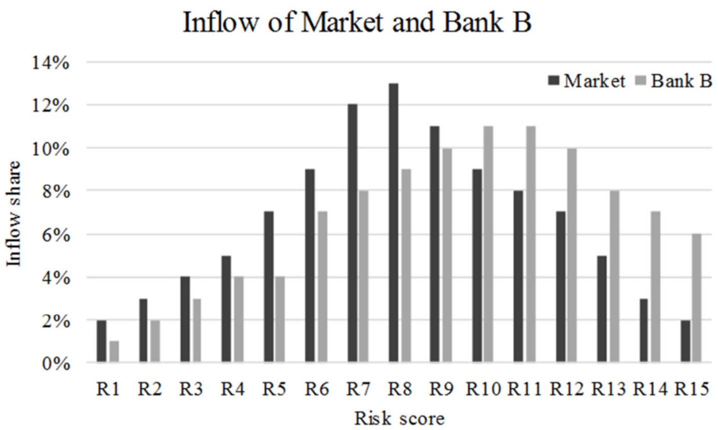


Figure 6. Comparison of market and bank inflows.

Source: authors` calculation on the base of [24].

Statistical data from credit bureaus provides lenders with meaningful information on the effectiveness of risk management indicators for the market in general. Based on them, lenders may develop benchmarking that will include dynamics of changes in the market.

We propose to consider the following five indices as indicators of the credit risk management effectiveness:

Bad Rate (BR). The percentage of borrowers with approved applications who have overdue payments of over 90 days. BR is one of basic indicators of the risk management system. Credit bureau data may be used to calculate the value of this indicator for the entire market or for a specific segment. Comparing BR of a particular lender to the market bad rate average helps assess the effectiveness of risk management in general.

First Payment Default (FPD). This is an indicator of the effectiveness of risk management in counteracting fraudulent actions. Failure to make the first payment on the loan, as a rule, is a sign of fraud.

Approval Rate (APR). This rate is a very important indicator that stands for the percentage of approved loans compared to application inflow. APR not only defines the effectiveness of differentiation between bad and good applications, but also illustrates the quality of the inflow. It is also an indirect indicator of the effectiveness of the risk management system.

Average Score Value (ASV). Bureau inflow ASV may be considered as an averaged indicator of inflow risk level. It is used to compare average score values for lender's inflow with similar market values. A more advanced approach may include comparing the distribution functions of the scoring values of the market inflow and values for the lender's inflow.

Rate of Collected Delinquency (RCD). This indicator compares the level of BR with overdue amounts repaid. RCD is an indicator of quality in managing overdue loans portfolio. Based on data from credit bureau, this rate can be calculated for the market and then compares to lender's RCD.

Benchmarking model based on abovementioned indicators is presented in Figure 7.

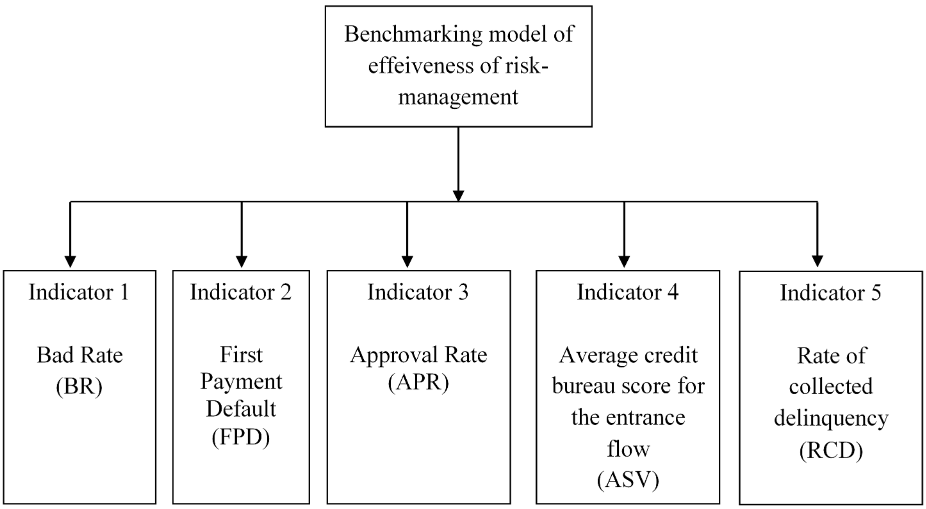


Figure 7. Benchmarking model based on credit bureau data.

Source: own elaboration.

To illustrate how the model works, let us consider it for two lenders A and B, whose data on risk management is presented in Table 4.

Table 4. Benchmarking of two lenders against market average

	Market (credit bureau statistics)	Lender A	Lender B
BR (%)	8%	6%	15%
FPD (%)	1,5%	1,5%	2%
APR (%)	40%	50%	60%
ASV (from 0 to 100)	54	62	49
RSD	8%	11%	4%

Source: own elaboration.

Taking market indicators as base value (value equals 1) for comparison, we have obtained the following benchmarking result, presented in Figure 8.

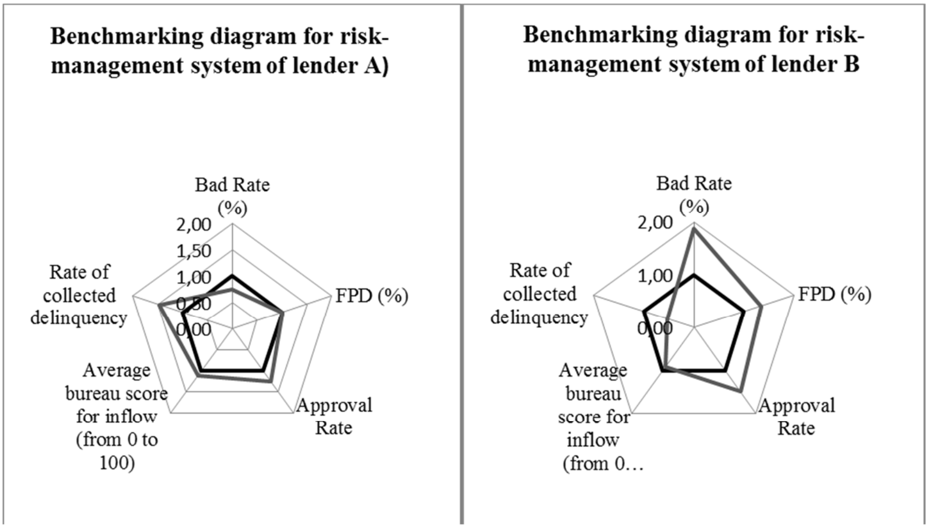


Figure 8. Benchmarking for lenders A and B: comparison of effectiveness of risk-management systems.

Source: own elaboration.

From comparison of the parameters of the risk management systems of lender A and market average, we conclude that the position of lender A is better than market average. Conversely, indicators of lender B are worse than market average. Therefore, the risk management system of lender A is considered more effective than that of lender B.

Naturally, benchmarking for assessing the effectiveness of risk-management may include more indicators that could be calculated using credit bureau data.

6 Conclusions

Credit bureaus today are inherent constituent of credit market. Especially, they are highly developing at the segment of consumer lending. Creditors include queries to bureau into the loan issuing procedure, especially when dealing with risk assessment risk procedures. Moreover, credit bureaus accumulate great volume of different statistics. These statistics using form good potential for analysis and solving different economic problems. This potential may be use more intensively. Our findings suggest that data stored by credit bureaus presents significant opportunities for improving effectiveness of credit risk management systems.

Indeed, implementation of effective credit risk-management system is a very important objective for lenders. Credit risk management systems are complex for large banks. All procedures have been realized automatically. Verification of effectiveness may be characterizes by non-clear, fuzzy results. Statistics of credit bureaus provide some good instruments for increasing effectiveness risk management systems. Comprehensive analysis of rejected applications (reject service), analysis of application inflow and benchmarking of the risk management system effectiveness based on data collected by credit bureaus has significant impact on the effectiveness of lenders' risk management systems

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