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Risk assessment of unsecured loans – example of entering a new market

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Abstract:

Aim: The aim of the paper is to show the risk assessment of unsecured loans in theory and practice.

Design / Research methods: In the first part, the paper does literature review concerning the theory of unsecured loans and their risk assessment. In the second part, a case study discusses the risk assessment process as a practical application in the hypothetical case if a Swedish bank enters the German market.

Conclusions / findings: The risk assessment of unsecured loans is a standardized process where scoring models make a crucial contribution. The case study shows how difficult that process is in the event of cross-border activities, for example, a bank enters a new market in a new country.

Originality / value of the article: The paper contributes to existing literature on risk assessment by applying scoring models to the case of cross-border activities.

Keywords: unsecured loans, scoring models, risk assessment

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1. Introduction

Consumer credit granting banks are faced with a different kind of risk in their daily business. The most important one is the credit risk. Banks are obliged to assess each customer whether to grant the loan or not. Finlay (2008) gives a broader

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overview of this field. Appraising the risk is possible by using credit scoring models. During the years, a plenty of approaches and classifications have been developed. Credit scoring can be classified according to the used algorithms, such as k-Nearest-neighbor classifiers, Bayesian network classifiers and linear programming (Baesens et al. 2003). The investigation of Baesens et al. (2003) has been updated by (Lessmann et al. 2015). They supplement the individual classifiers from the first research with homogeneous and heterogeneous ensembles. Appraising the credit risk by scoring models seems to be difficult in general s well as in the local area. A challenge is, apart from this, looking at cross-border activities. Schröder and Taeger (2014) contributed to this topic by comparing the credit reporting systems in Australia, Germany, France, UK and the US focused on credit scores. Concerning the European Union, for European credit institutions, it is important knowing the different credit reporting systems for transnational business because according to Ferretti (2015) new market entrants are faced with asymmetric information and adverse selection. Previous studies considered various aspects in that area. For example, Schröder and Taeger (2014) have shown an overview of different existing credit reporting systems in Europe and worldwide. Another study by Giannetti, Jentzsch, Spagnolo (2010) has demonstrated the effect of the existence of public and private credit registers on cross-border activities of banks. A method, which offers a scoring model for cross-border activities for foreign lenders is still missing in the literature.

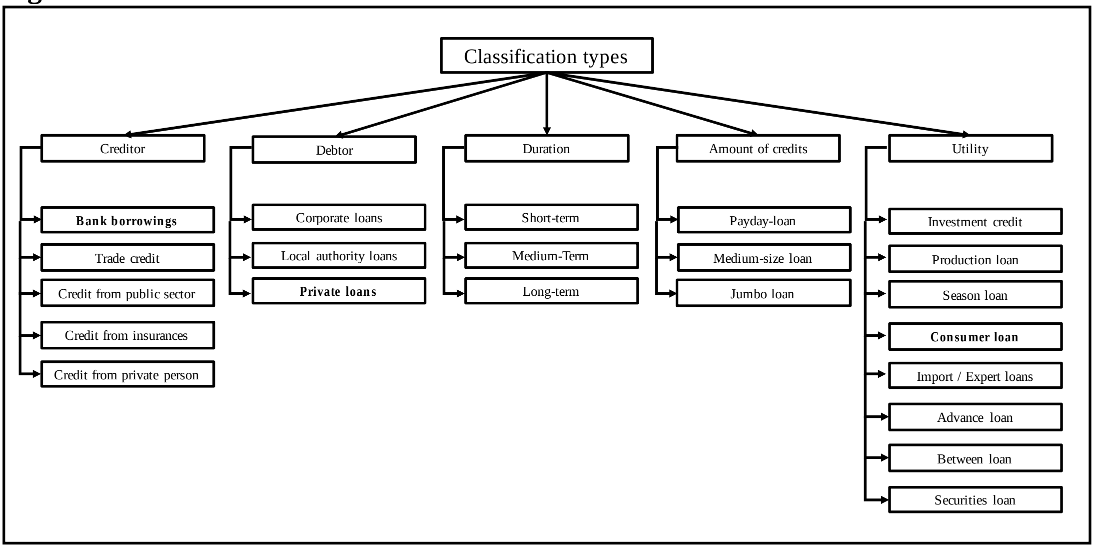
In the light of cross-border activities, this article will shed new light on the case when a bank enters a new country. For simplicity reasons, the article shows the case of a Swedish bank, which embarks on Germany, which is the strongest commercial country of the EU. The questions, the bank is faced with is the available data quality to build a precise model and the establishment of a credit risk assessment process for their new customers.

The article is divided into four sections. The first section examines the definition of unsecured loans. It classifies credits in general and presents the main types of consumer loans distinguished by their collateralization. The section finishes with the definition of consumer loans in the context of this article. The second section begins by laying out the theoretical dimension of risk and shows the assessment of risk o unsecured loans furthermore. Then, the third section is concerned with the scoring models of unsecured loans in general and analyses the differences in selected countries. The fourth part describes the case study. Finally, the conclusion summarizes the article and critiques the findings.

2. Unsecured loans

The selection of solution offered to private customers borrowing money from Banks is broad. Therefore, it is important to make a precise definition of unsecured loans and define them from other similar meanings. The overall standing designation for bank lending to private or corporate customers is credit. The meaning is borrowed from the Latin word *credere* and/or *creditum*, which express in general the trust of the lender in repayment of the credit by the debtor. This applies to both corporates and private customers. Credits, in general, can be classified as in Figure 1.

Figure 1. Credit classification



Source: Beyer et al. (1993: 9-10).

This overview does not explain the classification due to asset backing, secured or unsecured loans. There exist only vague explanations of the term consumer credit. One such definition was given by Kumar et al. (2009). They describe consumer credit as "Credit granted to consumers (…)". Beyer et al. (1993) were more precise with their description. They describe consumer loans or consumer credits as loans to private persons for buying consumer goods. There exist further expressions, like consumer lending, consumer loan, etc.

Table. 1 Types of consumer credit

Type of collateralization	Type of credit	Type of repayment	More features
Unsecured	Unsecured (personal) loan	Amortizing	Restricted; fixed sum
	Retail credit	Amortizing	Restricted; fixed sum;
	Credit card	Amortizing or balloon	Restricted (purchase) and unrestricted (cash withdrawal); running account;
	Charge card	Balloon	Running account; restricted and unrestricted;
	Overdraft	Balloon	Running account; unrestricted
Secured	Repayment mortgage	Amortizing	Restricted; fixed sum; home as security
	Interest only mortgage; bullet loan	Balloon	Fixed sum, restricted secured on home
	Secured (personal) loan	Amortizing	Fixed sum, secured on home, car, etc.; unrestricted

Source: Finlay (2008)

The above-noted table classifies consumer credits regarding its collateralization. A loan or credit is unsecured if both parties do not arrange specific assets in the credit agreement, which the lender can take in the case of borrowers insolvency (Finlay 2008). In addition to Finlay (2008), Beyer et al. (1993) mention the wage assignment and the mid-term duration as other features of unsecured credits.

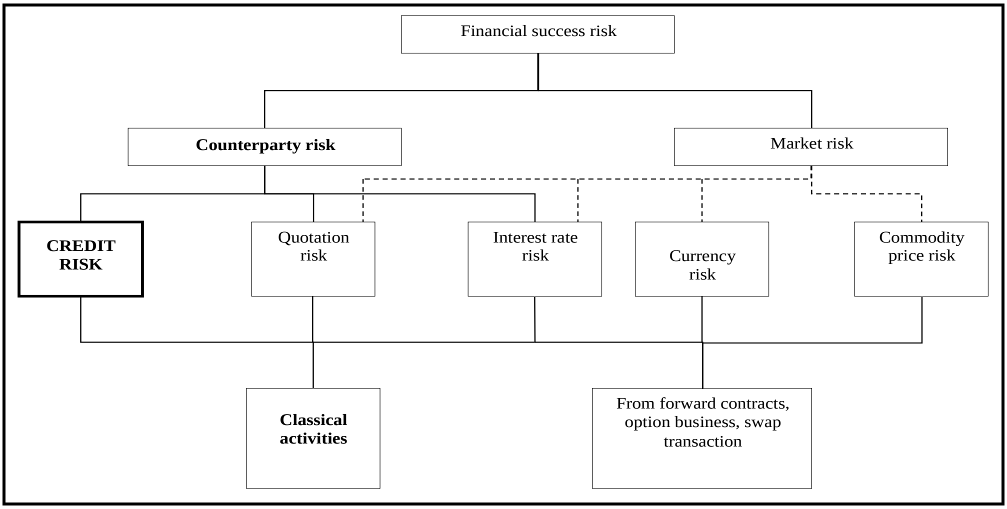
In the context of this article, an unsecured loan is an unrestricted mid-term credit to private customers as a fixed sum, an amortized repay and without securities agreements but with wage assignments.

3. Risk assessment of unsecured loans

The meaning of risk and uncertainty are close to each other, but they are slightly different. The first distinction was made by Knight (1964). He defines uncertainty as something immeasurable or uncountable. That means, the occurrence of a future event can not be predicted. Compared with this, by calculation of an expected value risk or a probability of occurrence, risk can be estimated (Horsch, Schulte 2010).

Banks are faced with different kinds of risks. Schierenbeck et al. (2008) distinguish and define six dichotomy conceptual pairs: 1. Financial risk vs. operational risk, 2. Transaction risk vs. position risk, 3. Performance risk vs. liquidity risk, 4. Counterparty risk vs. market risk, 5. Single business related vs. business structure related, 6. Unsystematic risk vs. systematic risk.

Figure 2. Credit classification



Source: Schierenbeck et al. (2008)

Figure 2 shows that the counterparty risk is a subclass of the financial success risk. Therefore, the counterparty risk plays an essential role in the field of unsecured loans in general and especially for those financial institutions which have only unsecured loans. As J. Holst (2001) points out, the counterparty risk occurs if one of the contract parties gets in trouble and as a consequence losses on the counterparty side will arise. Mäntysaari (2010) is more precise. He describes it as a risk that the debtor will not accomplish the payment commitments. Counterparty risks are usually credit risks (Schierenbeck et al. 2008). The credit risk expresses "…the volatility of the average expected credit loss and (…) the need for risk capital to be held…" (Lewis et al. 2000). The credit risk consists of the creditworthiness risk and the default risk. The latter describes the risk that one business partner becomes insolvent. The creditworthiness risk shows the hazard of credit deterioration during the duration of an unsecured loan (Schierenbeck et al. 2008), which concerns existing customers and has some influences in the behavioral scoring.

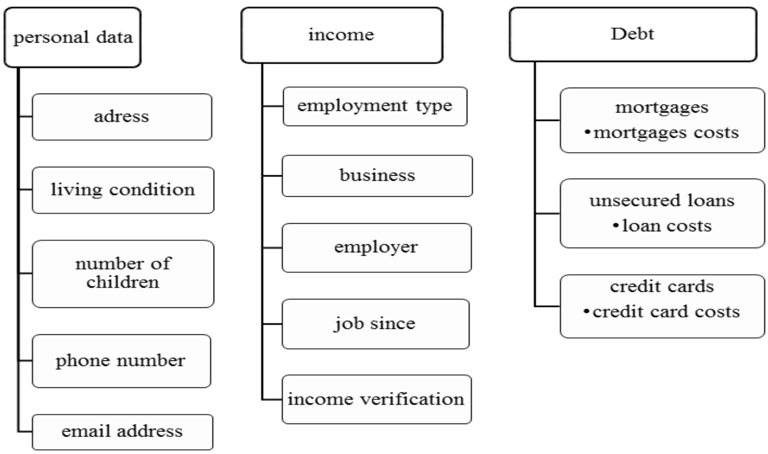
Before approving a new loan, credit institutions are obliged to judge customer's creditworthiness and their creditability. Creditability refers to the ability of the customer to conclude valid contracts (Horsch, Schulte 2010). Creditability expresses customer's legal capacity. Countries, which ratified the "Convention on the Rights of the Child," it is the age of eighteen (United Nations Human Rights Office of the high Commissioner 1990). Creditworthiness describes customer's ability, based on his income and his personal circumstances to pay back loans. A positive creditworthiness also expresses a positive donation of the customer to bank´s profit whereas a negative creditworthiness means the bank would generate losses if they lend money to a customer (Finlay 2008). Sinclair (1994) could not complete the definition of Finlay as he wrote 14 years earlier "…Creditworthiness is a dynamic condition and the quality of the rating output immediately starts to deteriorate as new events occur which impact on the liquidity and solvency of the debtor."

The aim of the assessment of creditworthiness or creditworthiness analysis is to judge the credit risk of each single customer. Depending on the level of objectivity, Horsch and Schulte (2010) distinguish three kinds of assessing methods. The first method, the verbal-qualitative method, is characterized by a high degree of subjectivity. Each customer is evaluated by his or her customer advisor employing credit reports. This kind of assessing has been used in the past. The subjectivity and consequently the low standardization make this method impractical for national credit institutions with high application frequency per day. In contrast to the first method, the mathematical-statistical method works on a high level of objectivity. The third method, the quantitative method includes subjective parts as well as objective parts. Scoring models are a commonly used represent of this method.

Assessing the creditability of a customer is challenging. Thereby, it is not to be meant as only birth date check. It is more the judgment if the customer can or is able to make an own declaration of intent. Credit institutions with own branches are in face-to-face contact with the customer. Hence, the creditability is an essential prerequisite granting consumer loans and as a result, the assessment of creditworthiness assumes the creditability as a "given".

Also, illustrating the creditworthiness poses a challenge. Only the positive statement that a customer is trustworthy is not meaningful for the risk management. The probability of default (PD) is a parameter which predicts the default of the customer during a given period, for example, twelve months in the future (Malik, Thomas 2010). It is a widely held view that the considered period is twelve months. Figure 3 shows relevant criteria assessing the creditworthiness of customers, which were evaluated within the assessment process.

Figure 3. Criteria assessing customers' creditworthiness



Source: author's own elaboration

Risk assessment can be supported by external information from credit bureaus. Those pool data about customers' credit performance by using information from credit grantors and official authorities (Thomas et al. 2005).

Table 2. Overview of European Public and Private credit register

Country	Credit Bureau (CB)	Positive Information (CB)	Negative Information (CB)	Public Credit Register
Austria	yes	yes	yes	yes
Belgium	yes	n/a	n/a	yes
Bulgaria	yes	-	-	yes
Cyprus	yes	yes	yes	no
Czech Republic	yes	yes	yes	yes
Denmark	yes	no	yes	no
Estonia	yes	yes	yes	no
Finland	yes	no	yes	no
France	yes	n/a	n/a	yes
Germany	yes	yes	yes	yes
Greece	yes	yes	yes	no
Hungary	yes	no	yes	no
Ireland	yes	yes	yes	no
Italy	yes	yes	yes	yes
Latvia	yes	yes	yes	yes
Lithuania	yes	no	yes	yes
Luxembourg	yes	-	-	no
Malta	yes	no	yes	no
Netherlands	yes	yes	yes	no
Portugal	yes	yes	yes	yes
Poland	yes	yes	yes	no
Romania	yes	yes	yes	yes
Slovakia	yes	yes	yes	yes
Slovenia	yes	-	-	yes
Spain	yes	yes	yes	yes
Sweden	yes	yes	ye	no
United Kingdom	yes	yes	yes	no
"-" means no information available; "n/a" means not applicable				

Source: adopted and adjusted from Giannetti et al. (2010).

Table 2 provides an overview of public credit registers (PCR) and private credit bureaus (CB) in Europe. According to Giannetti et al. (2010) PCR serve for statistical or supervision purposes and exists in approximately 14 countries whereas CB exist in all European countries and supply information to assess customers' creditworthiness and to monitor borrower continuously. In consequence of different data protection policies, the report from each bureau looks different. In regimes like Denmark, Finland, France, Latvia and Spain only negative information are stored in CB about individuals. That leads to adverse selection because positive information is not taken into consideration. All other countries offer positive information just as negative information. The most common credit bureau in Germany is SCHUFA whereas it is UC AB (UC) in Sweden. While SCHUFA stores only static credit information from private people, UC pools the currents balances of each loan, which present a more detailed picture of the individual applying for the loan.

4. Scoring models

In general, scoring describes a process by using information about a single person expressed by an individual number, called score, that the person will do something or act in a specific way (Finlay 2008). Scoring is applied in multiple fields, for example in marketing (Malthouse 1999: 2001) and banking, or more precisely in assessing customers´ creditworthiness.

Credit scoring has commonly been described as an application to judge the credit risk of an individual or an organization (Crook et al. 2007) by the inclusion of different statistical methods (Baesens et al. 2003). Credit scoring is a process. As a result, a credit score is determined which show the probability of default (PD). The PD expresses the likely share of expected loss per scoring class (Behr, Güttler 2004: 10). Depending on if an applicant or a(n) (existing) customer shall be observed, credit scoring can be classified as application scoring or behavioral scoring (Malik, Thomas 2010). The application scoring quantifies the credit risk of new customers whereas the behavioral assess the credit risk of existing customers (Martens et al. 2010). Therefore, the calculated score is referred to as either a credit score or a behavior score (Thomas et al. 2001). Beside the PD, applicants respective existing customers can be ranked according to their default risk (Malik, Thomas 2010).

Within the scoring process, the calculation of the score is crucial. Scoring models were used in the score calculation. It can be distinguished between binary models and predictive models. The former is based on binary classification whereby the result is either the applicant is approved or rejected (Verbraken et al. 2014). Applicants are grouped as good and bad customers respectively as low-risk and high-risk customers. According to Malik and Thomas (2010), binary models are usually applied at credit scoring. At this stage, no information are available concerning applicant's behavior. Assessing applicants is possible by the use of information from the application form and information from a credit bureau. Defining the level at which an applicant is perceived to be good or bad is crucial. Therefore, lending institutions establish cut-off scores. Applications below the cut-off score are rejected whereas applicants with a score above the cut-off point are accepted. The cut-off point might be fixed in the credit policy and can be either a separately determined score or a score from a credit bureau. Like Banasik and Crook (2007) describe, the appropriate cut-off score is essential for the performance of binary models. Predictive models also use binary classification (good/bad). But like Crone and Finlay (2012) describe, predictive models are applied to assess customer's payment behavior. Hence, behavior scoring is based on predictive models. This kind of scoring is only possible for customers with an existing payment history. In general, set in place a scoring model, a sufficiently large population of customers and characteristics is required. Crone and Finlay (2012) suggest a sample of 1.500 – 2.000 cases of each class.

For binary models as well as predictive models, different mathematical techniques are used. As described by Crook et al. (2007), the most used approach is the logistic regression. Other important used techniques are discriminant analysis, neural networks and decision trees (Crone, Finlay 2012). Many scientists have investigated the performance of these methods. Especially the predictive power has been in focus. For example, Desai, Crook and Overstreet (1996) compare neural networks with logistic regression (LR) and linear discriminant analysis (LDA). They have shown that the performance of LDA and LR in comparison to neural networks is corresponding. Only under a particular condition, neural networks have been presented a better output. In the field of consumer credits, scoring models are described as scorecards (Hand 2005). As shown in Table 3, in the literature there exist different classifications of scoring models.

Table 3. A review of scoring models

Author	Classification	Explanation
(Abdou, Pointon 2011)	1. Linear regression 2. Discriminant Analysis 3. Probit analysis 4. Logistic regression 5. Decision trees 6. Expert Systems 7. Neural Networks 8. Genetic Programming	They observed 214 studies in credit scoring. They conclude, "…there is no overall best statistical technique/method used for building credit scoring models and the best technique for all data sets does not exist yet."
(Baesens et al. 2003)	1. Logistic regression, linear and quadratic discriminant Analysis 2. Linear Programming (LP) 3. Support Vector Machines 4. Neural Networks 5. Bayesian Network Classifiers 6. Decision trees and Rules 7. K-nearest neighbor classifiers	They provide a study due to the performance of various classification techniques through assessing by the percentage correctly classified cases and the area under the receiver operating characteristic curve. The majority of the considered techniques deliver competitive results.
(Hand, Henley 1997)	1. Discriminant Analysis 2. Regression 3. Logistic regression 4. Mathematical Programming Methods 5. Recursive Partitioning 6. Expert Systems 7. Neural Networks 8. Smoothing non-parametric methods 9. Time-varying Models	The performance of the method depends on the different details. In cases of low classification accuracy, adaptable methods like neural networks are fragile. Especially the nearest neighborhood method requires analytical capacity.

Source: author's own elaboration

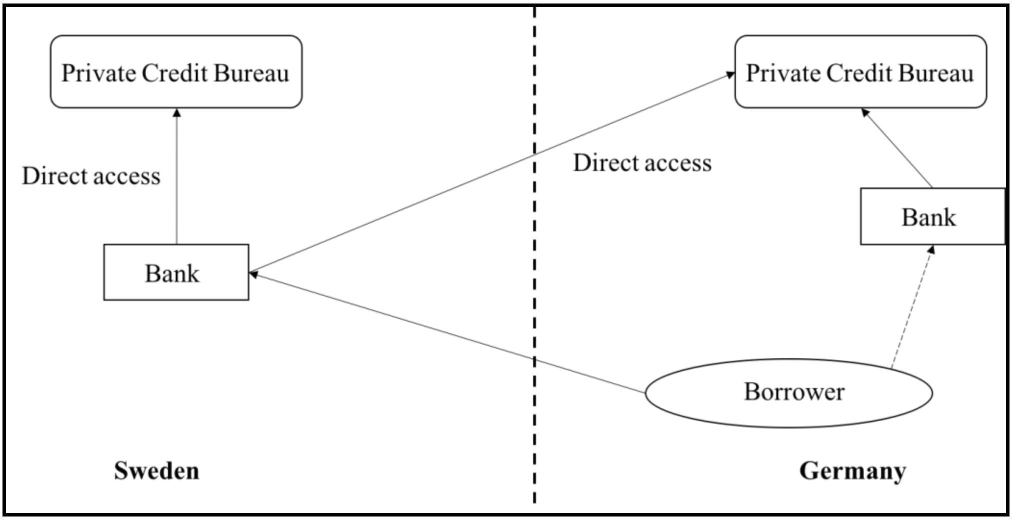
5. Example of entering a new credit market

Entering a new market is interesting from different perspectives, for example from the point of view of the market environment, the management perspective, the various aspects of the market and in general of the strategy of the bank. From the strategic point of view, the aim of entering a new market is a wider diversification of the asset portfolio as well as the credit risk and the earnings. Beyond this, to enter a new market is also full of pitfalls. Like Brown and Zehnder (2006) stated, in credit markets lenders are faced with asymmetric information. Usually, borrowers have an advantage of information due to their indebtedness, income situation and payment behavior. Asymmetric information occurs either before or after a transaction. In the first case it is called *adverse selection* and in the second case, it is known as *moral hazard*. Moral hazard in credit markets is described by Bisin (2002) as hidden action by the borrower with the purpose to avoid insolvency. Adverse selection on credit markets arises if a bank increases its interest rates for loans to cover its credit risk. But this will attract more likely bad customers because good customers are more price-sensitive. Information sharing might reduce adverse selection in the credit market (Stiglitz, Weiss 1981; Pagano, Jappelli 1993; Brown, Zehnder 2006). Adverse selection becomes even more important for banks by doing cross-border activities. Therefore the significance of information sharing increases. A significant contribution in that field serves credit bureaus. According to some authors, the existence of credit bureaus eases the market entry through reducing the risk of asymmetric information in cross-border activities of banks (Giannetti et al. 2010). The study of Giannetti, Jentzsch and Spagnolo (2010) deals with the entry modes branching and merger and acquisition. The following example presents the risk assessment process in the light of cross-border activities when a Swedish bank enters the German credit market for unsecured loans.

Germany is proved to be a stable country in the middle of Europe. It is a net exporter with a high prospering economy and it has ten times larger population than Sweden. Another factor is the attitude to unsecured loans. The research report of Dick et al. (2012) gives a good overview of that field. The study is based on expert interviews, the SAVE-Study and interviews with the banks. The purpose of the survey is to provide a summary of consumer’s attitude using overdrafts and unsecured loans. The study shows that 80% of the German households have an overdraft and 52% make use of it at least once a year. The usage frequency is at highest at household between the age of twenty-five and thirty-four.

Figure 4 explains the linkage between the credit bureaus and the bank on the one hand and between the bank and the borrower on the other hand graphically.

Figure 4. Cross-border activities



Source: author's own elaboration based on Jentzsch (2007)

Concerning unsecured loans, Dick et al. (2012) show that 17% of the households in the sample use unsecured loans. Furthermore, they show a positive relation between income and usage of unsecured loans. The higher the income, the more take people out unsecured loans. Independent of households' income, age, type of household, employment type and education at most 30% of the population make use of unsecured loans. To conclude, the study of Dick et al. (2012) emphasizes the potential in the market for unsecured loans in Germany.

The consideration proceeds under the condition that new customers were exclusively acquired by direct mailings. The assessment process is divided into five parts.

Part 1: After the bank has obtained the application form and before the data is transferred to the credit bureau the date of birth and the address must be complete. That is necessary because the German credit bureau SCHUFA authorizes customer by address and date of birth. If one of these features or both features is missing the customer cannot be identified. Consequently, the bank does not receive a credit report and the application cannot be processed.

Part 2: In the second part, the application data and the data from the credit report is transferred into the decision machine, which "… is a piece of software that can be thought as the ′brain′ of the application processing system, which makes a decision about how each application should be dealt with" (Finlay 2008: 78). At the decision machine, both data sets are analyzed for completeness and reasonableness. At this stage, the income and debt information are analyzed. The income is evaluated on completeness and income level. If the income level is missing, the customer has to be contacted and data has to be re-entered. Furthermore, a comparison between the stated profession and the income level must be taken because both must be in a particular relationship. Equally important is the indebtedness of the customer. For this reason, a comparison between customers' stated debt and the debt registered on the credit report is needed. If the deviation between stated debt and registered debt is seen, further information is needed to process the application. Due to the business policy of SCHUFA, the debt costs were not shown in the German credit report. Therefore, it is important that the costs are either stated on the application form or are asked at the applicant. When the income information and the debt information are complete, the bank calculates different parameters. This calculation is necessary for the scoring process and the decision process. The parameters are the left-to-live-on, debt-income-ration for unsecured loans ($\frac{amount\ of\ unsecured\ loans}{net\ income}$) and the debt-income-ration of all stated loans ($\frac{amount\ of\ all\ s\ loans}{net\ income}$). Figure 5 shows the left-to-live-on computation exemplarily.

This calculation is necessary to estimate customers' redemption ability. The resulting overhang is calculated without consideration of the new loan costs. The remaining positive excess shows the capability of the customer paying back the loan. The remaining negative excess implies the likelihood that the customer cannot repay the loan. The debt-income-ratio is needed to show if the customer is overindebted. An applicant is assessed as over-indebted by a debt-income-ratio of twenty-five (unsecured) or seventy-five (in total).

Figure 5. Left-to-live-on

Source: adopted, adjusted and translated from Finansinspektionen (2010)

Part 3: When customer's data is completed, the applicant needs to be judged by an appropriate scoring model, for example, LR. The basic formula for logistic regression is calculated by:

$$\ln\left[\frac{p}{1-p}\right] = a + \beta * X + e$$

$$p = \frac{1}{1 + e^{-(a+\beta * X)}}$$

$$p = \frac{1}{1 + e^{-z_i}}$$

a=coefficient of the constant term of the regression,

β=vector of the coefficient of the independent variable,

e=so called failure term

z_i=score value at point i

To build the scoring model, internal and external data are necessary, which the bank gets in the first case from its database and in the second case from an external credit bureau. Since SCHUFA stores only negative data about German customers, the bank cannot use the identical external data as for its Swedish customers. Rather, it has to make use of a different credit bureau.

The most difficult challenge is the necessity of internal data, which are not available for Germany or every new market in the beginning. The bank faces the problem with the development of an appropriate credit scorecard for German customers. Therefore, the bank has to make assumptions about the probability of default. For this reason, it uses all the granted and paid out applications of existing Swedish customers in a specific period. Furthermore, it defines good and bad customers. For example, all those customers who are in arrears on their loans for at least 90 days after 12 months on the book are defined as bad (Thomas 2010). Based on this evaluation, it is possible to express the share of bad customers per 100 good customers. Finally, the developed scorecard shows the probability of default of German customers based on the information from SCHUFA and on the payment behavior of granted and paid out Swedish customers. For every scorecard, it is important to define a cut-off score, where every customer below the cut-off score will be rejected and every customer higher than the cutoff score will be accepted (Verbraken et al. 2014). Because the bank uses two scorecards, it is necessary to define the cutoff score for both, the SCHUFA scorecard and the bank´s scorecard.

If the critical population of at least 1,500 good and bad customers is reached, the scorecard can be recalibrated.

Depending on the observations within the population, certain criteria can influence the score by overweighting or underweighting. For example, having an own property will have a more positive impact on the score as renting an apartment.

Part 4: At this stage, all applications are investigated against the policy rule. In general, applications with negative information in the credit report will not be accepted. Furthermore, all requests, which do not fulfill the policy rule, will be automatically rejected. The criteria can be a certain minimum income, probation time and cut-off score.

Part 5: In the last step, all remaining applications will be automatically categorized in different decision levels with the same characteristic.

6. Conclusion

Scoring models are crucial in assessing the risk of unsecured loans. The big advantage of scoring models is their high level of automation. There is no need for an individual creditworthiness check by a customer advisor. That is why it is applicable in the retail banking market. But there exists also disadvantages. One is the lack of objectivity in the risk assessment based on inadequate empirical data (Schierenbeck 2003).

Furthermore, scoring models do not assess fraud risks. Another disfavor is the prediction of the possibility of default based on an existing portfolio that means based on data from the past. Finally, scoring models do not take data or information beyond the existing database into consideration. For example, demographical or macroeconomic data do not influence the credit score. These weaknesses are uncertainty factors and include the following:

- Demographic influences
- Economic impacts, e.g. unemployment rate
- Fraud risk
- Sectors risk

The presented scenario shows exemplarily the risk assessment process of unsecured loans in the event of entering a new market in another country as a cross-border activity. The challenge the bank is faced with is that there are no reliable data available to assess the new customers. The developed scorecard composed of the information of the German credit report and the experiences with their existing customers would enable a Swedish bank to score the German customers until the critical mass of 1,500 good and bad customers is reached. Then a calibration of the scorecard is mandatory considering the payment behavior of the German customers.

The presented practice has different benefits and drawbacks. On the one hand, this kind of scoring consists hazardous elements. If the demographic factors and/or the population are less similar, the scorecard is not favorable. On the other hand, this kind of practice simplifies the scoring process. The existence of a similar population enables the bank to draw on existing experiences and payment behavior of Swedish customers. Furthermore, the cost for judging German customers can be held to a manageable level. The usage of only one credit bureau is less expensive than purchase of all possible information from different sources. Also, for the management is the presented approach more reliable because they know the existing scoring process and the payment behavior of existing customers. The presented scenario has several limitations. It is only focused on two countries in one direction. Furthermore, the study does not take into account the different lending attitudes in the various countries of the EU. Therefore, data sharing in the European credit market requires further research.

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Ocena ryzyka niezabezpieczonych pożyczek – przykład wchodzenia na nowy rynek

Streszczenie

Cel: Celem artykułu jest przedstawienie oceny ryzyka niezabezpieczonych pożyczek w teorii i praktyce.

Metodyka badań: W pierwszej części artykułu zawarto przegląd literatury dotyczącej teorii niezabezpieczonych pożyczek oraz oceny ich ryzyka. W drugiej części, omówiony został proces oceny ryzyka w studium przypadku dotyczącym praktycznej aplikacji hipotetycznego wejścia przez szwajcarski bank na rynek niemiecki.

Wnioski: Ocena ryzyka niezabezpieczonych pożyczek to zestandaryzowany proces, w którym główną role odgrywają modele scoringowe. Studium przypadku ukazuje, jak trudny jest ten proces w odniesieniu do działalności transgranicznych, na przykład, gdy bank wchodzi na nowy rynek w nowym kraju.

Wartość artykułu: Artykuł wzbogaca dotychczasowy dorobek literaturowy dotyczący oceny ryzyka poprzez zastosowanie modeli scoringowych w działalności transgranicznej.

Słowa kluczowe: niezabezpieczone pożyczki, modele scoringowe, ocean ryzyka.

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