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Abstract.

In this paper, we carry out a review of literature for both traditional and sophisticated credit assessment techniques, with a particular focus on credit scoring which is broadly used as a cost-effective credit risk management tool. The objective of the paper is to present a set-up of an application credit-scoring model and to estimate such a model using an auto loan data-set of one of the largest automobile manufacturers in China. The logistic regression approach, which is widely used in credit scoring, is employed to construct our scorecard. A detailed step-by-step development process is provided, as are discussions about specific modeling issues. The paper finally shows that “married”, “house owner”, “female”, age in years, “working in public institutions, foreign, or joint venture companies”, down payment rate, and maximum months on book of current accounts negatively impact the probability of default.

Keywords. Credit Risk, Credit Scoring, Auto Loans, Logistic Regression.

JEL Classification. G3, C51, C52.

1. Introduction

Credit evaluation plays a vital role in taking credit management decisions. This process involves gathering, analyzing and classifying different elements to assess the credit decisions. One of the most important methods to evaluate a loan and reduce the risk of a customer being bad is credit scoring.

Nowadays, credit scoring is broadly applied in consumer lending, especially in auto finance. In fact, auto industry is one of the industry's most recent developments over the past years. Going back to history, auto finance was started in the 1920s in the United States as payment agreements

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proposed by auto-manufacturers to purchasers. Nevertheless, in China, the practice had fallen behind, and has only risen since the People's Bank of China (PBOC) released the Administrative Rules Governing the Auto Financing Company in October 1998. This guideline has a huge impact on the auto finance growth in China, and auto loans flourished quickly over years. In 2013, among 22.1 million manufactured automobiles and 21.9 sold ones, passenger vehicles respectively recorded +16.5% and +15.7% compared to 2012 (**China Auto Finance Report – Deloitte**, 2014). As China tends to be no longer stranger to the consumer finance culture, and particularly to automobile credit, the need to employ stronger risk management practices in the retail lending activity is once again underscored. The powerful credit scoring models certainly will help Chinese lending institutions meet the consumer finance growth trend and reduce their default risks.

Although credit scoring presents undoubtedly the greatest value in the decision-making process by helping lenders in assessing risk more fairly, thanks to its consistency and objectivity, it is still interesting to look at the reasons why there were no credit scores in China. As a matter of fact, most of Asian banks, not only Chinese banks, are state-owned, and favor lending to public enterprises and high-net-worth individuals who have no difficulty to make significant deposits. Individuals without substantial financial capacity often have trouble to get a loan for their purchases, especially for dealing with emergency situations such as huge medical bills or home repair bills. In these cases, they often draw down their savings or ask for money from their family and friends. Likewise, the Chinese small and medium-sized private enterprises often raise money from the shadow banking system. The birth of nationwide credit-scoring system will lessen transaction costs, promote economic growth, and make life better by allowing everyone to get credit cards, car loans, and other products. A credit information system in China is founded to make this plan come true.

Credit information system in China is a basic financial information database founded by the government. From 2004 to 2006, the PBOC organized the financial institutions nationwide to create the centralized corporate and personal credit information system. The primary objectives are (i) to mitigate information asymmetry in the credit market; (ii) to boost the development of the credit market; and (iii) to enable regulators to better monitor their supervisory system and facilitate the implementation of monetary policies (**Cuiling Zhou**, 2012). By the end of November 2013, the system collected information on more than 830 million individuals and around 20 million firms and other organizations. The system covers credit information from banks and other financial institutions, along with general information such as the social insurance number, home address, paid/unpaid taxes, etc. The commercial banks, rural credit cooperatives, trust companies, finance companies and small-sized loan companies have access to the system. As the most basic product of Personal Credit Information System, the PBOC personal credit report records all historical data between the lenders and the borrowers. As long as a person

continues to maintain his credit card account, or apply for a loan or be a guarantor for others, his personal data and bank account information will be captured into the system, therefore his personal credit report is up-to-date.

As the credit-scoring technique has addressed the long-standing concern of any lender, which is how to differentiate correctly between good and bad clients prior to granting credit, in this study, we examine which characteristics of an auto loan application have a statistically significant impact on the probability of default or being bad. We construct an application credit-scoring model to investigate the auto lending policy of one of the largest automobile manufacturers in China. The company, hereafter called Company A, offers financing solutions to both end-customers and dealers. Using internal data provided by the company, along with PBOC data, the paper aims to provide a glimpse of the credit risk management process, how loans are classified, what is the data needed for scoring, how it is selected, and finally how the model is implemented and checked for performance and stability. The paper also zooms in on the final scorecard with a detailed analysis of each characteristic. The paper is expected to contribute to the growth of the auto loan market in China by providing an analysis on auto loan defaults for this potential promising market. Understanding the loan default factors may help to increase access to credit for all individuals while simultaneously mitigate default risk.

The rest of the paper is organized as follows. Sector 2 presents an overview of the relevant literature and the theoretical background on credit scoring. Sector 3 describes the empirical models, the estimation techniques, the data, and the results generated by the analysis. Sector 4 summarizes our major findings, and provides some recommendations for future studies.

2. Literature review

2.1. What is credit scoring?

According to **Steenackers and Goovaerts** (1989), credit scoring is a computerized procedure attributing a score to each borrower based on his information, such as income, profession, age, etc. If the score is higher than the cut-off fixed by the lender, a credit will be granted, otherwise the demand will be rejected. Credit scoring is then understood as a process of modeling creditworthiness or how likely applicants are to default on their repayments (**Hand and Henley**, 1997 and **Mester**, 1997). It is also useful to look at further definitions of credit scoring.

Thomas et al. (2002) define credit scoring as a set of decision models and their underlying techniques that aid lenders in the granting of consumer credit. These techniques allow lenders to answer questions such as whether to accept or reject a loan, what is the maximum loan amount a client should get, and what operational strategies will increase the profitability of the borrower to the lenders. As for **Anderson** (2007), credit scoring can be defined as “*the use of statistical*

models to transform relevant data into numerical measures that guide credit decision". It is a statistical approach to predicting the probability that a loan applicant or an existing borrower will default or become delinquent (**Berger and Frame**, 2007).

To sum up, credit scoring is a technique of evaluating the risk of loan applications, based on historical data and statistical techniques, so as to isolate applicants who are likely to default. This method attributes a score to each borrower so that the lender could rank its loan applicants in terms of risk. In almost scoring systems, a higher score indicates lower risk, and a lender sets a cut-off based on the level of risk it is willing to accept. Although a good scoring model cannot predict exactly any individual loan's performance, it still gives a fairly accurate forecasting of the probability that a loan applicant with certain characteristics will become delinquent. To build a good scoring model, the developer needs sufficient historical data, which reflects loan performance in both good and bad economic periods (**Mester**, 1997).

2.2. Judgmental assessment versus credit scoring

Crook (1996) mentions in his research two main techniques used to evaluate a borrower's creditworthiness: the judgmental technique (or the loan officer's subjective assessment) and the credit scoring technique.

In the judgmental technique, the loan officer evaluates each loan application individually (**Sullivan**, 1981 and **Bailey**, 2004). In this case, the experience of the loan officer is the key success of the process (**Chandler and Coffman**, 1979 and **Al Amari**, 2002). Therefore, the judgment technique often implies subjectivity, inconsistency and individual preferences of the loan officer. This process cannot make sure if the same evaluation criteria are applied to all borrowers regardless of their gender, race, color, religion, national origin, or other factors (**Mester**, 1997). Another serious limitation of the judgmental evaluation is that the difference in loan officers' experiences leads to different points of views on the relationship between risk and specific characteristics of loan applications. As a result, lending institutions cannot ensure loan officers' approval of loan applications is consistent with the risk objectives of the institutions (**Avery et al.**, 1996).

Rose (1993) points out the Six Basic C's of the judgmental appraisal: Character, Capacity, Cash, Collateral, Conditions and Control. Further discussions on this topic are presented in **Lewis** (1992), **Crook** (1996), and **Glassman and Wilkins** (1997). These authors also argue that the judgmental technique is inefficient, unexplainable, and inconsistent.

With time, increasing credit demand pressures in the economy, along with commercial competitions, have led to the development of the sophisticated statistical models that aid lenders in their credit-granting decision (**Hand and Henley**, 1997). Credit scoring is then created to address the limitations of the judgmental technique. As a matter of fact, credit scoring produces

more accurate classifications than subjective judgments. **Chandler and Coffman** (1979) and **Rosenberg and Gleit** (1994) present in their research the advantages of credit scoring over judgmental assessment. For instant, credit scoring helps lenders in assessing risk more fairly because they are consistent and objective. Thus, the credit-scoring technique becomes preferable in credit risk assessment.

2.3. Advantages and limitations of credit scoring

Chandler and Coffman (1979) are pioneers in comparing credit scoring with subjective judgmental assessment. Their arguments are first summarized in **Crook** (1996) and then in **Abdou and Pointon** (2011), who also present the advantages of credit scoring relative to judgmental technique.

First, less information is required to make a decision in credit scoring. Only variables statistically correlated with the probability of default of the client are used, while there is no statistical model in the judgmental assessment. No variable reduction method is thus available.

Second, credit scoring rectifies the bias from considering only approved accounts and not all accounts in assessing credit risk. In fact, judgmental technique is usually based on only approved accounts and those finally defaulted. Whereas, with reject inference, credit scoring assumes how rejected accounts would perform if they were accepted.

Third, credit scoring considers all good and bad characteristics of the clients, while judgmental method is usually focused on bad clients.

Fourth, all variables in a credit-scoring model are checked for being legal. In case of judgmental assessment, it is hard to make sure which variables are used in evaluating an application.

Fifth, in credit coring, the variables correlate with the payment behavior of the client. This correlation cannot be verified in judgmental evaluation.

Sixth, in case of credit scoring, a simple mathematical formula is used to help credit officers analyzing efficiently the loan applications.

Finally, credit scoring is cost-effective because it reduces turnaround time, and potentially, headcount requirement (**Lee et al.**, 2002 and **Ong et al.**, 2005). The real data based model, with an interrelation between considered variables, use of cut-off score, etc. are also advantages of credit scoring, mentioned in **Chandler and Coffman** (1979) and **Mester** (1997).

Besides these advantages, the accuracy of credit scoring is still an open issue that needs to be addressed. For example, economic factors are often not taken into account. Sometimes, clients may have the characteristics, which make them more similar to bad than good client, but may

entirely by chance (misclassification problem). Moreover, data used to develop credit-scoring models is historical and may make the model less accurate (backward looking). In fact, credit scoring based on the assumption that the future will be like the past may result in a situation analogous to “*driving a car by looking through the rear view mirror*” (Anderson, 2007). That is why the data should be updated, and the models should be monitored frequently to ensure that any change in the model is captured.

Despite the criticism of credit scoring, this technique is still considered as one of the most successful models used in evaluating credit risk (Sullivan, 1981 and Bailey, 2004).

Although the review of the literature shows that credit scoring outperforms judgmental assessment, credit scoring is not still simply a mathematical model of predicting defaults. In reality, it always requires an important degree of human judgment during its development and implementation process. In fact, by finding considerable differences between the implied loss distributions of the two banks with equal regulatory risk profiles, Jacobson et al. (2006) prove that the formal design of a rating system and the way in which it is implemented can be quantitatively important for the shape of credit loss distributions. Moreover, if the loan officers use unique data based on hard information to develop credit scoring models, and they are volume-incentivized, Puri et al. (2013) show that loan officers increasingly use multiple trials to move loans over the cut-off, both in a regression-discontinuity design and when the cut-off changes. Another relevant research to address the incentives of financial intermediaries is presented by Keys et al. (2010). Their empirical result proposes that securitization, by converting illiquid loans into liquid ones, could reduce lenders’ incentives to screen borrowers, thus limiting the utility of credit scoring.

2.4. Variables commonly used in credit scoring models

Variables such as marital status, age, gender, possession of a telephone, education, occupation, and time at present address are commonly used in developing scoring models (Orgler (1971), Steenackers and Goovarts (1989), Banasik et al. (2003), Chen and Huang (2003), Sarlija et al. (2004), Hand et al. (2005), Sustersic et al. (2009)). Time at present job, income, having bank accounts, loan amount, loan duration, loan purpose, and guarantees have been also frequently employed in constructing credit scoring models (Greene (1998), Schreiner (2004), Ong et al. (2005), Kleimeier and Dinh (2007), and Kocenda and Vojtek (2011)). Sometimes, the list of variables could be widened to include spouse information, such as age, income, bank account and others (Orgler (1971), Crook et al. (1992)).

Concerning small business and corporate loans, other variables, such as main business activity, age of business, business location, number of employees, loan amount, and some financial measures, for instance, productivity, profitability, and revenue stability, have been used in

scorecard applications (**Vigano** (1993), **Liang** (2003), **Cramer** (2004), **Emel et al.** (2003), **Bensic et al.** (2005), and **Min and Lee** (2008)).

It should be noted that in any case, the selection of the variables depends on the availability of the data and the capacity of collecting or buying additional data such as credit bureau data. Moreover, based on cultural and economic situation, along with what should be appropriate to a particular product or market, the choice of the variables differs from one study to another.

2.5. Credit scoring and modeling techniques

Various statistical methodologies have been investigated to construct credit-scoring models over the last 50 years. With time, academic researchers focused more and more on credit scoring techniques, and then replaced the first oversimplified univariate analysis. **Beaver** (1967) and **Altman** (1968)² examined a multiple discriminant analysis (MDA) by using financial ratios as predictors of failure.

Several years later, MDA was still the dominant statistical technique, and was further investigated by **Deakin** (1972), **Edmister** (1972), **Blum** (1974), **Altman et al.** (1977), **Taffler and Tisshaw** (1977), **Altman et al.** (1995), and **Lussier** (1995). Nevertheless, most of these authors mentioned in their works that two basic assumptions of MDA are often broken when applied to the failure prediction.³ Further discussions on this topic are presented by **Eisenbeis** (1978), **Barnes** (1982), **Karels and Prakash** (1987) and **McLeay and Omar** (2000). Regarding these issues, the conditional logit model has been employed for the first time by **Ohlson** (1980). By using this methodology, the restrictive assumptions of MDA are not required and the conditional logit model permits dealing with categorized data. The logistic model also returns a score between zero and one, which easily can be converted to the probability of default (PD). Another advantage is that the estimated coefficients can be interpreted one by one as the importance of each of the independent variables in the explanation of the PD. **Wiginton** (1980) in his research found that logit model outperforms discriminant analysis. Following Ohlson and Wiginton, many researchers such as **Campbell and Dietrich** (1983), **Zavgren** (1983), **Gentry et al.** (1985), **Aziz et al.** (1988), **Gardner and Mills** (1989), **Platt H.D. and Platt M.B.** (1990), **Lawrence and Arshadi** (1995), **Becchetti and Sierra** (2003), **Kleimeier and Dinh** (2007), **Avery et al.** (2012) also used logit models to predict default. Recently, **Charitou et al.** (2004)

² Altman (1968) developed the first corporate bankruptcy application scorecard (Z-Score) based on a set of five business ratios: EBIT/Total Assets, Net Sales/Total Assets, Market Value of Equity/Total Liabilities, Working Capital/Total Assets, and Retained Earnings/Total Assets.

³ The multiple discriminant analysis technique is based on two restrictive assumptions: (i) Multivariate normality of independent variables and (ii) Equal covariance matrices of groups (default/non-default).

demonstrated once again that the logit method outperforms other methods based on their empirical results.

Other statistical techniques have also been suggested to improve the prediction quality of credit scoring models such as Bayesian methods (**Ling-Jing et al.**, 2013), neural networks (**Altman** (1994), **Desay et al.** (1996), **West** (2000), **Zekic-Susac et al.** (2004)), decision trees (**Baesens et al.** (2003), and **Paleologo et al.** (2010)), k-nearest neighbors (**Holmes and Adams** (2002), **Hand and Vinciotti** (2003)), survival analysis (**Andreeva** (2006), **Banasik and Crook** (2010)), fuzzy rule-based system (**Hoffmann et al.** (2007), **Laha** (2007), **Yu et al.** (2009)), support vector machine (**Deschaine and Francone**, 2008), and hybrid models (**Lee and Chen**, 2005).

However, the logistic regression still remains the most popular method. Nowadays, even in the largest financial institutions in the world, logistic regression is always considered as one of the main approaches to predict defaults.

2.6. Credit scoring and how it works in China

As mentioned earlier in the introduction, credit scoring is still something new and has recently been implemented in the credit risk management in some Asian countries. In China, almost banks are still using the simple traditional methods. However, credit scoring has achieved initial successes in some commercial banks. An overview of current credit scoring systems in China has been discussed in **Li et al.** (2004), **Li and Zhong** (2012) and **Wang** (2014).

As credit scoring is faster developed in the joint-equity commercial banks than state-owned ones in China, Min Sheng Bank's credit scoring system is chosen as an example (**Wang**, 2014). The assessment is based upon (i) the applicants' personal characteristics such as age, marital status, education, occupation, residential status; (ii) their financial situation such as income, financial assets, and other assets; (iii) their insurance and indemnification ability such as medical insurance, endowment insurance, accumulation fund; (iv) their relationship with bank such as past loans; and (v) their financial records elsewhere. Min Sheng Bank then classifies the applicants into five levels of risk AAA, AA, A+, A and B so as to evaluate their loan applications.

In almost Chinese commercial banks, credit scoring is currently limited to the level of aggregated credit information. Quantitative evaluation criteria are not widely used. Along with the development of the national credit information system, credit scoring will promisingly be applied in the decision-making system in all commercial banks thanks to its considerable benefits.

3. Case study: Auto application scorecard

3.1. Scope and Purpose

The case study application scorecard has been developed for the first time for Company A's auto-loan portfolio. It has been three years since the company received its first applications. While the business is growing fast, the company is facing several difficulties. First, the current decision-making model does not consider any PBOC (or credit bureau) information and it is not statistically based. Second, the customer profiles change with time due to the development of the activity. Therefore, we decide to gather four-year historical data to build our statistically based scorecard. The model will help to better manage the credit risk and improve the efficiency of the underwriting decision. PBOC data will also be utilized to achieve better performance.

3.2. Data

As data is of paramount importance to the scorecard development, the three following types of data are collected to develop our scorecard: (i) application data, (ii) performance data, and (iii) PBOC data or credit bureau. Application data is the data collected at the time of application. Performance data is the data that covers total historical delinquency performance since the time of opening. PBOC data comes from the personal credit report from People's Bank of China. It records the historical data of the transaction occurring between the person and the banks and contains 5 years' delinquency information.

After the gathering step, data needs to be checked for quality, and to confirm that they satisfy the following conditions: (i) *complete* - contains all relevant information, (ii) *accurate* - being true, (iii) and the processing of data needs to be *robust* - able to withstand changes in the environment.

3.3. Scorecard Design

Exclusion rules

As loan applicants are directly rejected if one of the exclusion rules is valid, these applicants have to be removed in the model development. Based on the company's approval process, there are two main types of exclusion rules:

- *Hard decline rules*, such as: applicant age < 18 and > 65 years old, down payment ratio < 20%, loan term > 5 years, fraud, etc.
- *System decline rules*, such as: blacklist, failed identity verification, insufficient income, time on job too short, no contact information, unemployed situation, etc.

Moreover, there are some improper inclusions that must be excluded from our scorecard development database, such as VIP accounts, employee accounts and some cases that will be system declines in future.

Good/ Bad definition⁴

Good/ Bad account definition determines whether accounts are likely to roll to write off or not. For instance, *good accounts* are those that are likely to repay fully, whereas *bad accounts* are those that are likely to become delinquent. An analytical method called *Roll Rate Analysis* (Naeem, 2006) is carried out to choose the most appropriate good/bad definition for our auto loan portfolio. *Roll Rate Analysis* helps to predict losses based on delinquency, involves comparing worst delinquency in a specified previous bucket with that in the next buckets, and then computing the percentage of accounts that keep their worst delinquency, or improve their position in terms of risk, or roll forward into the next delinquency buckets. *Bad accounts* are then defined at a “point of no return” or at a level of being default at which most accounts become inalterable. *Good accounts* are those that are not likely to be default. *Indeterminate accounts* are those that are not classified into either *Good* or *Bad*, with roll rates neither low enough to be good, nor high enough to be bad.

The outcome of the analysis is found in **Table 1**.

Table 1. Roll Rate Analysis Outcome

Roll rate of month i to month i+1 (%)	Next Month		
	Turn Good	Remain	Turn Bad
0 dpd	N/A	98%	2%
1-29 dpd	58%	34%	8%
Current Month 30-59 dpd	26%	15%	59%
60-89 dpd	14%	13%	73%
90-119 dpd	11%	7%	82%
>=120 dpd	2%	98%	N/A

Table 2. Good/Bad Indicator

Category	G/B indicator
Good	0 dpd
Indeterminate	1-59 dpd
Bad	60+ dpd

As shown in **Table 1**, only 2% of current accounts turn bad, this can be considered as *Good*. Accounts with 1-29 days past due (dpd) have 8% turn bad, whereas 58% of them turn good, this can be defined as *Indeterminate*. Accounts with more than 60 dpd and less than 120 dpd have 73% to 82% chances turn worse. For accounts of 120 dpd and more, only 2% of them become good. Therefore, accounts with more than 60 dpd can be defined as *Bad*. The case with 30-59 dpd

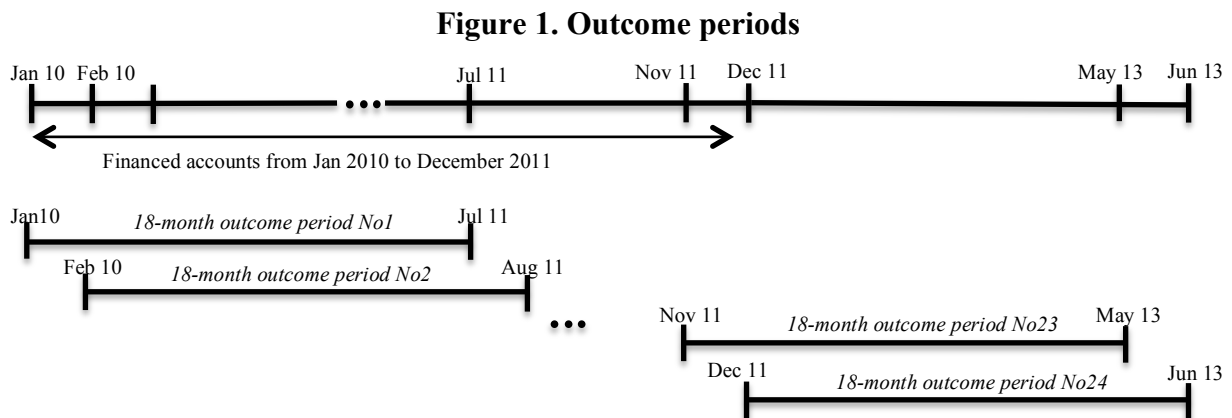
⁴ According to Anderson (2007), *Good/Bad definition* is used for scorecard developments, not a *not default/default definition* which is used for finance, regulatory, and other calculations. As a matter of fact, *Good/Bad definition* is usually used to adapt to specific portfolios, whereas default definition by Bank for International Settlements (BIS) is standardized, to make comparison across portfolios, or over time easier.

presents a high proportion of turning bad, meanwhile, and a certain proportion of being good or remaining the same. This case will be then considered as *Indeterminate*.

The final definition of Good/Bad/Indeterminate used for the development of our scorecard is summarized in **Table 2**.

Outcome Period

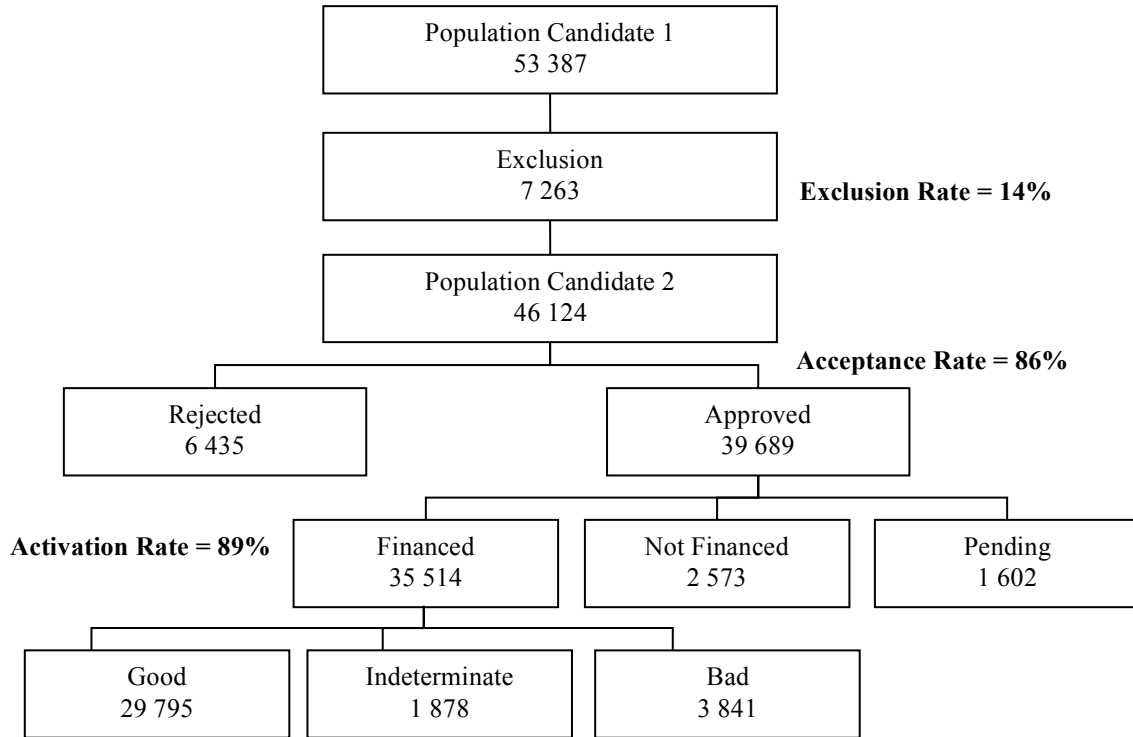
24 sample windows have been selected from January 2010 to December 2011, each having an 18-month performance window. Therefore, we will have 24 different outcome periods, which is described in **Figure 1**.



Population classification

As previously mentioned, our population covers all applications submitted from January 2010 to December 2011, each with an 18-month performance window. The classification of the population is shown in the following figure (**Figure 2**).

Figure 2. Population classification



The final population for the scorecard development is described as below (Table 3). Only Good and Bad will be taken in the development of the model.

Table 3. Good/ Bad of the Development Population

G/B Flag	#	%
Bad	3 841	11%
Good	29 795	89%
Total	33 636	100%

Training/Validation Sample

Our entire observation window was randomly divided into two samples: 80% for the training sample and 20% for the validation sample.

In addition, latest applications from July 2013 to December 2013 will be used to test the stability of the scorecard.

3.4. Data Selection

The characteristics selection methodology used to develop our scorecard consists of checking the four following elements: (i) checking for the predictiveness of the variable (Information Value – IV); (ii) checking for the stability of the variable (Population Stability Index – PSI); (iii) checking for correlation (collinearity check); and (iv) checking whether the characteristics trend is reasonable.

3.4.1. Information Value

Data transformation is done through two stages, namely fine classing and coarse classing.

Fine Classing

In the fine classing step, each attribute is broken down and analyzed. Fine classing presents an opportunity to review the data in a summarized form. It is the first step before proceeding to coarse classing data and identifying characteristics to be included in the scorecard.

At this stage, we determine if there are any characteristics that have low predictive power. The *Information Value* measures the ability of a characteristic to separate between good and bad accounts. Using the IV, we can exclude non-predictive variables.

$$IV = \sum_{i=1}^n (\%Good_i - \%Bad_i) \times \log\left(\frac{\%Good_i}{\%Bad_i}\right)$$

where $\%Good_i = \frac{\# Good_i}{\Sigma Good}$; $\%Bad_i = \frac{\# Bad_i}{\Sigma Bad}$, and i is the i^{th} category of the variable.

Coarse Classing

The objective of coarse classing is to combine fine classes into larger groups so that the number of accounts in each group is significant enough. This optimizes the discriminatory power of attributes and ensures the stability of the model. We look for similar bad rates when deciding which groups to put together.

The data transformation process is first applied to continuous variables and then to categorical variables. We categorize continuous variables as suggested by **Thomas et al.** (2002). First, the range of values for each continuous variable was split into ten categories, based on the assumption that all categories should have the same number of observations. Second, information values were computed for each category (fine classing) and categories with similar values were joined together (coarse classing). This step was also performed for categorical variables.

3.4.2. Population Stability Index

This indicator compares the distribution of a variable by attribute of the stability test population with that of the development sample.

For continuous variables, the population is divided into ten groups. This is done for efficiency, so that any shifts upward or downward can easily be identified (by setting the base for each group to 10%). This could be also done for categorical variables by listing each category separately.

$$IS = \sum_{i=1}^{10} (p_i - b_i) \times \ln \frac{p_i}{b_i}$$

where

- b_i : part of the development population pertaining to category i
- p_i : part of the stability test population pertaining to category i

3.4.3. Checking for correlation

At this stage, we focus on finding characteristics that are correlated with the target variable but not with each other, so as to minimize multicollinearity. Variance inflation factor (VIF) is the most widely used diagnostic for multicollinearity. VIF measures how much the variance of the estimated coefficient is increased over the case of no correlation among the variables. By using SAS, we can check VIF in the outcome logistic regression report. If one variable has a high VIF, it will be removed and the logistic regression is continued running.

3.4.4. Checking whether the characteristics trend is reasonable

We need to exclude characteristics if their trend is not reasonable, such as non-linear trend, no trend, or trend not aligned with the business, etc.

To sum up, when reviewing variables for possible inclusion in our scorecard, we consider the following primary factors: (i) the variables have a significant degree of predictive power; (ii) they are stable for use; (iii) they have a low correlation with each other; and (iv) they are reasonable enough to explain the business, and also compliant (no legal or ethical restrictions on their use), etc.

Back to our model, only variables that passed the pre-screening step, based upon checking for stability, discrimination power (through fine and coarse classing) and trend are finally selected for modeling.

3.5. Modeling & Final results

To model the relationship between variables, logistic regression is a standard statistical method that works best for binary outcomes. We decide to adopt this method for modeling the credit risk since the outcome of our model is a typical binary Good/ Bad.

After several trials, our final scorecard is presented in **Table 4**:

Table 4. Final scorecard

No	Characteristic	Calibrated Point	%Total	Bad rate	Pr > ChiSq
0	Intercept	207			0.7461
1	Marital status				
	Married	34	85%	1.24	0.0002
	Others	0	15%	2.31	----
2	Residential status				
	House owner	44	50%	0.87	<.0001
	Non-house owner	30	26%	1.59	0.0016
	Self-built housing in rural areas	0	24%	2.29	----
3	Gender				
	Female	52	24%	0.75	<.0001
	Male	0	76%	1.61	----
4	Age in years				
	≤ 33	0	42%	1.93	----
	> 34	36	58%	1.02	<.0001
5	Occupation				
	Employee in foreign companies, government, state-owned company, join venture	50	17%	0.51	0.0013
	Employee in private sector, self-employed, freelance, police and military, retired, worker	0	83%	1.59	----
6	Loan term in months				
	≤ 12	65	34%	0.41	0.0001
	13 – 35	37	17%	1.05	0.0015
	≥ 36	0	49%	2.20	----
7	Down payment rate				
	≤ 30%	0	26%	2.36	----
	30% – 40%	23	28%	1.85	0.0113
	> 40%	43	46%	0.58	0.0011
8	Total credit card utilization during the last month (PBOC variable)				
	< 15%	114	57%	0.55	<.0001
	15% – 39%	106	16%	0.86	<.0001
	40% – 74%	57	16%	1.68	<.0001
	≥ 75%	0	11%	5.24	----
9	Maximum months-on-book of accounts not closed and not delinquent (PBOC variable)				

	< 11	0	21%	2.84	----
	12 – 29	29	29%	1.59	0.0107
	30 – 59	80	32%	0.76	<.0001
	≥ 60	101	18%	0.4	<.0001
10	Number of delinquency occurrences in the last 6 months (PBOC variable)				
	0	49	80%	1.13	<.0001
	≥ 1	0	20%	2.89	----
11	Number of opened credit accounts (PBOC variable)				
	0 & Missing Value	95	38%	1.25	<.0001
	1 – 3	38	48%	1.37	0.002
	≥ 4	0	14%	1.93	----

Note: The attributes without “*Pr>Chi Sq*” statistics are considered as the reference attributes.

It’s clear from the above scorecard that the risky classes get lower points. Therefore, the greater the score, the better the client.

The 11 variables finally selected in the scorecard will be discussed in detail starting with the client’s personal characteristics and followed by variables describing the borrower–lender relationship.

Marital status may have an effect on the applicant’s responsibility, reliability, and financial wealth. In the scorecard, our expected results show that the risk is lower for married than single or divorced clients.

Residential status shows whether the applicant owns or rents a house, or lives with his parent. The variable may indicate the financial wealth of the client, especially in case of house owner. It is also a signal of a financial burden that the applicant may face, such as rent, tax, electricity, and water costs. In the scorecard, house owners have a lower risk while non-house owners and self-constructed house owners in rural areas have a higher risk. In fact, self-built housing is a typical case in China that stands for people living in rural areas and usually having a very limited income.

Gender is no longer utilized in the scoring models of many industrialized countries since it is regarded as discriminatory. However, in China, there is no law expressly prohibiting the use of *Gender* as one of credit rating factors. Our scorecard shows that women default less frequently on loan. **Dinh and Kleimer (2007)** say that this phenomenon is possible because women are more risk adverse.

Age measures the applicant’s age in years. Elders (excluding older than 65) are possibly more risk adverse and therefore less likely to be delinquent, empirically confirmed by **Boyle et al. (1992)**, **Thomas (2000)**, and **Dinh and Kleimer (2007)**. This is once again proved in our empirical case study.

Regarding *Occupation*, people working in public institutions, foreign, or joint venture companies are less risky than others. Since occupation is probably highly correlated with income, *occupation* may indicate whether an applicant has a high and stable income.

Loan term measures the maturity of the loan in months. Longer loan terms carry more risk to the lender.

Down payment rate measures the part of the initial amount paid at the time of purchase, reducing the amount of the loan. Therefore, higher down payment rate is less risky.

Total credit card utilization during the last month of an applicant is calculated by taking total outstanding balance divided by total credit limit at month end. The information is found in the PBOC report. In our scorecard, higher credit card utilization is more risky.

Concerning the variable *Maximum month on book of accounts not closed and not delinquent*, we select opened accounts that are not yet delinquent, and then calculate the maximum month on book among these accounts. For this variable, longer month on book history is less risky.

Number of delinquency occurrences in the last 6 months is another PBOC variable. PBOC covers five-year delinquency history of each account. This variable counts the number of occurrences of delinquency in the past 6 months. As expected, accounts with more delinquency occurrences are more risky.

Number of opened credit accounts is the fourth PBOC variable selected in our final scorecard. It represents the number of opened accounts such as credit cards, or any kind of loans, etc. of an applicant. In the scorecard, more opened credit accounts are more risky.

Aside from four variables calculated based on the Chinese credit bureau data, our remaining variables overlap extensively with the existing literature (**Section 2.4**).

3.6. Final Model Validation

3.6.1. Final Model Performance Measures

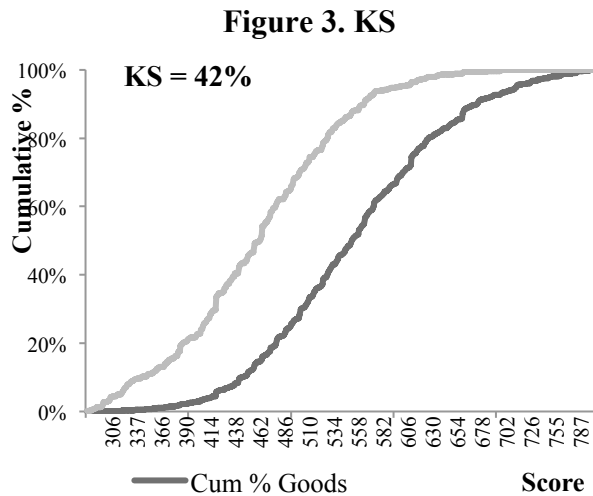
There are a number of measures that are used to check the scorecard's performance before its implementation.

KS & Gini

The KS and Gini statistics are used to measure the discrimination of the scorecard. The KS measures the widest spread between cumulative Goods and cumulative Bads. The divergence between the two curves determines the strength or weakness of the scorecard to differentiate good customers from bad ones. In other words, the higher KS, the better the model since Goods

are more separated from Bads. Like the KS, the Gini coefficient is a quantitative measure of how well the model discriminates between Goods and Bads, but by looking at actual discrimination versus perfect discrimination.

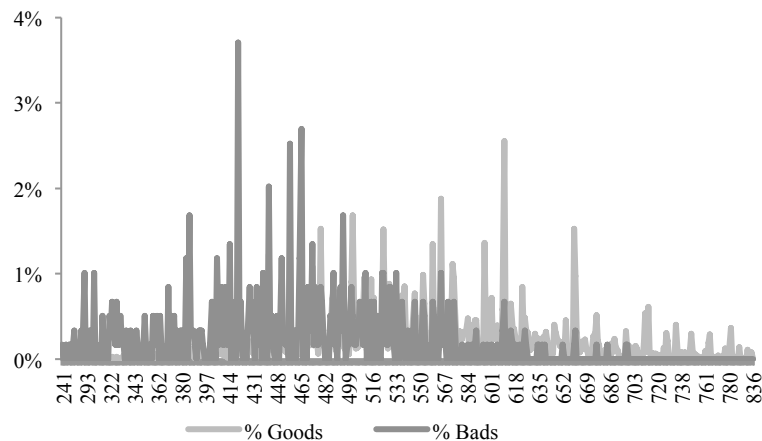
Figures 3 and 4 display our expected KS and Gini results that are calculated on the whole population.



Score Distribution

The score distribution (**Figure 5**) shows our expected result. This is a well-distributed plot with no score having more than 4% of accounts. In other words, the scores given by the model are homogeneous and not concentrated.

Figure 5. %Good and %Bad by Single Score



All these results confirm the performance of our selected model.

3.6.2. Final Model Stability

The stability indicator compares the distributions by scores of the latest applicant population with those of the development population. This is done to detect shifts in the applicant profile, represented by the distribution of applications by score.

Table 5. Population Stability Index

Score	Latest ⁵ (1)	% Latest (2)	Dev. ⁶ (3)	% Dev. (4)	(5) = (2) – (4)	(6) = $\ln((2)/(4))$	PSI % = (5) * (6)
[Low : 443]	1 851	14%	3 383	10%	3.8%	32.1%	1.2%
[444 : 479]	1 538	12%	3 389	10%	1.4%	13.4%	0.2%
[480 : 503]	1 365	10%	3 488	10%	-0.1%	-1.4%	0.0%
[504 : 529]	1 487	11%	3 464	10%	0.8%	7.9%	0.1%
[530 : 553]	1 436	11%	3 304	10%	0.9%	9.1%	0.1%
[554 : 574]	1 127	8%	3 360	10%	-1.5%	-16.8%	0.3%
[575 : 604]	1 375	10%	3 415	10%	0.2%	1.5%	0.0%
[605 : 631]	1 017	8%	3 369	10%	-2.4%	-27.3%	0.7%
[632 : 676]	1 119	8%	3 280	10%	-1.4%	-15.1%	0.2%
[677 : High]	1 030	8%	3 184	9%	-1.7%	-20.4%	0.4%
Total	13 345	100%	33 636	100%			3.1%

The PSI value of 3.1% confirms the stability of the scorecard. In other words, it indicates that the scorecard is stable over time.

After the implementation of the scorecard, we will review the clients’ creditworthiness periodically, as any change in economic condition may affect the loan performance, in line with the finding of **McAllister and Mingo’s** (1994).

4. Conclusion

The objective of the paper is to analyze the most important analytical issues in credit scoring with a real and extensive set of data taken from one of the largest automobile manufacturers in China. The paper has identified the factors influencing the lending decision of the company. The empirical results show that “Married” (*marital status* type 1); “House owner” (*residential status* type 1); “Female” (*gender* type 1); *age* in years; “Working in public institutions, foreign, or joint venture companies” (*occupation* type 1); *down payment rate*; and *maximum months-on-book of accounts not closed and not delinquent* negatively impact the probability of default. There are eight variables which positively impact the probability of being delinquent: *marital status* type 2;

⁵ Latest population : applications submitted from 07/2013 to 12/2013

⁶ Development population: financed contracts from 01/2010 to 12/2011

residential status type 2 and 3; *gender* type 2; *occupation* type 2; *loan term*; *total credit card utilization during the last month*; *number of delinquency occurrences in the last 6 months*; and *number of opened credit accounts*. Our results are mostly in line with existing research. The findings also suggest that it is necessary to back-test the scorecard periodically, as any substantial changes in macroeconomic environment, government regulation, product specifications, and population might affect its stability.

The paper may be extended for further research. First, it would be interesting to compare the results from the logistic regression with the results of other statistical techniques. Second, analyzing the advantages/defaults of different performance indicators (such as KS, Gini, Score distribution, etc.) used to assess scorecard power would be also a promising extension. Third, as the past and the future will generally not be the same, it is necessary to monitor the scorecard to identify and incorporate any differences into the scorecard as quickly as possible. Therefore focusing on the methodology of backtesting a credit-scoring model after its implementation would also be a potential extension.

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