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Credit Scoring: A Tool for Credit Risk Reduction

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Abstract: This article provides an overview of credit scoring, including how it functions, what it is, and how the methods for scoring have changed over time. It discusses various scoring models and the sources of data used for credit scoring, such as combined models, traditional credit bureau scores, and custom models. In this article, modern scoring methods and traditional scoring methods are also compared. Furthermore, it outlines the main steps in creating credit scoring models, describes different ways to estimate statistics, and emphasizes the important factors for assessing their effectiveness. The article explained credit scoring is a key method for reducing the risk of lending money, giving lenders a fair and organized way to check if a borrower is reliable. Beginning in the 1950s, credit scoring has expanded from being used for personal loans to also include small business loans. This growth is mainly due to advancements in statistical techniques and better access to data. The advantages of credit scoring, such as speeding up the lending process and making it more fair, are recognized. However, potential problems like concerns over data accuracy and the risk of excluding borrowers who don't fit the typical profile are also considered. Overall, this study highlights the important role credit scoring plays in current lending practices and its influence on risk management in the financial sector.

Keywords: credit scoring, credit bureau scores, customized models, pooling models, credit risk

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1. Introduction

1.1. Background Information

An essential technique for lowering credit risk is credit scoring. It assists lenders in efficiently managing credit risk since it can offer a consistent and unbiased assessment of creditworthiness. According to Hand and Henley (1997), credit is a sum of money that is lent to a customer by a financial organization and must be repaid with interest over time in equal installments. The scoring method, on the other hand, uses statistical modeling to create a numerical score for each borrower or loan by applying it to a representative database. Individual borrowers or loans can be categorized into risk groups using the score. A credit score is a number used to estimate a borrower's likelihood of repaying a loan. A loan score goes beyond a credit score by adding elements that are specific to loans (Stanton, 1999). Shareholders need not fear that these bankers are spending time talking about the game when they ask each other, "What's the score?" More likely, they are going about their business while talking about the credit rating of one of their loan applicants. The likelihood that a loan applicant or current borrower will default or become late is predicted statistically using credit scoring. Introduced in the 1950s, the technique is now widely utilized for consumer lending, particularly credit cards, and is increasingly employed in mortgage lending. Although it hasn't been used frequently in commercial loans, this is beginning to change. One factor contributing to the delay is that it is challenging to build a reliable grading system because business loans frequently vary greatly between borrowers. But as new approaches, more powerful computers, and better data accessibility have emerged, scoring has become more feasible, and many banks are starting to utilize scoring to assess small-business loan applications. The nature of small-business lending is probably going to alter as a result of credit scoring. It will become less important for a bank to be present in the local market where it loans, say, by way of a branch. The small business borrower's relationship with his or her lender will change as a result. Large banks have traditionally been less engaged in the small-business lending sector, but credit scoring is now enabling them to do so. Another crucial step in making the securitization of small company loans more possible is scoring. Insofar as securitization enables greater risk diversification, the expected outcome would be improved capital availability for small enterprises and better terms.

2. Conceptual Review

2.1. Credit Score Concept

The relative risk of a bad financial occurrence, such as defaulting on a credit commitment, is predicted using a person's credit score, which is a summary of their apparent creditworthiness. According to Hurley and Adebayo (2016), it is a numerical figure used to determine if a loan application is likely to default or not. Similar to this, a credit history score shows how likely it is that a borrower would default on a loan based on information about their credit histories as provided in credit bureau records (Avery, Bostic, Calem, & Canner, 1996).

2.2. Concept of Credit Scoring

Credit scoring is the process of using historical data in calculating a score or numerical value to forecast whether a loan applicant is worthy or not worthy of being granted the applied loan. Similar to that, credit scoring is the practice of giving a potential borrower a single quantitative measure or score that serves as an estimation of how well they will perform on future loans (Feldman, 1997, as referenced in Berger & Frame, 2007). Based on applicants' socioeconomic status and credit history, this method aids financial intermediaries in determining whether to extend credit to them (Bofondi & Lotti, 2006).

The idea of credit scoring has been put in place as a quantitative analysis method of reducing credit risk associated with lending. In general, scoring is a procedure that makes use of data that has been gathered about people and their loan requests to forecast, quantitatively and consistently, how they will behave in the future with regard to repaying debt. Scores are an assessment of the association between data from loan applications or credit bureau records and the possibility of subpar loan performance, which is often assessed as delinquency or default. For decades, scoring has been used to evaluate applications for auto loans, credit cards, and other forms of consumer credit. The lending sector is being pushed to include scoring in the loan guaranteeing process by technological advancements in information processing and risk analysis, as well as competitive pressures to process applications more quickly and effectively (Avery, Bostic, Calem, & Canner, 1996).

Loan application credit risk is assessed using credit scoring. Credit scoring seeks to separate the impacts of different applicant qualities on delinquencies and defaults using historical data and statistical methodologies. The process generates a "score" that a bank may use to assess the riskiness of its potential borrowers or loan applications (Mester, 1997). A loan applicant's creditworthiness is assessed using credit scoring, which involves simply adding up the points awarded for each of the application features to determine the applicant's overall score. Depending on the architecture of the system, the score may be handled in a variety of ways (Capon, 1982).

2.3. Sources of Credit Scoring Information

Credit bureaus and loan applications provide information about borrowers. The scorecard may include information on the applicant's monthly income, outstanding debt, financial assets, length of employment, history of default or delinquency on prior loans, ownership or tenancy of a home, type of bank account, and whether the applicant owns or rents a home (Mester, 1997). These are all potential factors that may be related to loan performance.

2.4. Candidates for Credit Scoring

The first places where credit scoring was used were in consumer loans. Score-based systems were first used by finance organizations to analyze prospective consumers and evaluate credit applications in the 1960s, and then by merchants and credit card corporations. Data management companies started creating credit models for customers who had obtained consumer loans using data culled from credit agency records. These businesses created databases and mined the information for connections between a borrower's credit-related details and that borrower's statistical chance of defaulting on a consumer loan. Fair Isaac and Company (FICO), one of these companies, developed a range of ratings to account for these risks, ranging from a low FICO score of 200 to a high score of 800. Fair, Isaac, and users improved the scorecards in response to user input as lenders increased their usage of them to strengthen the relationship between score and real credit performance. For credit cards, installment loans, and auto loans, lenders started using these scorecards and creating their own unique models and ratings. To decide whether to provide consumer credit and under what conditions, lenders now frequently employ scoring (Stanton, 1999).

Additionally, banks formerly relied on judgment when making credit decisions and used credit reports, personal histories, and both. However, over the past 25 years, credit scoring has grown in popularity and is now often utilized in the issuance of credit cards as well as other consumer loans like auto loans and home equity loans. The use of scoring is expanding in the mortgage origination industry as well (Mester, 1997). Since the middle of the 1990s, credit analysts have argued that credit scoring could have profitably been applied to small business lending as well, as the personal credit histories of small business owners have proven to be highly predictive of the likelihood that they will be able to repay their loans (Akhavein et al., 2005; Berger et al., 2005, as cited in Bofondi & Lotti, 2006).

2.5. Different Credit Scoring Methods

There are several methods of credit scoring. According to Thomas, 2000, as referenced in Van Gool et al. (2009), there are three basic categories of credit scoring approaches: (i) judgemental; (ii) statistical; and (iii) non-statistical, non-judgmental. Most microlenders still use the judging technique, which determines risk based on the loan officer's knowledge and judgment. Comparatively, statistical methods rely on past data and include logistic regression and discriminant analysis. Various operational research techniques, neural networks, and genetic algorithms are examples of non-statistical, non-judgmental methodology (Schreiner, 2004 as quoted in Van Gool et al., 2009). Results on the performance of various credit scoring algorithms are frequently ambiguous, as reported by Baesens et al. in 2003.

2.6. Credit Scoring Model

Credit scoring models (CSM) have been created that mathematically "score" or weigh some or all of the elements taken into account throughout the underwriting procedure and show the relative risk provided by each application (Avery, Bostic, Calem, & Canner, 1996). A CSM essentially calculates a borrower's credit risk based on a variety of measurable borrower attributes, such as their chance of repaying the loan as agreed (Dinh & Kleimeier, 2007). According to Dinh and Kleimeier (2007), CSMs are frequently organized in a manner similar to Altman's Z-score model from 1968. The promise of a well-designed credit scoring system is that it will, in theory, make the process of evaluating credit faster, more accurate, and more consistent while also costing less. Credit scoring can thereby decrease risk by assisting lenders in eliminating candidates who pose an excessive amount of risk and can also improve the number of loans by more accurately identifying applicants who are creditworthy (Avery, Bostic, Calem, & Canner, 1996). The development of a scoring model, or "scorecard," begins with an analysis of historical data on the performance of previously made loans to identify the borrower attributes that are helpful in forecasting whether the loan worked successfully (Mester, 1997). In a well-designed model, borrowers with loans that will perform well should receive a larger percentage of high scores, while borrowers with loans that will perform poorly should receive a higher percentage of bad scores. However, as no model is flawless, some poor accounts will score better than some good accounts (Mester, 1997). Testing a model's precision is necessary. The data on which the model is built should encompass both expansions and recessions since a strong model must be able to make precise forecasts during both good and bad economic periods. Additionally, loan samples that weren't initially utilized to create the model should be used for testing (Mester, 1997). Credit scoring for loan applicants uses three models: credit bureau scores, customized models, and pooling models (Crouhy, Galai, & Mark, 2006, as referenced in Chin'Anga, 2015). Below is an explanation of them.

2.6.1. Credit Bureau Scores

Credit bureau companies gather information on each consumer's credit history and credit utilization ratio to create credit scores (Frame, Padhi, & Woosley, 2001, quoted in Chin'Anga, 2015). The lending industry, including banks and other financial organizations, can benefit from such information. Due to the fact that each consumer's different credit accounts reflect changes in their repayment behavior, credit bureau scores are continuously updated (Mays, 2001, as cited in Chin'Anga, 2015). According to Rose and Hudgins (2013), using credit bureaus may offer banks the most benefits because it is less expensive than developing internal credit scoring models and gives a comprehensive picture of the likelihood that loan applicants will default on their payments.

2.6.2. Customized Models

These models are adapted or modified to the requirements of the lender. According to Crouhy et al. (2006), as referenced in Chin'Anga (2015), custom models are internally developed models that employ bank-specific data about potential borrowers to decide whether or not to grant credit. If a potential borrower is eligible for a specific type of credit requested, it can be determined using the applicant's credit profile. By using these models, banks have been able to minimize risks and maximize returns on credit supplied to groups of creditworthy customers.

2.6.3. Pooling models

A pooling model uses secondary data collected from many sources to build a secondary-based credit rating model. According to Gupta (2013), in order to create credit scoring models, also known as pooled models, external suppliers may obtain data from different lenders with the same loan portfolios. Information from credit cards that has been obtained from a variety of institutions is a good example of data that can be used. These models can be modified to meet many industry kinds, but they cannot be unique to a single company. Fair Isaac is one of the well-known global suppliers of these models (Gupta, 2013).

2.7. System Comparison: Traditional vs. Automated Credit Scoring

Automated credit scoring systems, such as those created by the Fair Isaac Corporation (FICO), have been a crucial factor in determining financial success for the majority of Americans during the past three decades (Hurley & Adebayo, 2016). Application/automated credit scoring models forecast whether a new credit product applicant will pay the bills on time over a specified outcome period, often 12 or 18 months (Djeundje et al., 2021). Examples of credit-scoring data management firms that use non-traditional data are given in Table 1.

Table 1: Credit Scoring Data Management Firms

SN	*Firms/Companies*	*Product*
1	Lexis Nexis	Risk View
2	FICO	Expansion Score
3	Experian	Income Insight
4	Equifax	Decision 360
5	Trans Union	Credit Vision

According to Thomas et al. (2017), in traditional models, the covariates (or inputs into a machine learning model) would include factors measured at the time of application, such as years at address, years in employment, income, age, and credit bureau data, such as repayment history on prior loans at that institution and other institutions, the percentage of the population in the postcode that defaults, etc. Traditional credit-scoring algorithms, which use a relatively small collection of data points, have long struggled with the issue of accuracy (Hurley & Adebayo, 2016).

2.8. Methods of Statistical Estimation for Credit Scoring

Credit scoring techniques may be divided into two categories, according to Kiss (2003):
Models for parametric credit scoring:

1. Model of linear probability
2. Models for probit and logit
3. Based on discriminant analysis
4. Neural systems

Models for non-parametric credit scoring:

1. Computational mathematics
2. Classification trees (recursive techniques for partitioning)
3. Model of closest neighbors
4. Procedure of analytical hierarchy
5. Seasoned systems

Genetic algorithms are a different category of artificial intelligence techniques that are frequently employed in scoring systems. These don't, however, represent a distinct modeling procedure; rather, they mutate the current collection of scorecards to discover the best version (Kiss, 2003).

2.9. Statistical Credit Scoring Model Developmental Steps

To determine which borrower traits are most effective in differentiating between defaulted and non-defaulted loans, credit scoring models (CSMs) often employ previous loan and borrower data. All potentially important borrower features must be discovered and coded during this development stage, as well as judgments on the estimate strategy for the model. Last but not least, it is important to choose the pertinent borrower traits and determine how they affect default rates. To put it another way, the model must be approximated. New loan applications for which the probability of default (PD) is unknown can now be evaluated using the CSM. Each new loan application can have their credit score generated based on the predicted CSM; a higher score signals better expected performance from the borrower and, consequently, a lower PD. To decide if a loan application is accepted, refused, or needs more evaluation, this score must be contrasted with the CSM's cutoff rate (Dinh & Kleimeier, 2007). Five steps are involved, as mentioned in Dinh and Kleimeier (2007), and are listed below:

1. Choosing a model's estimate strategy
2. Next, decide which variable "x" should be the first thing taken into account for the equation.
3. Once the first collection of independent variables has been decided upon, both qualitative and quantitative variables must be coded.
4. The selected model may be estimated after coding of the variables.
5. The CSM's prognostication accuracy should then be evaluated or calibrated.

Figure 1 is a diagrammatic presentation of the credit scoring model's developmental stages:

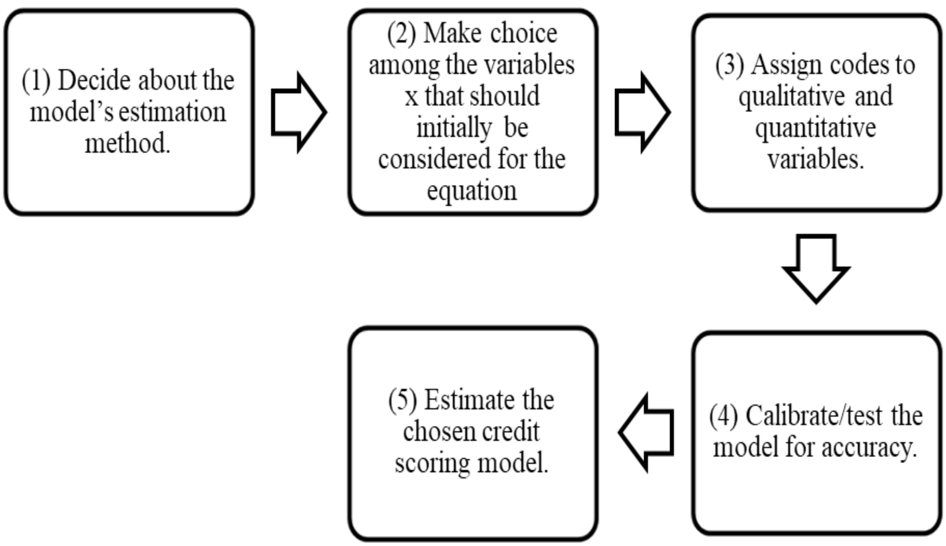

Figure 1: Diagrammatic Presentation of the Credit Scoring Model Developmental Stages.

2.10. Conditions for a Credit Scoring Model's Validation

Van Gestel et al. (2006) state that stability, readability, and power of discrimination (SRP) are the three primary criteria that must be met for a credit scoring model to be regarded as acceptable.

1. Stability: When evaluated both in-sample and out-of-sample, a stable model exhibits identical performance characteristics and calls for well-determined coefficients with high confidence.
2. Readability: When a model's coefficients are simple to comprehend, it is said to be readable.
3. Power of discrimination: According to Van Gool et al. (2009), the term "discriminatory power" refers to the capacity to appropriately position or arrange observations according to default probability by assigning scores. It was first used by the Basel Committee on Banking Supervision in 2005.

2.11. The Advantages of Credit Scoring

Numerous potential advantages are offered by credit and loan scoring (Stanton, 1999). Mester (1997) stated that these advantages include:

1. Scoring significantly shortens the time required for loan approval.
2. Credit scoring can boost efficiency by allowing loan officers to concentrate on the less straightforward instances, even if a bank does not intend to use it exclusively for credit decisions.
3. Increased impartiality in the loan approval process is a further advantage of credit scoring.
4. A credit scoring model makes it simpler for a lender to prove the economic case for employing a factor that can unfairly disadvantage some applicant groups who are protected by anti-discrimination legislation.
5. Scoring-based systems can also be used to develop or improve financial early warning systems, monitor lender performance, better target federal credit to the most qualified borrowers, and test out lending to underserved subgroups in an effort to increase their access to credit, to name just a few important applications (Stanton, 1999).

2.12. Credit Scoring Restrictions

The following disadvantages are mentioned in the literature:

1. According to Avery, Bostic, Calem, and Canner (1996), the correctness, completeness, and timeliness of the data utilized to produce the ratings determine how reliable credit scoring is. A credit rating system's accuracy will also depend on how carefully it is created (Mester, 1997).
2. Creditworthiness of people whose experiences differ markedly from those on which the index is built may not be effectively assessed by credit ratings, according to some worries (Avery, Bostic, Calem, & Canner, 1996).
3. If lenders place an excessive amount of emphasis on scores, they may fail to take into account unique situations that may offset a low score, such as a recent sickness (Avery, Bostic, Calem, & Canner, 1996).
4. If the underlying model that was used to create the scores does not accurately reflect the current correlations between risk factors and measures of loan performance, scores may lack predictive value (Avery, Bostic, Calem, & Canner, 1996).
5. Alternative credit scoring may ultimately help some customers, but it also carries a lot of risk. Transparency issues are greatly exacerbated by credit-scoring technologies that combine hundreds of data pieces, the majority of which are gathered without the consent of the consumer (Hurley & Adebayo, 2016).

3. Conclusion

Finally, in the lending sector, credit scoring is a potent instrument for lowering credit risk. The merits and drawbacks of credit scoring, as well as its conceptual underpinnings, validation procedure, and other key elements, have all been thoroughly covered in this article. The importance of credit scoring and its function in enhancing credit risk assessment becomes clearer after carefully reviewing each component.

Credit scoring has become a trustworthy approach for assessing a person's or an organization's creditworthiness. Credit scoring models give lenders a uniform way to evaluate the possibility of borrowers defaulting on their loans by using statistical estimate methods and different data sources. This aids financial firms in making wise choices and effectively allocating credit resources.

The described credit rating methods are adaptable to a variety of lending contexts. Credit scoring may be customized to match the unique requirements of various lending institutions and sectors, whether it be through application scoring or traditional scoring.

Credit scoring has broadened its scope beyond traditional credit information due to the growing accessibility of non-traditional data. Credit scoring models' forecasting abilities can be improved, and they can offer a more thorough evaluation of a person's creditworthiness by combining different data sources.

In order to guarantee the accuracy and dependability of credit scoring models, creation and validation are essential procedures. Lenders may trust in the predicted performance of their credit scoring models by adhering to the validation requirements and the suggested developmental steps.

The advantages of credit scoring are clear. Lenders may automate their credit-decision-making procedures, cut back on human work, and lower the risk of defaults. Additionally, credit scoring is advantageous to borrowers since it offers them a uniform rating based on objective standards, fostering equitable access to credit.

However, credit scoring also has its limitations. It relies heavily on historical data, which may not capture changes in individual circumstances or market dynamics. Additionally, credit scoring models may be less effective in assessing borrowers with limited credit histories or those from marginalized communities.

In conclusion, by embracing credit scoring, financial institutions may improve their risk management procedures, support financial inclusion, and support the credit market's stability.

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