

Credit Scoring: Probabilities and Pitfalls

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The concept of credit scoring originated in academia, as have many business applications. Almost twenty years ago, corporate distress, failure, and default came under academic scrutiny, primarily as a result of passage of the Bankruptcy Code of 1978. A key outcome of that scholarly research was probability-based modeling.

Bankruptcy-prediction models were developed as a method to predict company failures. As these models proved their statistical effectiveness, a new potential application for the modeling process was envisioned: predicting the likelihood of repayment of individual credits. Applying predictive statistical models to credit decisions required two developments:

- *technology* to allow the models to work quickly enough, while accessing the neces-

sary information, so that the process speed would allow for reasonable response time to loan applications; and

- *databases*, which provide the inputs to these predictive models, that included information regarding payment histories, demographic characteristics, and current financial condition of prospective buyers.

Once technology was available cost effectively, and the necessary data were readily accessible, the door was open for credit scoring to move ahead.

Over the past few years, a surge in interest regarding credit-scoring models has been driven primarily by two requirements of lending institutions: emphasis on increased efficiencies in the processing of applications and in making loans, and a desire to manage risk by creating consistent, fair methods for offering credit. The statistical models that are used for credit scoring have increased in complexity and flexibility over time to meet the evolving needs of those using them. Clearly, credit scoring is a cost-effective credit management tool. However, it

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is important to understand the potential pitfalls of credit scoring in order to maximize its benefits and minimize its risks.

How The Models Work

The premise of credit scoring models is simple. A large sample of similar-type, historical loans is divided into those that paid and those that defaulted. Based on statistical probabilities, the combination of borrower characteristics that differentiate the "good" from the "bad" loans generate a score that is an estimate of riskiness of each new loan of this type. Based on the score, the lender decides whether to make the loan and how to price it.

In practice, applications are run through the model (often electronically via a laptop at the point of contact). Credit history information is combined with other data regarding an applicant's ability to repay. The model then attempts to predict that applicant's likelihood of default based on prior experience with applicants of a similar profile. Depending on the model, most will result in an accept/reject decision and suggest pricing commensurate with the riskiness of the credit, or indicate if the model is unable to determine risk due to a lack of information.

Many financial institutions and third-party providers have developed models using various technologies and data sources. Nonetheless, the basic process does not vary substantially from model to model. The lender determines the criteria for judging the likelihood of repayment, and the acceptable risk levels for each criterion. In models provided by third parties, the criteria are predetermined, and the lender need only tailor the model to its desired risk levels.

Some of the common criteria used in these models are credit history, current income, investment/asset levels, home ownership, job stability, education level, debt-to-equity ratios, and current credit outstandings. It is important to note that there is no "magic bullet." Effective scoring models are based on many characteristics, and the weightings of these and other factors vary from model to model.

It is important to note that the models are

less automatically useful as the quality of the credit decreases. General consensus exists on what defines an "A" credit. Such agreement does not exist for what defines, for example, a "C" versus a "D" credit. Therefore, sub-prime lenders tend to rely on the credit score less heavily, and use it only as a guide.

The Benefits

Credit scoring benefits both lenders and customers. Over the past several years, usage has expanded across business lines — from credit cards to mortgage banking, and most recently into small-business lending. In fact, several large banks have employed credit scoring and direct mail techniques to generate small-business loans nationwide, creating a new level of competition in that arena for community banks. The perceived benefits that have led to the recent explosion in the usage of credit scoring include:

- *Increased efficiencies and reduced costs.* Scoring systems remove much of the labor time traditionally associated with the origination of a loan. The models allow for immediate handling of the definite yes/no decisions, leaving credit officers available to focus on the borderline credits that are least well handled by the models, and often very profitable. Response times are also reduced for customers. Application processes that used to take weeks are reduced to days or hours, and fewer employees can handle a far greater number of applications than in traditional loan departments.
- *Reduced potential for bias.* By instituting a standard process for grading an applicant's risk, banks should reduce the possibility of unfair lending practices. When dealing with regulators, banks can point to the criteria built into the model and state with certainty that applicants are measured against these standards, which are quantifiable. Nevertheless, as discussed below, there is a danger of inherent bias in criteria that on the surface may appear to be non-discriminatory.
- *Ability to target specific risk segments.*

Lenders can use credit scoring to target large numbers of borrowers in higher-risk loan segments than they might otherwise, because they can estimate with a reasonable degree of confidence the losses of the whole portfolio. Thus, they can better price and reserve for the risk that they are explicitly taking on a portfolio basis.

- *“Learning” systems.* Credit scoring models are based on statistical comparisons to previous history. As such, the systems can “learn” over time. By continually reestimating the model with a broader base of data, the lender can better predict what the next applicant’s behavior will be. This is particularly true with proprietary systems that draw on the financial institution’s own experiences. Proprietary systems can better reflect the specific experience of the institution, but by necessity draw on a smaller sample size than third-party systems. The longer the system is in place, the greater the historical record from which to draw. With the recent advent of neural networks — “self-learning” computer programs modeled on the human mind — the level to which the credit scoring process can develop in terms of complexity and accuracy is unknown. One thing that is certain is that these models will only get “smarter” in the coming months and years.
- *Simplified securitization.* With a standardized credit score, it is easier to rate a credit for the purposes of bundling and securitization. The standardization imposed on the credits allows the financial institution to take on more risk and then shift it to the market.

The Pitfalls

While the benefits of credit scoring are fairly well known, the dangers of using this tool should not be ignored. Any financial institution employing this model as a primary method for evaluating creditworthiness needs to be aware of the pitfalls. The potential downside for falling into any of these traps can be costly. The

most essential cautions are discussed below.

- *GIGO.* The most basic risk is one that exists with any modeling process: garbage in, garbage out. Although these models are extremely complex, they are nonetheless only as good as the data feeding them. Inaccurate credit report information, for example, can invalidate results. The model is based on statistical analyses. Without an accurate and appropriate database of historical loan behavior, an institution is better served by more traditional human application handling.
- *Knowing your customer.* The presence of a scoring system does not replace the value gained by knowing your customer. The character issue is central to the likelihood of repayment, as evidenced by the recent problems with rising defaults. Although these models attempt to mimic actual behavior, there is no substitute for knowing the borrower. This is especially important in dealing with customers without a pristine credit history or where ability to repay may be marginal and willingness to repay may be the primary factor on which a credit decision should be based. In these cases, the credit score may be valuable as a guide, but may not represent the true repayment likelihood of the applicant.
- *Seasoning is important.* Because these models are based on historical repayment data, they are susceptible to biases due to the timeframe of the data and the business cycle. If the data on which the model is based has not included repayment behavior in an economic downturn, a financial institution can find itself facing a much higher risk frontier than it had planned on if adjustments are not made.
- *Dealing with atypical applicants.* Another danger of credit scoring is the potential to misdiagnose an applicant who does not fit “the mold.” Horror stories exist of highly qualified applicants being denied credit due to inconsistencies in a credit profile or unusual employment history. Scoring models are very efficient at dealing with

the mainstream, but a human backstop is better equipped to deal with the "exceptional" applications.

- *Privacy.* Any time large amounts of data are drawn together into one place — particularly data that are as sensitive as income and employment information, credit histories, and so on — concerns regarding privacy arise. Financial institutions must take strong steps to ensure the security of their systems and to have appropriate practices and policies to protect their customer information. Inappropriate handling of the data could result in major lawsuits, as well as create a public relations nightmare for an affected institution.
- *Unintended bias/fairness.* One of the perceived benefits of credit scoring is its ability to remove bias from the credit analysis process. However, this only occurs if the characteristics used in making a decision are themselves free of bias. The primary goal of a credit score is to measure an applicant's ability and willingness to pay his or her obligations on time. For example, credit history has been a good predictor of how a borrower will handle new credits. But lack of a credit history has had the effect of eliminating potentially good candidates who otherwise have a good track record in paying their rent, utilities, or other obligations on time. This measure also has tended to create a bias against women, who on average have had shorter credit histories than men. As a result, most of today's models factor in alternative methods of measuring a person's likelihood of repayment. Nonetheless, all institutions must ensure that their models do not build in subtle bias. It is important not only to consider whether the factors of the model are fair on the surface, but also to analyze whether the inclusion of a factor could create an unintended bias in the decision process. A model must discriminate between good and bad individual credits without discriminating against groups of people.

Failure to do so represents a significant risk in terms of regulatory criticisms and discrimination suits.

Things to Remember

The most important question to ask in evaluating your risk scoring system is, "Is the system providing me with my desired risk profile?" The answer to this question should be tracked over time, with adjustments being made to the decision points in order to create the desired risk profile.

These scoring models do not decide the desired risk level of the portfolio. That decision is made by the financial institution in determining the scoring levels and decision points within the model. The risk decision is the bank's to make.

A credit scoring model can be an excellent tool to assist lenders in increasing efficiencies, managing risk, and even facilitating securitization. In addition to being used in the credit granting process, models are now being used for marketing; for determining fees, rates, and terms; and for allocating collection resources. However, the model is merely an operational tool that must be managed and monitored to ensure that it is used correctly, produces outcomes that match the lender's desired credit risk profile, and does not raise compliance or legal risks.

Most scoring models still have shortcomings in dealing with the "human element." Applications that do not fit the model still often require a manual decision to avoid losing an otherwise good credit. And knowing your customer still is worth a lot when assessing whether a subprime credit is likely to pay on time. Models are still not able to look a customer in the eye.

Credit scoring can provide tremendous advantages to both a financial institution and its customers, as long as the model is used properly, within the framework of an overall credit management system. Failure to use caution in developing and implementing these systems can leave an institution exposed to both credit risk and legal risk. What is true of credit scoring is true of most tools — you have to be especially careful when using the powerful ones. ■