Contact: Rob Wright

E-mail: Rwright@ifc.org

Tel. # 202-473-7997

Fax # 202-522-3742

NEW IDEAS FROM THE WORLD OF SMALL AND MEDIUM ENTERPRISES Vol. 1, No. 2 November 2000

Credit Scoring: A Tool for More Efficient SME Lending

IN BRIEF

SMEs are underserved by the credit infrastructure in many countries. While banks, finance companies and other institutions can profitably lend to larger commercial enterprises, SMEs typically require less money, and the costs to both make and service their smaller loans erode the lender's margin. The high rate of SME failure poses another hurdle for risk-averse banks. This article explores the lessons to be learned from the US experience with SME credit scoring—a tool with many potential applications in developing countries.

Latimer Asch Senior Vice President, Fair, Isaac and Co. San Rafael, Calif., USA

Tntil recently, US banks applied to SMEs the same procedures and criteria they used in lending to big businesses. Studies by lending associations have shown that so-called "manual underwriting"—involving collection and review of financial statements and other labor-intensive work—would take at least 12 hours and cost from \$500 to \$1,800. As a result, SME lending was not viewed as a profitable venture.

The burgeoning use of credit scoring to assess SME loan applicants began in about 1993, and marked a major change in the way banks consider SME lending. Rather than apply the procedures developed for large enterprises, banks adopted technology that had been used in consumer lending since the 1960s. With credit scoring, data on an applicant are passed through an analytical model embedded in software. The model delivers a number—the score—that indicates the level of credit risk associated with the applicant or customer (see box on page three). In a typical financial institution, neither scoring nor automated underwriting completely replaces manual underwriting. However, effective use of these techniques can sharply reduce the number of applications that need manual review, often by 50-80%.

Banks rapidly took up the concept of SME scoring, particularly for credits up to \$100,000 (microloans in the US context). In two 1998 surveys of small business lenders, 90% of respondents—mainly larger institutions—had adopted credit scoring for SME loans.

¹ Small Business Banking Study, Consumer Bankers Association, and Small Business Risk Management Study, RMA, the Association of Lending and Credit Risk Professionals (both 1998).

Benefits seen from SME scoring

Both banks and borrowers have gained from SME scoring. SME scoring has enabled banks to:

- Reduce the cost and time of making a loan. Because SME loan nonperforming rates have historically been so low in the US—due to lenders' cautious underwriting practices—the primary focus for banks adopting SME scoring has been to increase the efficiency of the lending process, rather than to reduce the risk assumed by the bank. Microloans were a priority for improvement—the \$500 to \$1,800 it cost to underwrite such a loan clearly made microlending less desirable if not downright unprofitable. Using automated scoring, lenders can bring the time needed to process and approve/decline a credit request down to as little as 15 minutes—compared to the 12 hours or so associated with traditional manual underwriting² —at an estimated cost of \$100. Today, small businesses applying for credit over the Internet can receive a response to their application in less than a minute.
- Make more loans to SMEs. By quantifying the risk of applicants and reducing the resources needed to make a loan, banks have been able to approve and process a higher loan volume. From 1994 to 1998, during the period of greatest growth, the number of loans to small businesses grew by 78.5% for loans under \$100,000, compared to 31.4% for loans of \$250,000 to \$1 million.
- Control risk more effectively. The bad rate of SME loans has remained extremely low since 1993, despite the large increase in the number of microloans to SMEs. This speaks both to the strong U.S. economy and to the effectiveness of scoring models based on rigorous statistical analysis. For example, Fair, Isaac—the company that pioneered both consumer and SME scoring in the United States—found a surprising amount of statistical correlation between SME credit payment behavior and the personal credit and financial status of the principals. It also found that lenders relied more heavily on business financial statement information than was warranted by its predictive value.
- Remove human bias from the lending decision. Credit scoring systems evaluate only those pieces of data found to correlate with future credit performance. Scoring systems in the United States do not use any of the factors prohibited by US law from consideration in a lending decision, such as race, religion, marital status or gender.

• Focus on assessing questionable loans. Credit scoring enables banks to make a large number of loans based on only score and automated decision criteria. Freed from having to review these loans, loan officers can spend more time reviewing questionable loan requests, requests for larger amounts and existing loans that may be in trouble.

The advantages credit scoring offers have been noted at the regulatory level as well. "Credit scoring increases the consistency, speed, and, in many cases, accuracy of credit evaluations while it lowers costs of gathering relevant information," according to the Board of Governors of the Federal Reserve System. "The use of credit scoring eliminates variation in the way risks are assessed among loan officers or by a single loan officer over time, both of which can be important issues for lenders. Also, because credit-scoring procedures are automated, loan decisions can be rendered in minutes or hours rather than in days and weeks."³

As credit scoring has made SME lending more efficient and profitable, it has also become more competitive. Combined with a 1995 change to the Federal Community Reinvestment Act that gave banks license to solicit business beyond where they were located, credit scoring has helped banks target prospects through direct mail and other techniques. SMEs owned by principals with good credit histories now find themselves receiving competitive offers in the mail. For example, Wells Fargo pioneered the use of credit scoring in offering pre-approved loans to SMEs nationwide.⁴ Wells Fargo launched an aggressive direct mail program in 1995, and by 1996 had jumped from number 11 to number two in US SME lending, with \$3.5 billion in outstanding loans.⁵

The success of SME scoring in the underwriting environment has spawned new applications of SME scoring. Models built for account management can reduce the costs of monitoring and servicing loans, by eliminating annual renewals on low-risk customers, prioritizing collections queues, and repricing/cross-selling profitable accounts.

One of the most promising future applications involves the securitization of pools of loans (collateralized loan obligations). Securitization enables banks to generate more revenue on the same base of capital, increasing their return on equity and assets. From

² Maximizing Underwriting Efficiency: The "Retail" Breakthrough, Business Banking Board (1994).

^{3.} Report to the Congress on the Availability of Credit to Small Businesses, Board of Governors of the Federal Reserve System (1998).

DEVELOPING A SCORING MODEL

Scoring model development involves statistical analysis of large amounts of data to find which pieces of information available at the time of a key lending decision—such as whether to approve a request for credit—correlate most reliably with subsequent credit performance. The skill of the analyst is paramount in ensuring that the model will produce sound and interpretable results.

To develop a model, analysts collect and analyze two types of data on a large sample of accounts:

- Predictive data. These are data available at the time of the decision, such as the time at which credit was granted to an account. For SME models, sources would include credit applications, financial statements and (where available) "external" data such as data from consumer and business credit reporting agencies/bureaus. Only those types of data that will be consistently available once the final scoring model is implemented can be used for model development.
- **Performance data.** These data reflect the payment history of the accounts in the sample. They reflect the period after the lending decision was made, such as the first year or two of an account's life.

Statistical analysis identifies factors in the predictive data that correlate with subsequent account performance. These factors will be considered in relation to each other and assigned weights based on their importance.

the SME's perspective, securitization enables banks to make more capital available in the form of loans. Credit scoring facilitates securitization by providing the standard underwriting needed to create pools of loans with similar risk characteristics. The potential for SME loan securitization can be seen in the secondary mortgage market, where Fair, Isaac's scores have "become the lingua franca of Wall Street's huge secondary mortgage market—the de facto standard by which all lenders and buyers of mortgage-backed bonds classify borrowers."

Another interesting new wrinkle in SME scoring has been its application to business-to-business trade credit loans. Web technology is the enabler here: A business evaluating another small business' application for trade credit can purchase an affordable credit risk assessment online in under a minute. Traditional lenders participate by offering the service through Web

The result is a complex algorithm or scoring model. This model scores applicant or account data, returning a numerical score for each applicant or account. Each score along the range will reflect different odds of satisfactory repayment. Typically, the higher the score, the lower the credit risk associated with the applicant or account. In most institutions, lenders set score cutoffs, above or below which they will take different actions: approve or decline the application, offer a lower or higher interest rate, etc.

Scores rank-order credit risk—they do not predict the amounts that an applicant, if booked, will generate in profits or incur in losses. However, scores can be "calibrated" by the user to determine the likely payment risk, future profit level or other expected outcome for accounts in each score range. Experience in the United States has shown that scores can continue to rank-order credit risk even when economic downturns reduce credit quality across the board. Scoring models specifically address an individual's or a business level of credit risk—they do not consider environmental factors such as political or economic risk.

A better scoring model will achieve greater "separation"—meaning that it does a better job distinguishing between future good and bad accounts. It will also be more "robust"—meaning that its ability to rank-order risk will not rapidly deteriorate, and that it will retain its rank-ordering power as the applicant population grows and changes.

sites they have created specifically for small businesses. The service can benefit lenders' clients by reducing their losses from bad trade debts.

Requirements for SME scoring

Clearly, conditions in the United States were and are very favorable for SME scoring. But SME scoring is exportable to other countries—Fair, Isaac has built SME scoring models in countries such as Japan, Mexico, Belgium, Italy, Portugal, and Germany. The scoring and automated workflow software involved are flexible, and can be used on platforms from large

⁴ Wells Fargo is a diversified financial services company providing banking, insurance, investments, mortgage and consumer finance in 6,000 locations in the United States and across North America. ⁵ "Wells' Small Business Lending via Mail Pays Off," American Banker (December 23, 1996).

^{6. &}quot;The Boys in the Back Room," Forbes (May 4, 1998).

THE BIRTH OF SME SCORING

The first widely available SME credit scoring systems were introduced in 1993. The frontrunner was the Small Business Scoring Service (SBSS) developed by Fair, Isaac, already the nation's leader in consumer credit scoring. It is designed to process credit lines and term loans up to \$250,000, equipment leases up to \$100,000 and business credit cards with limits up to \$50,000. Today, more than 300 US banks use Fair, Isaac's SBSS models, including 90% of the top small business lenders that choose Fair, Isaac solutions to improve turnaround time and responsiveness to small business applicants.

To develop robust scoring models, analysts require a data sample with several hundred delinquent loans.

The low SME loan numbers and very low SME bad rates at most banks make custom-developed models out of the question for all but the very largest SME lenders. To surmount this hurdle, Fair, Isaac built SME models from a nationwide pooled sample of SME loans. The models analyze data on the business principals as well as on the business, including publicly available data retrieved from both consumer credit bureaus, reporting agencies (about the principals' credit history) and business credit data repositories (about the business' credit history). The large development sample enabled Fair, Isaac to build several SBSS scoring models for different loan types, credit amounts, etc.

mainframes to desktop PCs. The difficulty that must be overcome in bringing SME scoring to new regions involves the analytics. In particular, plentiful data are needed for model development.

US-based SME scoring systems typically access credit history data from both consumer credit reporting agencies/bureaus (on business owners) and business bureaus. In many international markets, such bureaus frequently contain only "negative data"—records of delinquency or default—and not positive payment data. Positive data give scores based on U.S. bureau data a boost in predictive power. For instance, within a consumer population that has 90-day delinquencies or worse—i.e., that would be classified as "bad" using negative data alone—those with the lowest Fair, Isaac credit bureaucredit reporting agency scores had a subsequent bad rate of 93%, while those with the highest scores had a bad rate of under 6%.7 This kind of differentiation would not be possible without positive data.

However, SME scoring systems can be developed without bureau-based data, using only credit application and financial data combined with performance data. As noted above, to develop a powerful scoring system requires a large data sample with approximately 800-1200 "bad" loans (and an equal or greater number of "good loans"). A"small sample" model can be empirically developed with about 300 "bads," although segmentation analysis is constrained.

Many institutions do not have enough data (bad SME loans) to develop a custom model. Two options are open for them:

• *First*, individual institutions can develop or commission so-called "expert" or "judgmental" scoring mod-

els, which are based on knowledge of predictive factors for similar environments.

• Second, institutions can pool their data, possibly through a lenders' association, as part of a model development project. This option may pose initial difficulties, as data must be collected on a common basis, but will result in more powerful and accurate models. Because expert models can be developed with little lending data, the critical factor for introducing SME scoring is the engagement of financial institutions. In markets where there are many SMEs, the return can be quite large for the bank. Fair, Isaac believes that the most immediate possibilities for SME scoring systems are in South America, and we are exploring possibilities now in Argentina, Chile, and Peru.

Scoring for consumer loans and credit cards has already been implemented in credit markets at various levels of maturity around the globe. The benefits seen by lenders and borrowers could be migrated to SME lending, which would make credit more accessible to entrepreneurs and help "bootstrap" the economy in some regions. For credit markets looking to increase the profitability of SME lending, pooling both positive and negative data is a good way to start.

Latimer Asch, is senior vice president for commercial markets solutions at Fair, Isaac and Company, Inc. (www.fairisaac.com) He has directed the development and implementation of all small business risk management and marketing services, including Fair, Isaac's pioneering Small Business Scoring Service.

^{7.} Fair, Isaac research, summarized in "The Value of Positive Credit Bureau Information," ViewPoints, a Fair, Isaac publication (Autumn 1996).