What's the Point of Credit Scoring?

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When one banker asks another "What's the score?" shareholders needn't worry that these bankers are wasting time discussing the ball game. More likely they're doing their jobs and discussing the credit score of one of their loan applicants. Credit scoring is a statistical method used to predict the probability that a loan applicant or existing borrower will default or become delinquent. The method, introduced in the 1950s, is now widely used for consumer lending, especially credit cards, and is becoming more commonly used in mortgage lending. It has not been widely applied in business lending, but this, too, is changing. One reason for the delay is that business loans typically differ substantially across borrowers, making it harder to develop an accurate method of scoring. But the advent of new methodologies, enhanced computer power, and increased data availability have helped to make such scoring possible, and many banks are beginning to use scoring to evaluate small-business loan applications.

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Credit scoring is likely to change the nature of small-business lending. It will make it less necessary for a bank to have a presence, say, via a branch, in the local market in which it lends. This will change the relationship between the small-business borrower and his or her lender. Credit scoring is already allowing large banks to expand into small-business lending, a market in which they have tended to be less active. Scoring is also an important step in making the securitization of small-business loans more feasible. The likely result would be increased availability of funding to small businesses, and at better terms, to the extent that securitization allows better diversification of risk.

WHAT IS CREDIT SCORING?

Credit scoring is a method of evaluating the credit risk of loan applications. Using historical data and statistical techniques, credit scoring tries to isolate the effects of various applicant characteristics on delinquencies and defaults. The method produces a "score" that a bank can use to rank its loan applicants or borrowers in terms of risk. To build a scoring model, or "scorecard," developers analyze historical data on the performance of previously made loans to determine which borrower characteristics are useful in predicting whether the loan performed well. A well-designed model should give a higher percentage of high scores to borrowers whose loans will perform well and a higher percentage of low scores to borrowers whose loans won't perform well. But no model is perfect, and some bad accounts will receive higher scores than some good accounts.

Information on borrowers is obtained from their loan applications and from credit bureaus. Data such as the applicant's monthly income, outstanding debt, financial assets, how long the applicant has been in the same job, whether the applicant has defaulted or was ever delinquent on a previous loan, whether the applicant owns or rents a home, and the type of bank account the applicant has are all potential factors that may relate to loan performance and may end up being used in the scorecard.[1] Regression analysis relating loan performance to these variables is used to pick out which combination of factors best predicts delinquency or default, and how much weight should be given to each of the factors. (See *Scoring Methods* for a brief overview of the statistical methods being used.) Given the correlations between the factors, it is quite possible some of the factors the model developer begins with won't make it into the final model, since they have little value added given the other variables in the model. Indeed, according to Fair, Isaac and Company, Inc., a leading developer of scoring models, 50 or 60 variables might be considered when developing a typical model, but eight to 12 might end up in the final scorecard as yielding the most predictive combination (Fair, Isaac). Anthony Saunders reports that First Data Resources, on the other hand, uses 48 factors to evaluate the probability of credit card defaults.

In most (but not all) scoring systems, a higher score indicates lower risk, and a lender sets a cutoff score based on the amount of risk it is willing to accept. Strictly adhering to the model, the lender would approve applicants with scores above the cutoff and deny applicants with scores below (although many lenders may take a closer look at applications near the cutoff before making the final credit decision).

Even a good scoring system won't predict with certainty any individual loan's performance, but it should give a fairly accurate prediction of the likelihood that a loan applicant with certain characteristics will default. To

[1]Some of the models used for mortgage applications also take into account information about the property and the loans, for example, the loan-to-value ratio, the loan type, and real estate market conditions (DeZube).

Scoring Methods

Several statistical methods are used to develop credit scoring systems, including linear probability models, logit models, probit models, and discriminant analysis models. (Saunders discusses these methods.) The first three are standard statistical techniques for estimating the probability of default based on historical data on loan performance and characteristics of the borrower. These techniques differ in that the linear probability model assumes there is a linear relationship between the probability of default and the factors; the logit model assumes that the probability of default is logistically distributed; and the probit model assumes that the probability of default has a (cumulative) normal distribution. Discriminant analysis differs in that instead of estimating a borrower's probability of default, it divides borrowers into high and low default-risk classes.

Two newer methods beginning to be used in estimating default probabilities include options-pricing theory models and neural networks. These methods have the potential to be more useful in developing models for commercial loans, which tend to be more heterogeneous than consumer or mortgage loans, making the traditional statistical methods harder to apply. Options-pricing theory models start with the observation that a borrower's limited liability is comparable to a put option written on the borrower's assets, with strike price equal to the value of the debt outstanding. If, in some future period, the value of the borrower's assets falls below the value of its outstanding debt, the borrower may default. The models infer the probability a firm will default from an estimate of the firm's asset-price volatility, which is usually based on the observed volatility of the firm's equity prices (although, as McAllister and Mingo point out, it has not been empirically verified that short-run volatility of stock prices is related to volatility of asset values in a predictable way. Saunders discusses other assumptions of the options-pricing approach that are likely to be violated in certain applications.) Saunders reports that KMV Corporation has developed a credit monitoring model based on options-pricing theory.

Neural networks are artificial intelligence algorithms that allow for some learning through experience to discern the relationship between borrower characteristics and the probability of default and to determine which characteristics are most important in predicting default. (See the articles by D.K. Malhotra and coauthors and by Edward Altman and coauthors for further discussion.) This method is more flexible than the standard statistical techniques, since no assumptions have to be made about the functional form of the relationship between characteristics and default probability or about the distributions of the variables or errors of the model, and correlations among the characteristics are accounted for.

Some argue that neural networks show much promise in credit scoring for commercial loans, but others have argued that the approach is more ad hoc than that of standard statistical methods. (The article by Edward Altman and Anthony Saunders discusses the drawbacks.) A study by Edward Altman, Giancarlo Marco, and Franco Varetto analyzed over 1000 healthy, vulnerable, and unsound Italian industrial firms from 1982-92 and found that performance models derived using neural networks and those derived using the more standard statistical techniques yielded about the same degree of accuracy. They concluded that neural networks were not clearly better than the standard methods, but suggested using both types of methods in certain applications, especially complex ones in which the flexibility of neural networks would be particularly valuable.

build a good scoring model, developers need sufficient historical data, which reflect loan performance in periods of both good and bad economic conditions.[2]

WHERE IS CREDIT SCORING USED?

In the past, banks used credit reports, personal histories, and judgment to make credit decisions. But over the past 25 years, credit scoring has become widely used in issuing

[2]Patrick McAllister and John Mingo estimate that to develop a predictive model for commercial loans, some 20,000 to 30,000 applications would be needed.

credit cards and in other types of consumer lending, such as auto loans and home equity loans. The Federal Reserve's November 1996 Senior Loan Officer Opinion Survey of Bank Lending Practices reported that 97 percent of the responding banks that use credit scoring in their credit card lending operations use it for approving card applications and 82 percent use it to determine from whom to solicit applications. About 20 percent said they used scoring for either setting terms or adjusting terms on their credit cards.

Scoring is also becoming more widely used in mortgage origination. Both the Federal Home Loan Mortgage Corporation (Freddie Mac) and the Federal National Mortgage Corporation (Fannie Mae) have encouraged mortgage lenders to use credit scoring, which should encourage consistency across underwriters. Freddie Mac sent a letter to its lenders in July 1995 encouraging the use of credit scoring in loans submitted for sale to the agency. The agency suggested the scores could be used to determine which mortgage applicants should be given a closer look and that the score could be overridden if the underwriter determined the applicant was a good credit risk. In a letter to its lenders in October 1995, Fannie Mae also reported it was depending more on credit scoring for assessing risk. Both agencies have developed automatic underwriting systems that incorporate scoring so that lenders can determine whether a loan is clearly eligible for sale to these agencies or whether the lender has to certify that the loan is of low enough risk to qualify (Avery and coauthors).

Private mortgage insurance companies, such as GE Capital Mortgage Corporation, are using scoring to help screen mortgage insurance applications (Prakash, 1995). And it was recently reported that four mortgage companies—Chase Manhattan Mortgage Corp., First Nationwide, First Tennessee, and HomeSide—are involved in a test of the use of credit scoring models for assessing mortgage performance, prepayments, collection, and foreclosure patterns (Talley). This test is being conducted by Mortgage Information Corp.

A growing number of banks are using credit scoring models in their small-business lending operations, most often for loans under $100,000, although scoring is by no means universally used.[3] It has taken longer for scoring to be adopted for business loans, since these loans are less homogeneous than credit card loans and other types of consumer loans and also because the volume of this type of lending is smaller, so there is less information with which to build a model.

The first banks to use scoring for small-business loans were larger banks that had enough historical loan data to build a reliable model; these banks include Hibernia Corporation, Wells Fargo, BankAmerica, Citicorp, NationsBank, Fleet, and Bank One. BankAmerica's model was developed based on 15,000 good and 15,000 bad loans, with face values up to $50,000 (Oppenheim, 1996); Fleet Financial Group uses scoring for loans under $100,000 (Zuckerman). Bank One relies solely on scores for loans up to $35,000 and approves 30 percent of its loans up to $1 million by scorecard alone (Wantland). This spring, a regional bank in Pennsylvania began basing its lending decision for small-business loans up

[3]A survey reported in the *American Banker* in May 1995 with responses from 150 U.S. banks indicated that only 8 percent of banks with up to $5 billion in assets used scoring for small-business loans, while 23 percent of larger banks did (Racine). The smaller banks were less inclined to adopt scoring, citing small loan volumes. Fifty-five percent of banks with more than $5 billion in assets reported they planned to implement scoring in the next two years. In a more recent survey of larger banks—the Federal Reserve's January 1997 Senior Loan Officer Opinion Survey on Bank Lending Practices—70 percent of the respondents, that is, 38 banks, indicated that they use credit scoring in their small-business lending, and 22 of these banks said that they usually or always do so.

to $35,000 exclusively on a credit score.[4] Other banks have loan officers review the decisions based on credit scores: at First National Bank of Chicago it's been reported that about a quarter of the small-business loan applications rejected by credit scoring are approved after review, and an equal number that pass the scoring model are rejected. First Union looks at credit scores as a supplement to more traditional analyses of businesses' financial statements (Hansell).

Credit scoring is now available to lenders who do not have sufficient volumes to build their own small-business loan scoring models. In March 1995, Fair, Isaac introduced its "Small Business Scoring Service (SBSS)," a scoring model that was developed with RMA, a trade association of commercial lenders. The model was built using five years' worth of data on small-business loans from 17 banks in the United States, a sample of more than 5000 loan applications from businesses with gross sales of less than $5 million and loan face values up to $250,000; banks provided data on good and bad accounts and on declined applications, as well as credit reports on at least two of a business's principals and on the business (Asch; Hansell; and Neill and Danforth).[5] Separate scorecards were created for loans under $35,000 and for loans between $35,000 and $250,000. The models found that the most important indicators of small-business loan performance were characteristics of the business owner rather than the business itself. For example, the owner's credit history was more predictive than the net worth or profitability of the business. While this might seem surprising at first, it's worth remembering that small businesses' financial statements are less sophisticated than those of larger businesses and that the owners' and businesses' finances are often commingled (Hansell). Other companies such as CCN-MDS, Dun & Bradstreet, and Experian (formerly TRW) are developing or already have competitive products. These standardized products make scoring available to lenders with smaller loan volumes, but the models may not be as predictive for these lenders to the extent that their applicant pool differs from that used to create the scorecard.[6]

Despite its growing use for evaluating small-business lending, credit scoring is not being used to evaluate larger commercial loans. While the loan performance of a small business is closely related to the credit history of its owners, this is much less likely to be the case for larger businesses. Although some models have been developed to estimate the default probabilities of large firms, they have been based on the performance of corporate bonds of publicly traded companies. It is not at all clear that these models would accurately predict the default performance of bank loans to these or other companies. (See McAllister and Mingo for more discussion on this point.) To develop a more accurate loan scoring model for larger businesses, a necessary first step would be the collection of a vast array of data on many different types of businesses along with the performance of loans made to these businesses; the data would have to include a large number of bad, as well as good, loans.

[4]For its small-business loans between $35,000 and $250,000, a lender makes the decision, but a credit score is also calculated as a guideline. At this bank, a small-business borrower is one with annual sales of $2 million or less.

[5]A good account was defined as one that had not been 30 days delinquent more than twice during the first four years of account history, while a bad account was one that at least once had been 60 days or more delinquent (Asch).

[6]In personal conversation, the manager of the small-business lending department of a regional bank in Pennsylvania reported that it was because of this concern that the bank does not rely on the credit score from a standardized model to make the approval decision for loans between $35,000 to $250,000.

Since the typical default rate on business loans is in the range of 1 percent to 3 percent annually, banks would have to pool their data. Such data-collection efforts are currently under way.[7] But the fact that loans to large businesses vary in so many dimensions will make the development of a credit scoring model for these types of loans very difficult.

BENEFITS OF CREDIT SCORING: QUICKER, CHEAPER, MORE OBJECTIVE

Credit scoring has some obvious benefits that have led to its increasing use in loan evaluation. First, scoring greatly reduces the time needed in the loan approval process. A study by the Business Banking Board found that the traditional loan approval process averages about 12-1/2 hours per small-business loan, and in the past, lenders have taken up to two weeks to process a loan (Allen). Credit scoring can reduce this time to well under an hour, although the time savings will vary depending on whether the bank adheres strictly to the credit score cutoff or whether it reevaluates applications with scores near the cutoff. For example, Kevin Leonard's study of a Canadian bank found that the approval time for consumer loan applications averaged nine days before the bank started using scoring, but three days after scoring had been in use for 18 months. Barnett Bank reports a decrease from three or four weeks' processing time for a small-business loan application before scoring to a few hours with scoring (Lawson).

This time savings means cost savings to the bank and benefits the customer as well. Customers need to provide only the information used in the scoring system, so applications can be shorter. And the scoring systems themselves are not prohibitively expensive: the price per loan of a commercially available credit scoring model averages about $1.50 to $10 per loan, depending on volume (Muolo). Even if a bank does not want to depend solely on credit scoring for making its credit decisions, scoring can increase efficiency by allowing loan officers to concentrate on the less clear-cut cases.[8]

Another benefit of credit scoring is improved objectivity in the loan approval process. This objectivity helps lenders ensure they are applying the same underwriting criteria to all borrowers regardless of race, gender, or other factors prohibited by law from being used in credit decisions (see *Credit Scoring and Regulation B*). Bank regulators require that the factors in a scoring model have some fundamental relationship with creditworthiness. Even if a factor is not explicitly banned, if it has a disparate impact on borrowers of a certain race or gender or with respect to some other prohibited characteristic, the lender needs to show there is a business reason for using the factor and there is no equally effective way of making the credit decision that has less of a disparate impact. A credit scoring model makes it easier for a lender to document the business reason for using a factor that might have a disproportionately negative effect on certain groups of applicants protected by law from discrimination. The weights in the model give a measure of the relative strength of each factor's correlation with credit performance

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[7]Loan Pricing Corporation and several of its clients are pooling their data on commercial loans so that in several years there may be information on a sufficiently large number of good and bad loans to begin building a scoring model for commercial loans to larger businesses (correspondence from John Mingo, Board of Governors of the Federal Reserve System staff).

[8]Scoring is one part of an automated loan system, which permits banks to offer loans over the phone or via direct mail, so that a costly branch network can be avoided. It's worth mentioning, however, that the costs of a fully automated lending operation at a large bank could be quite high, since reliability would be essential. As one lender has pointed out, when an automated loan system goes down, the bank's lending operation is out of business. Hence, backup systems are necessary.

Credit Scoring and Regulation B

The Equal Credit Opportunity Act (implemented by the Federal Reserve Board's Regulation B) prohibits creditors from discriminating in any aspect of a credit transaction because of an applicant's race, color, religion, national origin, gender, marital status, or age (provided the applicant has the capacity to contract), because all or part of an applicant's income derives from public assistance, or because the applicant has in good faith exercised any right under the Consumer Credit Protection Act.

Scoring models cannot include information on race, gender, or marital status. Recently, the Board amended its commentary on Reg B to clarify the use of age in credit scoring models. Reg B defines an "empirically derived, demonstrably and statistically sound, credit scoring system" as one that is: (i) based on data that are derived from an empirical comparison of sample groups or the population of creditworthy and noncreditworthy applicants who applied for credit within a reasonable preceding period of time; (ii) developed for the purpose of evaluating the creditworthiness of applicants with respect to the legitimate business interest of the creditor; (iii) developed and validated using accepted statistical principles and methodology; and (iv) periodically reevaluated by the use of appropriate statistical principles and methodology and adjusted as necessary to maintain predictive ability. Reg B classifies any other system as a judgmental system, and such systems cannot use age directly as a predictive variable in the model. However, if the model does qualify as an empirically derived, demonstrably and statistically sound system, the Board has determined that it can use age directly in the model as long as the weight assigned to an applicant 62 years or older is not lower than that assigned to any other age category. And if a system assigns points to some other variable based on the applicant's age, applicants who are 62 years and older must receive at least the same number of points as the most favored class of nonelderly applicants. (Any system of evaluating creditworthiness may favor a credit applicant aged 62 years or older.)

(given the other factors contained in the model). Also, a well-built model will include all allowable factors that produce the most accurate prediction of credit performance, so a lender using such a model might be able to argue that a similarly effective alternative was not available.[9]

But not everyone agrees that the objectivity in scoring will benefit minorities or low-income individuals, who may have had limited access to credit in the past. Some argue that since these potential borrowers are not well represented in the loan data on which the scoring models have been built, the models are less accurate predictors of their loan performance. (See, for example, the discussion in "Mortgage Credit Partnership Project: 1996-1997.") This is a legitimate concern. But it need not be the case that the models are less accurate, since the factors and their weights identified in the model could also be those that determine creditworthiness of the underrepresented groups. One study by Fair, Isaac indicated that their scoring model for installment loans was as predictive for low- to moderate-income loan applicants as for the entire sample of applicants, although the low-income subsample had lower scores. (With a cutoff

[9]But banks that override the model for certain borrowers need to be particularly careful in documenting the reasons for the override to avoid violating fair lending laws. Similarly, borrowers right at the margin of cutoff for approval must be handled carefully.

score of 200, the acceptance rate for low- to moderate-income applicants was 46 percent, while for higher income applicants it was 67 percent. See Fair, Isaac.)[10] Freddie Mac also says its system, called Loan Prospector, is equally predictive of loan performance, regardless of borrower race or income (Prakash, 1997).

LIMITATIONS OF CREDIT SCORING

The accuracy of the scoring systems for underrepresented groups is still an open question. Accuracy is a very important consideration in using credit scoring. Even if the lender can lower its costs of evaluating loan applications by using scoring, if the models are not accurate, these cost savings would be eaten away by poorly performing loans.

The accuracy of a credit scoring system will depend on the care with which it is developed. The data on which the system is based need to be a rich sample of both well-performing and poorly performing loans. The data should be up to date, and the models should be reestimated frequently to ensure that changes in the relationships between potential factors and loan performance are captured. If the bank using scoring increases its applicant pool by mass marketing, it must ensure that the new pool of applicants behaves similarly to the pool on which the model was built; otherwise, the model may not accurately predict the behavior of these new applicants. The use of credit scoring itself may change a bank's applicant pool in unpredictable ways, since it changes the cost of lending to certain types of borrowers. Again, this change in applicant pool may hurt the accuracy of a model that was built using information from the past pool of applicants.

Account should be taken not only of the characteristics of borrowers who were granted credit but also of those who were denied. Otherwise, a "selection bias" in the loan approval process could lead to bias in the estimated weights in the scoring model.[11] A model's accuracy should be tested. A good model needs to make accurate predictions in good economic times and bad, so the data on which the model is based should cover both expansions and recessions. And the testing should be done using loan samples that were not used to develop the model in the first place.

It is probably too soon to determine the accuracy of small-business loan scoring models because they are fairly new and we have not been through an economic downturn since their implementation. Studies of the mortgage scoring systems suggest that they are fairly accurate in predicting loan performance. In its November 11, 1995, industry letter, Freddie Mac reported some of its own research on the predictive power of mortgage credit scores by Fair, Isaac and CCN-MDS. The agency studied hundreds of thousands of Freddie Mac loans originated over several years and selected from a wide distribution of lenders, product and loan types, and geographic areas; it found a high correlation between the scores and loan performance. The agency also had its underwriters review thousands of loans and found a strong correlation between the underwriters'

[10]Fair, Isaac's study used data on direct installment loan applicants from July 1992 to December 1994. Low- and moderate-income applicants were defined as those having gross monthly incomes of less then $1750. By this definition, one-third of their sample and one-fifth to one-half of the applicants of each of the individual lenders were deemed low- to moderate-income applicants.

[11]For example, suppose owning a home means a person is less likely to default on a loan. Then if the majority of applicants that a bank approves are home owners, the distribution of home ownership in the approved applicant pool will differ from that in the total applicant pool. If this fact is ignored in estimating the model, the model could not accurately uncover the relationship between home ownership and loan default. The model would show that home ownership is less predictive of good performance than it actually is.

judgments and the Fair, Isaac credit scores. Avery and coauthors also found that credit scores based on the credit history of mortgage applicants generally were predictive of mortgage loan performance.[12]

Not all the news on accuracy is good, however. In the November 1996 Senior Loan Officer Opinion Survey, 56 percent of the 33 banks that used credit scoring in their credit card operations reported that their models failed to accurately predict loan-quality problems by being too optimistic. The bankers attributed part of the problem to a new willingness by consumers to declare bankruptcy. This is a reasonable supposition: this type of "regime shift" (to a world in which there's less stigma attached to declaring bankruptcy) would not be picked up in a scoring model if it was not reflected in the historical data on which the model was based. In response, 54 percent of the banks have redefined or reestimated their models, and 80 percent have raised the cutoff score an applicant needs to qualify for credit.

It's important to remember, though, that a credit scoring model is not going to tell a lender with certainty what the future performance of an individual loan will be. When loan approval decisions are based solely on credit scores, some borrowers will be granted credit but will ultimately default, which visibly hurts the lender's bottom line. Other borrowers won't be granted credit even though they would have repaid, which, though less visible, also hurts the lender's profitability. No scoring model can prevent these types of errors, but a good model should be able to accurately predict the average performance of loans made to groups of individuals who share similar values of the factors identified as being relevant to credit quality.

Many considered the well-publicized denial of then Federal Reserve System Governor Lawrence Lindsey's application for a Toys 'R' Us credit card a failure of a credit scoring model. But the denial does not necessarily mean the model was faulty. The denial was based on the fact that his credit report showed too many voluntary credit bureau inquiries, and research by Fair, Isaac shows that *as a group*, applicants with seven to eight such inquiries are three times riskier than the average applicant and six times riskier than applicants with no such inquiries (McCorkell).[13]

IMPLICATIONS FOR THE BANKING INDUSTRY

The spread of credit scoring, especially its growing use in small-business lending, should lead to increased competition among providers of this type of credit and increased availability of credit for small businesses. Traditionally, lenders to small businesses have been smaller banks that have had a physical presence, usually in the form of a branch, in the

[12]Avery and coauthors examined data from Equifax on all mortgages that were outstanding and whose payments were current as of September 1994 at three of the largest lenders in the United States. Each loan had a mortgage credit history score and measures of performance over the subsequent 12 months, to September 1995. For each loan type (conventional fixed rate, conventional variable rate, or government-backed fixed rate), regardless of seasoning status (newly originated or seasoned), borrowers with low scores had substantially higher delinquency rates than those with medium or higher scores, although most borrowers with low scores were not delinquent. They also examined data from Freddie Mac on loans for single-family owner-occupied properties purchased by Freddie Mac in the first six months of 1994, which showed that borrowers with low scores had higher foreclosure rates (by the end of 1995), and that loans with both low credit scores and higher loan-to-value ratios had particularly high foreclosure rates. In addition, credit scores were much stronger predictors of foreclosure than was income.

[13]A credit bureau inquiry refers to an inquiry into someone's credit history at a credit bureau. A so-called voluntary inquiry is initiated when a person seeks credit. An involuntary inquiry can occur without a person's knowledge as part of a routine review of existing accounts or a prescreening for a promotional mailing, for example.

borrower's neighborhood. The local presence gives the banker a good knowledge of the area, which is thought to be useful in the credit decision. Small businesses are likely to have deposit accounts at the small bank in town, and the information the bank can gain by observing the firm's cash flows can give the bank an information advantage in lending to these businesses. (Leonard Nakamura's article discusses the advantages small banks have had in small-business lending.)

However, credit scoring is changing the way banks make small-business loans, and large banks are entering the market using credit scoring and processing applications using automated and centralized systems. These banks are able to generate large volumes of small-business loans even in areas where they do not have extensive branch networks. Applications are being accepted over the phone, and some banks are soliciting customers via direct mail, as credit card lenders do. For example, Wells Fargo uses centralized processing for loans under $100,000, soliciting these loans nationwide, and uses credit scores not only in the approval process but also for loan pricing. For loans over $100,000, it still uses traditional underwriting, soliciting in areas where it has branches (Zuckerman).

Out west, in the 12th Federal Reserve District, the largest banks have increased their commercial loans of less than $100,000 and have taken market share from smaller banks, while they have reduced their commercial loans in the $100,000 to $1 million size range, which are less easy to automate (Levonian).[14] Many of the larger banks are finding that automated small-business lending allows them to profitably make loans of a smaller size than they could using traditional methods. For example, at Hibernia Corp., the break-even loan size was about $200,000 before automation, but now Hibernia has a large portfolio of loans under $50,000 (Zuckerman). At Wells Fargo, the average size of a small-business loan is $18,242 (Oppenheim, January 1997).

This spring, a regional bank in Pennsylvania planned to solicit small-business loan applications with a direct mail campaign to 50,000 current and prospective customers who will be prescreened using the bank's scoring model. The bank will exclude certain lines of business and businesses less than three years old. A simple application form will be used, with no financial statements required, and loans up to $35,000 will be approved based solely on the credit score. Also this spring, PNC Bank Corp. opened an automated loan center in suburban Philadelphia through which it plans to process 25,000 small-business loan applications from across the nation in the next year. While much of the application process is automated and credit scores are used, a lender makes the final approval decision on a loan application (Oppenheim, May 1997).

For many creditworthy small-business borrowers, the entry of the larger banks into the market means more potential sources for credit. Some banks have found they've been able to extend more loans under credit scoring than under their judgmental credit approval systems without increasing their default rates (Asch). Credit scoring may also encourage more lending because it gives banks a tool for more accurately pricing risk.[15] However, the relationship that a borrower has with its large

[14]Mark Levonian reports that between June 1995 and June 1996, the largest banks in the 12th District increased their holdings of loans under $100,000 by over 26 percent, while other banks increased their holdings of these loans by a little over 3 percent. (These figures are adjusted for bank mergers.)

[15]Banks that use scoring to develop risk-related loan pricing need to keep in mind fair lending rules and should avoid selectively overriding the model for some borrowers and not others.

creditor is likely to be very different from the one it has traditionally had with its small bank. The typical bank-borrower relationship, which is built up over years of lending, allows for substantial flexibility in loan terms. A long-term relationship allows the bank to offer concessionary rates to a borrower facing temporary credit problems, which the bank can later make up for when the firm returns to health. (Mitchell Berlin's article discusses relationship lending.)

But automated small-business loans are likely to be more like credit card loans than traditional business loans, with the terms being less flexible and set to maximize a bank's profits period-by-period rather than over the life of a relationship. Monitoring these borrowers would likely be more expensive for the bank, since the borrowers may come from outside the bank's traditional lending markets. This would tend to make the bank less flexible on its loan terms. Small businesses that value the flexibility of the traditional relationship loan will have to seek banks that make loans on this basis, most likely smaller banks, as has been the case in the past. These smaller banks will maintain their advantage over larger banks in monitoring loans, since they have a good knowledge of the local markets in which they and their borrowers operate. Businesses that find it hard to qualify for loans based solely on their credit scores but that, nevertheless, are creditworthy on closer inspection will need to seek funding from these relationship lenders as well.

Another way credit scoring may encourage lending to small businesses is by making securitization of these loans more feasible. Securitization involves pooling together a group of loans and then using the cash flows of the loan pool to back publicly traded securities; the loans in the pool serve as collateral for the securities. The loan pool will typically have more predictable cash flows than any individual loan, since the failure of one borrower to make a payment can be offset by another borrower who does make a payment. The expected cash flows from the loan pool determine the prices of the securities, which are sold to investors. Securitization can reduce the costs of bank lending, since typically the loan pool is moved off the bank's books to a third-party trustee so that the bank need not hold capital against the loans and the securities provide what is often a cheaper source of funding than deposits. (See Christine Pavel's article for an overview of securitization.)

Securitization has occurred with mortgage loans, credit card receivables, and auto loans, all of which tend to be homogeneous with regard to collateral, the loan terms, and the underwriting standards used. This homogeneity is important, since a crucial aspect of securitization is being able to accurately predict the cash flows from the pool of loans so that the securities can be accurately priced. There have not been many securitizations of small-business loans, partly because of their heterogeneous nature.[16] But credit scoring will tend to standardize these loans and make default risk more predictable, steps that should make securitization more feasible.[17] As was true in the mortgage market, securitization would probably lead to an increase in small-

[16]In his 1995 article, Ron Feldman indicates that less than $900 million in small-business loans had been securitized, while $155 billion of these types of loans were outstanding at year-end 1994. He also provides descriptions of some of these securitizations.

[17]The difficulty that the borrower's option to prepay a mortgage poses for pricing mortgaged-backed securities is not an issue for small-business loan securitizations, since small-business loans have short maturities. For example, the November 1996 Survey of Terms of Bank Lending indicated that 85 percent of loans made in the survey period either had no stated maturity or a stated maturity of less than one year. The average maturity, weighted by loan size, of loans with stated maturities of longer than one day but less than a year was 64 days *(Federal Reserve Bulletin).*

business lending, with nonbank lenders playing a larger role. The market would become more liquid, since unlike loans, the securities are easily bought and sold; thus, diversification would be easier to achieve. Since diversification lowers risk, loan rates could be lower.

CONCLUSION

Widespread securitizations of small-business loans are still in the future. But credit scoring is increasingly being used to evaluate small-business loan applications, something that was not widely anticipated a decade ago. Credit scoring will never be able to predict with certainty the performance of an individual loan, but it does provide a method of quantifying the relative risks of different groups of borrowers. Scoring has the potential to be one of the factors that change small-business banking as we know it.

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