A HANDBOOK FOR DEVELOPING CREDIT SCORING SYSTEMS IN A MICROFINANCE CONTEXT

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The Accelerated Microenterprise Advancement Project (AMAP) is a four-year contracting facility that U.S. Agency for International Development (USAID)/Washington and Missions can use to acquire technical services to design, implement, or evaluate microenterprise development, which is an important tool for economic growth and poverty alleviation.

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ABSTRACT

This paper is meant to be a guide for banks, microfinance institutions (MFIs), and donors who are considering applying credit scoring as part of their business model. The research team draws on the experience of microlenders from three continents to illustrate a four-step framework for designing and implementing custom credit scorecards. The framework is flexible, does not advocate any one rigid methodology or technology, and is thus appropriate to any organization with a clear strategy and some experience lending to its target market.

Keywords: microlending, credit scoring, risk management

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ABBREVIATIONS

ABIL	African Bank Investments Limited
AMAP	Accelerated Microenterprise Advancement Project
APS	application processing system
CEE	Central and Eastern European
EU	European Union
EBRD	European Bank for Reconstruction and Development
IT	information technology
MFI	microfinance institution
MIS	management information system
SME	Small and Medium Enterprises
USAID	U.S. Agency for International Development

1. INTRODUCTION AND PURPOSE

This paper is meant to be a guide for banks, microfinance institutions (MFIs), and donors who are considering applying credit scoring as part of their business model. The research team draws on the experience of microlenders from three continents to illustrate a four-step framework for designing and implementing custom credit scorecards. The framework is flexible, does not advocate any one rigid methodology or technology, and is thus appropriate to any organization with a clear strategy and some experience lending to its target market.

1.1 BACKGROUND AND SCOPE

Application credit scoring is used throughout the world to process many types of small-value loan transactions. It has been applied most widely and successfully for personal credit cards and consumer and mortgage loans. Repayment risk for these products is closely linked to verifiable factors such as income, credit bureau information, and demographic factors such as age, education, and homeowner status. More recently, credit scoring has been used to evaluate loans to small and micro businesses, but even in the most developed financial markets, credit scoring for small business loans generally works in conjunction with a judgmental process rather than as an independent decision-making tool (Business Banking Board, 2000).

Credit scoring systems help to:

- Streamline the lending process;
- Improve loan officer efficiency;
- Increase the consistency of the evaluation process;
- Reduce human bias in the lending decision;
- Enable the bank to vary the credit policy according to risk classification, such as underwriting or monitoring some lower risk loans without on-site business inspections;
- Better quantify expected losses for different risk classes of borrowers; and
- Reduce time spent on collections, which in some markets claim up to 50 percent of loan officers' time (ACCION, Credit Scoring for Microenterprise Brief, www.accion.org).

One conceptual difficulty with embracing credit scoring for microfinance is that a data-driven business approach does not intuitively seem like a good fit for reaching data-poor clients who have been typically excluded by banks. Some examples of data limitations in the microfinance field are:

- The self-employed poor frequently cannot document income and credit history (Dellien and Schreiner, 2005);
- Small businesses purposefully misstate tax accounting statements, particularly profit, to reduce their tax burden; and
- Microfinance borrowers are rarely included in credit bureaus, or credit bureaus themselves are underdeveloped in many markets.

In light of such data limitations, thoughtful innovation is required to identify meaningful risk factors for microfinance clients and to measure them in terms of characteristics that are feasible to collect. Credit bureau information, if available, will definitely enhance the value of a credit scoring system, but it is not a pre-requisite for developing scorecards. Similarly, the presence of good bureau data does not eliminate the need to analyze institution-specific client data and experience.

Developing scorecards appropriate to microfinance requires a combination of technical modeling skills and practical knowledge of the credit risks associated with borrowers in the micro segment. Banks and MFIs often lack the technical expertise in-house, but it can be purchased for varying costs from large international credit bureau operators and a wide range of consultancies. However, practical knowledge of the credit risks associated with micro-borrowers should come at least partially from the microfinance organization itself. Any consultancies hired to build models should vet their data-based findings with senior credit managers. Bearing this in mind, off-the-shelf products or "generic" models are unlikely to be appropriate, particularly if they were developed outside of the market in which they are to be applied.

We have found no literature on the use of credit scoring using joint liability or village banking settings. Although it would be problematic to use purely statistical techniques to build factor models for group situations (Schreiner, 2003), the scorecard development principles provided in this handbook could also be applied to a group lending situation given a combination of modeling expertise and significant group lending experience in the local market. For example, a hybrid model, which will be explained in more detail in Section 3, might combine some statistically derived measures of individual borrowers' repayment risk with a judgmental score quantifying some perceived relationships between group composition and repayment success.

If we can construct models with reasonable power to distinguish between high- and low-risk applicants, a scorecard can be an effective tool to speed up the processing of the highest and lowest risk applicants and to set lending policy and pricing decisions according to risk. The scorecard does not replace loan officers and human judgment—it augments them to improve decision making.

In summary, expertise in microfinance credit scoring grows each year as more banks and MFIs design and implement scoring systems. The organizations surveyed here are a few of the pioneers of credit scoring for microfinance. Building on the lessons they have learned, and drawing on the principles of developed market credit scoring (Dickens and Keppler, 1998; Mays, 2000), we can further develop credit scoring as a tool enabling profitable and sustainable microlending, thus expanding overall availability of credit for micro-borrowers.

2. OVERVIEW OF BANKS/MFIS INCLUDED IN STUDY

This study draws on the experience of seven institutions from six countries on three continents:

- BancoSol (Bolivia);
- CAC Leasing (Slovakia);
- African Bank/Credit Indemnity (South Africa);
- Mibanco (Peru);
- Teba Bank (South Africa);
- Unibanka (Latvia); and
- United Bulgarian Bank (Bulgaria).

Each of these banks or MFIs has developed a credit scorecard or credit scoring system for specific microfinance products. The scorecards range in developmental complexity from purely judgmental in Teba Bank, Unibanka, and United Bulgarian Bank, to a combination of statistical and judgmental techniques in CAC Leasing and Credit Indemnity, to empirically derived statistical models in BancoSol and Mibanco.

The banks range in size and strategy. The large Latin American banks focus on microenterprise clients. The South African banks are more oriented toward consumer loans and clients who were underserved by the formal banking sector. The Central and Eastern European (CEE) banks/leasing companies historically focused on corporate clients and have more recently expanded into microenterprise lending.

The market information infrastructure varies widely across our study, with South Africa most advanced in credit bureau services, Latin America not so far behind, and CEE much less developed, but slowly and surely progressing. Credit bureau scores and data are integral to credit scoring models in the markets in which they are most widely used, namely North America and Continental Europe.

As different as these organizations and markets may be, the case studies attached to this guide illustrate that the defining factors for successful implementation of credit scoring are neither bound by geography, nor dependent on the presence or absence of credit bureaus. Furthermore, they are not tied to any one particular type of scorecard or technology. Each project examined here developed an appropriate scorecard for its market based on its own data, institutional experience, and strategy. Each organization followed a number of common steps, and we will make them the focus of the body of this handbook.

3. GUIDELINES ON HOW TO APPLY CREDIT SCORING IN A MICROFINANCE CONTEXT

This handbook describes a four-step process for developing a credit-scoring model in the microfinance context. The main difference between this framework and other credit-scoring literature is that it offers recommendations for situations in which historic data are limited or do not match future strategy and objectives.

Before embarking on developing the scoring system itself, let us consider some of the costs and benefits of developing and implementing a credit scoring system. In all cases, it requires at least the intermittent time of a senior manager and in-house information technology (IT) specialist for anywhere from 6 to 24 months. Outside expertise could charge $10,000 to $65,000 to develop a scorecard. Specialized software to deploy a scorecard can also cost thousands of dollars. (Salazar, 2003). However, cost savings from improved efficiency in operations, pricing and provisioning can run in the hundreds of thousand of dollars, depending on the volume of transactions to be scored. Thus, the payback period for a credit-scoring project is likely to be relatively short for banks and MFIs with significant lending volume in the target segments. Once development costs are recovered, a scoring system can significantly increase long-term profitability.

Table 1 shows some potential benefits of scoring as well as some potential challenges for different types of organizations: those with centralized or decentralized credit decision making, in-house expertise or lack thereof in risk modeling and IT, and advanced or limited IT systems. The table is designed to illustrate that organizational factors generally do not determine *whether* scoring is appropriate, but influence how credit-scoring systems are developed, implemented, and maintained. We assume that credit scoring can provide a benefit to any organization with a clear strategy for issuing a high volume of standardized, low-valued loans and with a willingness to accept and manage the organizational change that scoring will bring. Similarly, we assume that all banks and MFIs use scoring to improve efficiency and increase the profitability and/or outreach of microlending, although these improvements are possible only if the scorecard is developed and tested thoroughly. Over-reliance on the scorecard and the neglect of adequate human judgment and oversight can also be detrimental to loan performance and subsequently to the confidence in this and future scorecards.

TABLE 1: FACTORS TO CONSIDER BEFORE EMBARKING ON SCORECARD DEVELOPMENT			
Organizational Factors		**Benefits**	**Challenges**
Credit decision making	Decentralized	• Reduce visits to business sites for best and worst customers • Increase standardization of: – Lending decisions – Pricing	• Gaining branch-wide buy-in • Enforcing scorecard use and compliance with policy • Management of scoring data
	Centralized	• Quicker decisions to sales offices • Model used only by a small group of analysts	• Requires improved connectivity between branches and credit center • Less transparent to loan officers
Human resources	Advanced in-house modeling /IT skills	• Reduces cost of project • Can refresh, alter the model • Can do programming in-house	• Need to purchase statistical software • Statistical expertise may or may not be accompanied by practical modeling experience • IT resources may be allocated to competing projects
	Limited in-house modeling /IT skills	• Outside consultancies bring additional experience • No need to purchase statistical modeling software	• Need outside assistance to modify the model increases cost • Dependent on developers • Sharing of intellectual property • Vendors require management by someone knowledgeable
IT systems	Advanced and flexible IT systems	• Easier to integrate scorecard • Capacity to store and access score • Data, create reports	• May not be able to modify source code
	Limited IT capabilities	• Impetus to automate loan documentation process	• Higher cost to develop system • May need hardware upgrades to integrate scoring in software • Time for development
Credit scoring experience/ exposure	Advanced exposure to credit scoring	• Understanding leads to vision among management and focus on the development process • Ability to optimize the benefits in terms of risk-based pricing, segmenting market for loyalty programs, and so on	• Possible competing views on types of scorecards needed, lack of cooperation in implementation • Potentially unrealistic expectations in certain data-poor environments
	Limited exposure to credit scoring	• With commitment and outside assistance, can start with most appropriate scorecard	• Do not see the ultimate potential of credit scoring • Buy-in compromised due to lack of understanding • Slower development process

3.1 STEP 1: DEFINE THE SCORING SEGMENT

The first step in a scoring project is to identify the type of customers and products scoring for which the scoring model will be used. Rather than one manager or one department making this decision unilaterally, the organization should form a working group/steering committee with representatives from each functional area (credit risk, credit operations, marketing, IT, consultancy) that will be touched by credit scoring. This working group will guide the development and implementation of the scorecard. One or two senior managers should assume the role of "champion" to promote the proper use and understanding of scoring throughout the organization (Caire and Kossmann, 2003).

We will call the choice of product and customer type the "scoring segment." Segmentation is a marketing term used for a group of customers who share specific characteristics. In the context of scoring, the segment identifies a group of clients and products for which scoring is an appropriate risk appraisal method. Scoring is most appropriate for high-volume, standard products and smaller loan amounts, which makes scoring a natural fit for microfinance. Some possible scoring segments are term loans up to $5,000, borrowers with total assets less than $50,000, all sole-proprietors, and so on. Table 2 lists the scoring segments for the seven organizations in our study.

TABLE 2: TYPES OF SCORECARDS AND SCORING SEGMENTS FOR BANKS IN STUDY

Name of Bank/MFI	Scoring Segment	Scorecard Type
BancoSol	Working capital loans <= $20,000	Statistical
CAC Leasing	Light vehicle leases up to €125,000	Hybrid
Credit Indemnity[1]	Consumer finance loan <= R 10,000 (€1,350)	Judgmental (application) Statistical (behavioral)
Latvijas Unibanka	Term and working capital loans <= €30,000	Judgmental
Mibanco	Working Capital loans <= $20,000	Statistical
Teba Bank	Multipurpose loan <= R5,000 (€675)	Judgmental
United Bulgarian Bank	Term and working capital loans <= €30,000	Judgmental

In addition to the scoring segment for a given scorecard, there can be several types of scoring for various purposes, as illustrated in the Table 3. BancoSol and Mibanco use separate application scorecards for pre-visit and post-visit, loan renewal, and collections. Credit Indemnity has separate scorecards for first time borrowers (judgmental application scorecard) and repeat borrowers (statistical behavioral scorecard), as well as a collections scorecard (hybrid). Alternatively, one scorecard can be built with a combination of factors that makes its one score appropriate for several purposes (Dellien and Schreiner, 2005).

TABLE 3: TYPES OF SCORING

Type of Scoring	Primary Use
Application Scoring	Predicts probability that a loan will go "bad"
Behavioral Scoring	Predicts the probability that the next loan installment will be late
Collections Scoring	Predicts probability that a loan late for a given number of days (x) will be late for another given number (y) of days
Desertion Scoring	Predicts the probability a borrower will apply for a new loan once the current loan is paid off

(Source: Schreiner, 2001)

[1] Credit Indemnity is a fully integrated division of African Bank Investments Limited (ABIL).

Where scoring is new to an organization, it may be beneficial to phase in scorecards one at a time, as opposed to trying to introduce several simultaneously. For example, Credit Indemnity went through the following phases of scorecard development and implementation:

- Paper based judgmental application scorecard;
- System driven judgmental application scorecard;
- Statistically developed behavioral scorecard;
- Collections scorecard; and
- Plan to develop a fraud prevention scorecard.

A phased-in approach is particularly appropriate for organizations lacking data or historical experience. Use of scorecards can be a stimulus for improving data collection and data management. More and better data open opportunities for developing more powerful scorecards over time. Figure 1 from the Credit Indemnity study indicates how this progression can look.

FIGURE 1: PROGRESSIVE SCORECARD DEVELOPMENT

Banks starting with a wealth of statistical data and the willingness to engage outside modeling expertise can consider developing several types of scorecards simultaneously. ACCION's experiences in BancoSol and Mibanco (described in Appendixes A and D, respectively) provide two examples of how separate application and behavioral scoring models can be introduced concurrently.

Regardless of the type of scorecard to be developed, the working group should assemble all available information on the chosen segment. Information refers not only to electronic or hard copy data available for statistical analysis, but also to institutional experience, credit policy and the "rules-of-thumb" used in credit decisions. The type and availability of information will influence the choices made in Step 2: Select the Type of Scorecard.

3.2 STEP 2: SELECT THE TYPE OF SCORECARD

There are three main types of scorecards:

- **Statistical**: empirically derived from data on past loans;
- **Judgmental**: structured from expert judgment and institutional experience; and
- **Hybrid**: some cross of statistical and judgmental techniques.

A statistical model score predicts the probability of default for an individual borrower. This degree of precision makes it the most powerful scorecard type for risk management, pricing and provisioning. Judgmental and hybrid model scores rank the relative risk of a borrower, with high scores indicate less risk than lower scores. A judgmental or hybrid model, however, can be back-tested on all historic cases to define historic probability of default at various score levels.

In reality, all scorecards will contain some mixture of statistics and expert judgment. Where there is an abundance of data for statistical modeling, expert judgment must be exercised in defining, selecting, and excluding some factors. Where there is a lack of data for advanced statistical techniques, judgmental models, parameters, and classification should nevertheless be back-tested to the extent possible on past data. The term “hybrid” is thus reserved for mixed models where, for example, a set of factors with statistically derived coefficients or weights are joined with other factors weighted judgmentally.

The selection of scorecard type can be influenced by several factors:

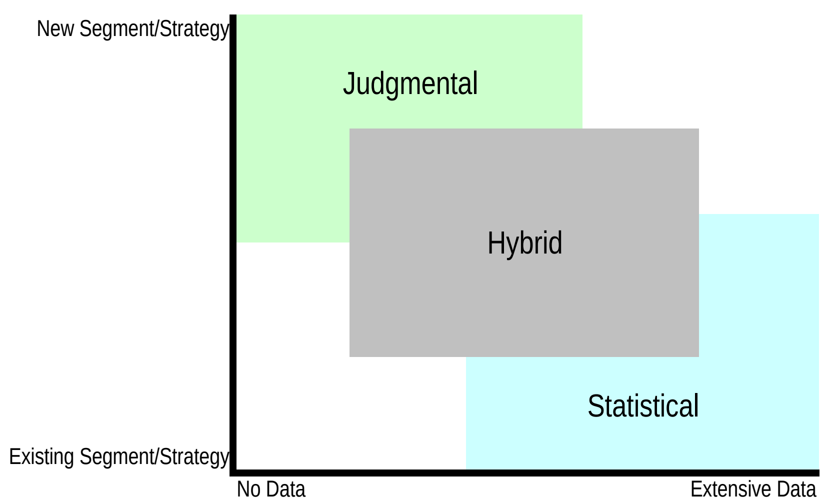
- Quality and quantity of historical data on good and problem loans;
- The extent to which the scoring segment resembles past clients and products;
- The modeling expertise available in-house and/or the cost of consultants; and
- The limitations of the information technology (IT) systems.

The quality and quantity of historical data available are the most important factors to determining what type of scorecard should be developed. Sometimes the data are available, but only in hard copy format. In the case of BancoSol, the bank hired dedicated staff to key in historical data over a two-month period in order to proceed with the development of a statistical model.

Second in importance is the extent to which an organization expects its future business to resemble its past business. In the case of CAC Leasing, management wanted to add cash-flow measures to its risk analysis in order to extend express processing to clients making lower down payments. CAC Leasing had statistical data on a number of factors, but had not previously collected cash flow information. Regression analysis was used to derive a statistically weighted scorecard, and expert judgment was used to assign weights to the new cash flow measures, thus creating a hybrid scorecard.

Figure 2 graphically represents the choice of scorecard with an x-axis representing availability of data and a y-axis representing the degree to which the strategy or segment differs from existing strategies or segments. The three shaded squares represent the types of models and the trade-offs involved in the selection of scorecard type.

FIGURE 2: MODEL SELECTION DRIVERS



For example:

- Teba Bank had no historical data available and was developing the scorecard for a completely new segment as part of a USAID program. This combination can be found in the top left corner on Figure 2; they did, in fact, develop a judgmental scorecard.
- CAC Leasing had extensive data on some, but not all, of the risk factors it wanted to evaluate. It also had extensive experience in the vehicle segment, but was modifying its appraisal strategy slightly. CAC was somewhere in the middle of Figure 2; not surprisingly, they developed a hybrid scorecard.
- Mibanco had a wealth of transaction data covering a two-year period to design a scoring tool for a segment in which had extensive experience. This experiences places Mibanco to the bottom right of Figure 2; Mibanco did indeed develop a statistical scorecard.

In summary, the scorecard development methodology depends on the availability of quality historical data and on future strategy. Different modeling methodologies may return scorecards with a wide range of predictive power. The more accurate a scorecard is in predicting ‘good’ or ‘bad’ cases, the better. However, considering that microlenders should not base lending decisions solely on scoring, any relatively accurate scorecard will deliver the bulk of scoring’s benefits by identifying the best and worst of clients and providing a common scale on which to base policy measures. Thus, credit-scoring success may depend less on statistical measures of predictive accuracy than on the degree to which the organization thoughtfully incorporates scoring into its overall credit policy. This is a valuable point of consideration for organizations that have forgone scoring due to perceived high development costs and/or lack of historical data for statistical modeling.

3.3 STEP 3: DESIGN THE CREDIT SCORECARD

The scorecard design process, regardless of the type of scorecard, can be grouped into the following three phases:

- **Definition:** what is a bad loan?
- **Discovery:** which characteristics most influence risk?
- **Development:** which combination of factors provides the best results in back testing?

With this new 3-“D” terminology, we attempt to simplify and unify the presentation of a topic that can tend to lose the layperson in scoring-specific terminology. We will demonstrate that, on a conceptual level, we follow the same basic steps to develop statistical, judgmental, and hybrid models, only use different tools for each job.

3.3.1 DEFINITION

The financial institution must determine what it considers a “bad” client. “Bad” means a loss-making client that with perfect hindsight the bank would have chosen to avoid. A precise, quantitative definition of “bad” is crucial for developing statistical models as these derive numeric relationships between each risk measure and the “bad” loans. A judgmental model can be developed without a precise “bad” definition, but requires a definition of “bad” for testing and validation.

An MFI’s “bad” client might have been more than 15 days late per installment on average, while for commercial banks, the definition is commonly arrears of 90 or more days, the Basel 2 measure for probability of default. It is important that the “bad” definition fit the institution and its risk appetite.

3.3.2 DISCOVERY

Discovery is the process of identifying the characteristics that will be included as variables in the model.

For a statistical model, discovery involves rigorous statistical analysis of all available borrower and repayment data in relation to the "bad" variable. Software packages such as STATA, SAS, SPSS, and others facilitate a range of analytical techniques, from relatively simple cross-tabulations and classification trees to more complex neural networks. Exploratory analysis should result in a list of characteristics to consider for inclusion in the model and a basic understanding of the shape of the relationship between each characteristic and repayment risk.

To make informed judgments in the statistical modeling process, the modeler should understand not only statistics, but also the business of credit, including how the financial institution gathers, stores, and uses credit information. Consultants are frequently hired not only because they possess this relatively rare combination of skills, but also because they will bring experience from other markets. An illustration of the statistical modeling process is included in the BancoSol (Appendix A) and Mibanco (Appendix D) cases.

A Laundry List of Microfinance Client Characteristics

- Demographics: gender, year of birth, marital status, highest education
- Household Information: number of people in household
- Household Assets: homeowner status, years at residence, number of rooms, vehicles owned
- Business Demographics: sector, type of business, years in business, number of employees
- Financial Flows: business revenue, household income, rent payment
- Balance Sheet: total assets, total liabilities (formal debt, informal debt), total equity
- Repayment History: number of loans, longest spell in arrears, days in arrears per installment
- Credit Bureau Information: bureau score, presence on "black list"
- Quantified Subjective Judgments: managerial skills, cash-flow variability, business prospects
- Loan Characteristics: amount requested, type of loan, borrower's contribution to financing

(Source: Schreiner, 2003)

For a judgmental model, no advanced statistical knowledge or software is necessary in the discovery phase. Instead, a panel of credit decision makers should discuss which factors guide their current decisions. One technique is to rank the risk factors used in the credit review process according to their perceived importance in determining a client's creditworthiness. Consultants may provide advice during this process, but the bank and the MFI's staff should contribute actively since they generally have an intuitive in depth knowledge of their client base.

Hybrid models combine statistical and judgmental techniques. For example, a list of key characteristics identified by statistical analysis might be augmented with other factors that a panel of experts suggests are strongly related to repayment risk.

Discovery ends with what we can call a "debriefing." The list of potential scorecard variables is presented to senior credit decision makers, such as credit committee members, to review and verify or question the strength and direction of each factor's relationship with repayment risk. This debriefing is most important for statistical analysis, where data irregularities or peculiar past customers may have distorted the results. For judgmental scorecards, it is more of a chance for the modeling team to share the proposed scorecard characteristics with a wider audience for comment.

The list of potential scorecard characteristics will vary according to each organization, the data it collects and analyzes, and local market factors. An example of characteristics used in ACCION's scorecards in BancoSol and Mibanco include business profile information, such as business type, years of experience, and ownership of premises, as well as information related to the client's credit history, such as the length of relationship with the institution and number of active and repaid loans. Some additional factors that may be widely applicable to microfinance are shown in the accompanying text box. A guiding principal is that micro-businesses analysis should include characteristics of both the business and its owner.

3.3.3 DEVELOPMENT

Development involves applying weights to the selected model factors and creating a scorecard. Statistical model weights are taken directly from the statistical outputs, such as a regression equation, while judgmental model weights are set manually based on the perceived importance of individual factors and the implications of their interactions. No matter which type of model is being developed, it is important to document the development process as outlined in the accompanying text box.

Documentation in Scorecard Development

From the Credit Indemnity Study: One of the most important tasks to conduct when developing a scorecard is documenting every step of the process. Documentation should include information on:

- Basic decisions taken;
- Data sampling techniques;
- Data quality issues;
- Steps taken with the data (manipulation); and
- Details of back testing.

Such documentation enables the developer to go back later and identify errors or make necessary changes.

3.3.3.1 Development of Statistical Scorecards

Statistical scorecard development requires specialized skills and software. We would recommend that only people with a working knowledge of applied statistics and at least some experience in modeling credit risk attempt to develop such scorecards.

Banks and MFIs who have the data to develop statistical models will find that a majority of the model development time is spent on preparing the data for modeling. As a rule of thumb, the larger the set of development data, the more time will be necessary to clean data, calculate variables, set bin ranges for categorical values, and so on. The more variables that are selected for the final model, the more programming work will be required to develop a test model, program a scoring module, and link it to the IT system. For ease of memory, we can simply call this the “Big Data Rule:” the more data involved in scorecard development and implementation, the longer we should expect to work on the scorecard in all phases of the project.

3.3.3.2 Development of Judgmental Scorecards

Judgmental scorecard characteristics are selected and weighted using the expert judgment of experienced lenders/consultants. To help banks and MFIs develop their own judgmental scorecards, we provide an example of how weightings can be set. In Figure 3, three judgmental scorecards are presented. Scorecard 1 is equally weighted, while Scorecards 2 and 3 are variably weighted.

Looking at the equal weighted Scorecard 1, assume the bank requires a score of 5 to approve new applicants. A successful applicant must have a loan to collateral value of less than 70 percent, annual turnover at least three times more than the loan amount, a business track record longer than one year, a current ratio greater than 0.5, and total assets of greater than €100,000. This simplest form of scoring could just as easily be represented by a checklist.

FIGURE 3: THREE JUDGMENTAL SCORECARDS

JUDGMENTAL SCORECARD 1

Variable		
1	Loan to Collateral Value	
	>70%	<70%
	0	1
2	Annual Turnover to Loan Value	
	<3x	>3x
	0	1
3	Years in Business	
	<1	>1
	0	1
4	Current Ratio	
	< 0.5	> 0.5
	0	1
5	Total Assets (EUR)	
	<100K	> 100K
	0	1

JUDGMENTAL SCORECARD 2

Variable		
1	Loan to Collateral Value	
	>70%	<70%
	0	3
2	Annual Turnover to Loan Value	
	<3x	>3x
	0	2
3	Years in Business	
	<1	>1
	0	1
4	Current Ratio	
	< 0.5	> 0.5
	0	1
5	Total Assets (EUR)	
	<100K	> 100K
	0	1

JUDGMENTAL SCORECARD 3

Variable			
1	Loan to Collateral Value		
	>70%	50-70%	<50%
	0	1	2
2	Annual Turnover to Loan Value		
	<3x	3-5x	>5x
	0	1	2
3	Years in Business		
	<1	2-4	>4
	-2	1	2
4	Current Ratio		
	< 0.5	0.5 - 1	> 1
	0	1	2
5	Total Assets (EUR)		
	<100K	100-500K	> 500K
	0	1	2

For scorecards 2 and 3, assume the passing score is still 5 points. Now an applicant who would have failed Judgmental Scorecard 1 for having a current ratio of less than 0.5 would still pass scorecards 2 and 3 with a Loan to Collateral Value of less than 50 percent. Judgmental scorecard weights should be set carefully. The scorecards should be tested on a combination of actual clients and hypothetical future clients to ensure that the scores adequately represent risk profiles for which the bank is prepared to prescribe standard policies such as approve, reject, review, or require additional securities.

The Dual Score Matrix

In 1998 and 1999 in South Africa, Trans Union ITC and Fair Isaac developed a bureau score called Emperica. This score was an additional field that Credit Indemnity could access during the bureau enquiry. The Emperica score was combined with Credit Indemnity's judgmental scorecard in a dual score matrix, or the cross-tabulation of Credit Indemnity's application score and the Emperica bureau score. Integrating the bureau score improved the quality of Credit Indemnity's decision making.

3.3.3.3 Development of Hybrid Scorecards

Hybrid scorecards combine the statistical and judgmental techniques explained above. One potential "hybridization" is the combination of a statistically derived score, such as a bureau score, with a judgmental score using a matrix approach, as described in the accompanying text box.

Whether it is statistically or judgmentally derived, ideally the scoring equation can finally be represented in a visually simple scorecard that is intuitive for end-users. This step is not necessary, but it makes it easier to present the scorecard to a working group, users, or programmers. Judgmental scorecards can be limited to no more than 30 variables—15 to 20 is a common range. For statistical scorecards, the number of variables should be determined by balancing improved predictive power with cost of data collection and programming complexity. Some microfinance models have included from 50 to 80 variables in order to improve predictive variance and reduce predictive variance (Schreiner, 2003).

3.4 STEP 4: TEST, IMPLEMENT, AND MANAGE THE SCORECARD

3.4.1 BACK TESTING

The first crucial test any scorecard should pass is the back test[2] using historical data. Back test results can be a key tool in setting scoring policy. For statistical models, back tests present the scorecard's classifications for the entire set of data used to develop the card. For judgmental models, we can perform similar analysis if we can gather a sample of data on repaid loans for which we know whether the client was always good or at any point became bad. Table 4 taken from the Mibanco experience, shows an example of a Good/Bad Classification by Score.

TABLE 4: GOOD/BAD CLASSIFICATION BY SCORE

Score	Good		Bad	
	#	%	#	%
< 675	259	67.10%	127	32.90%
676 A 701	409	72.50%	155	27.50%
702 A 729	927	74.50%	318	25.50%
730 A 762	2401	81.00%	562	19.00%
763 A 785	2427	81.90%	536	18.10%
786 A 806	2702	83.10%	549	16.90%
807 A 822	2547	85.50%	433	14.50%
823 A 842	3569	85.50%	604	14.50%
843 A 859	3374	87.80%	470	12.20%
860 A 875	2857	88.60%	369	11.40%
876 A 898	3515	90.30%	378	9.70%
899 A 924	2993	91.50%	278	8.50%
> 924	2366	93.90%	153	6.10%
No Data	31	83.80%	6	16.20%
Total	30377	86.00%	4938	14.00%

The percentage column in this table represents the concentration of good or bad loans respectively in each score band. In general, if a scorecard has discriminatory power, scores indicating higher risk (lower scores in this example) should have a higher concentration of bad cases. This table shows that more than 30 percent of cases scoring less than 675 points are bad versus less than 10 percent for cases scoring between 876 and 898. This performance data suggests that the scorecard accurately sorts the good loans from the bad loans.

Table 5 expands on the type of analysis presented in Table 4. It presents not only the numbers of good and bad cases, but also the cumulative figures and percentages of total cases at any given score level. Tables such as these can be used to set scoring policy and determine thresholds for rejection, review, and approval.

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[2] Back testing is the process of testing a scorecard's performance on a sample of past borrowers.

We illustrate below the effects of one policy decision: approve all loans scoring 350 or more points and review all others. Table 5 contains data on a total of 37,123 loans (the sums of the last row in each of the Cumulative Good and Cumulative Bad columns (36,045 + 1,078 = 37,123). Applying the policy of "approve over 350", the far right column, the percentage of total cases, indicates that 71.3 percent (1-28.7% = 71.3%) of customers would have been automatically approved. The shaded region of the table, which includes scores between 350 to 700 shows that, in the past, the bank would have approved 26,115 good loans and 337 bad loans, for a total of 26,452 loans. The last row of the table, labeled "Over 350" presents the total numbers for the shaded score ranges 350 – 700. The historic "bad" rate for loans scoring over 350 is 1.3 percent (337/26,452 = 1.3%).

TABLE 5: BACK TEST WITH GOOD/BAD INTERVAL AND CUMULATIVE ANALYSIS

Score Range	Interval Good	Interval Bad	Cumulative Good	Cumulative Bad	Percent of All Cases	POLICY
0-50	3	14	3	14	0.0%	REVIEW
51-100	11	23	14	37	0.1%	
101-150	48	19	62	56	0.3%	
151-200	295	101	357	157	1.4%	
201-250	1,078	190	1,435	347	4.8%	
251-300	2,838	183	4,273	530	12.9%	
301-350	5,657	211	9,930	741	28.7%	
351-400	8,233	181	18,163	922	51.4%	APPROVE
401-450	7,410	102	25,573	1,024	71.6%	
451-500	6,360	34	31,933	1,058	88.9%	
501-550	3,110	20	35,043	1,078	97.3%	
551-700	1,002	0	36,045	1,078	100.0%	
OVER 350	**26,115**	**337**			**71.3%**	

Thus, Table 5 illustrates that a policy of approving all loans scoring over 350 will result in an expected bad rate of 1.3 percent. At the same time, more than 70 percent of clients could be approved in a fraction of the time, while the rest would be subject to standard review.

To illustrate the proposed scoring policy's impact on costs, let us assume that from the moment of scoring is completed it takes 5 minutes to process an automatic approval, 30 minutes to conduct a standard review, and 4 hours (240 minutes) to process and work out a bad loan. To keep the computations simple, assume wages and overhead cost $1 per minute. Finally, assume that before introducing scoring all loans were processed using standard review techniques. With this set of assumptions, Table 6 shows that automatically approving all loans with scores over 350 would have reduced wages and overhead costs by $580,420. As overhead and wages are to some degree fixed, this implies that business volumes can be increased with the same human resources, or spare resources can be focused in other areas.

TABLE 6: REDUCTION IN COSTS CALCULATION

Costs Element	Intermediate Calculation	Total
Cost of Standard Review	26,452 x 30	793,560
Minus Cost of Automatic Approval	26,452 x 5	- 132,260
Minus Cost of Processing Bad Loans	337 x 240	- 80,880
Total Costs Reduction	793,560 – 132,260 -80,880	= $580,420

The better the a bank or MFI can estimate the income for 'good' loans and the cost of 'bad' loans, the more precisely it can estimate the effects of scoring on profits. Another way to look at scoring's relation to profit is to apply the below formula to any cut-off point below which loans would be rejected.

(Cost per Bad x Bads Avoided) + (Benefit per Good x Goods Lost)
(Source: Schreiner, 2003)

Policy thresholds, such as cut-off scores, enable banks and MFIs to increase or decrease their risk exposure in response to the quality of the loan book and market forces. Combined with information on work-out costs and interest income, tabular analysis can be used to set risk-based pricing: for example, rather than rejecting riskier clients, pricing can be set so that interest income will cover expected losses for that segment.

Using tabular analysis of back-testing results, we can examine the expected effects of any number of different scoring policies. Thus, the back test is perhaps the most valuable tool in setting scoring policy.

3.4.2 PILOT TESTING

The real work begins once back testing is completed. As noted earlier in this handbook, and highlighted in all the cases, successful implementation depends less on the model's predictive accuracy than on factors such as management and loan officer buy in, accurate data capture, a well thought-out credit policy, and good management information system (MIS) reporting (for more detail, please see Key Success Factors in the Credit Indemnity case).

The first step of putting the scorecard into practice is a pilot test. For pilot testing, we need some method of performing the scoring calculations. Generally, the scorecard will be put into some sort of user-friendly format so that users can begin testing it on new cases.

If the scorecard has relatively few factors, the least IT-intensive method of testing it would be to calculate the scores on paper, as in the case of Credit Indemnity when the application scorecard was first introduced in 1978. In the cases of CAC Leasing, Unibanka, and United Bulgarian Bank, the scorecards were tested in specially designed, user-friendly programs written in Visual Basic for Microsoft Excel. Excel is available on most workstations and programs for it are relatively easy to write. Simple scorecards can also be programmed directly into the institution's core IT system or application processing system (APS) in a relatively short time, if the APS allows.

For scorecards with more variables or calculations, we need to consider again the Big Data Rule, this time applied to the programming of test scorecards. One key issue is whether scorecard calculations are based on user inputs only or also require repayment data captured directly from the core IT system, as is the case for many behavioral scorecards. The more data taken directly from the core IT system, the more time is needed for core system programming and the less feasible are any of the quicker options suggested above. Debugging complicated programs also takes more time. In the Mibanco case, development of the scorecard module in the banking system took six months. Project management should keep the Big Data Rule in mind to help set realistic project implementation timelines.

The goal of pilot testing is to get a feel for how the model works in practice: What are the score ranges? Do the scores coincide with perceived risk levels? Are there any unexpected complications in collecting data needed for scoring? The answers to these questions can shape scorecard policy and procedures.

A pilot test can last for a certain period of time, such as 3 to 6 months or until a certain number of new cases have been processed, such as 500 scored loans. It can also run in parallel to standard procedures, where credit committees review test model scores either before or after making the credit decision. The new procedures could also be tested on a stand-alone basis in selected branches. As the case studies indicate, there are no set rules. The choice of best approach depends on the type of scorecard (What type and volume of data are needed to evaluate the pilot test?) and the credit decision process in each organization (Are decisions are centralized or decentralized?).

3.4.3 TRAINING

The pilot testing phase should start with adequate training of scorecard users. Topics to cover include the basics of how the scorecard was developed, organizational goals for using scoring, as well as procedural training. The pilot test training is where we can first secure the buy-in of loan officers. Without the interest and cooperation of loan officers, the pilot test is likely to face delays, as was the case in the beginning of the BancoSol project. In any case, feedback from “frontline” users should be solicited throughout the testing period.

As highlighted throughout the case studies, training is not limited to pilot testing or roll out, but should be an ongoing part of the scoring process. If scorecards are developed by outside consultants, senior managers need to be trained in the how the scorecard works and how it can be used to set scoring policy. Risk managers and IT staff must understand the model parameters and how they can be modified. Human resource and project managers must provide follow-up training to loan officers each time significant changes are made to the scorecard or scoring process. Finally, the scorecard should become a part of the organization, not remain in the purview of only a consultancy or one project manager. The Four-Eyes of Scoring principle presented in the accompanying text box highlights the importance of spreading knowledge of the scorecard throughout the organization.

3.4.4 INTEGRATION WITH IT SYSTEMS

In modern financial institutions, a scorecard can be deployed most effectively as an additional module to an existing software platform. As such, scoring is often just one part of an automated APS. For institutions that do not have an APS, a scoring project can provide the stimulus to either develop or purchase a system that either includes or can be adapted to include a scorecard deployment module. Scoring’s role in the development of an APS is described in the case of United Bulgarian Bank. Automated application processing and scoring fit well together since one common benefit of scoring is that it can recommend different policy actions or processes for clients with different levels of risk.

The maturity and flexibility of IT systems will influence how best to integrate the scorecard. Remembering the Big Data Rule one last time, the more complex a scorecard, the more complex will be its integration with the IT system. If scoring’s user interface cannot be easily integrated directly into the existing IT system, it may pay to develop a separate

The Four-Eyes Principal for Scoring

Many bankers are familiar with the Four-Eyes Principle as a staple of underwriting policy that guards against fraud. At least two people, and thus “four eyes,” must review and sign off on any credit decisions. This same principle can be applied, with a twist, to long-term scoring model management. At least two people should understand and be involved with the model. Otherwise there is a risk that one person with all operative institutional knowledge of the scoring models could take another job and leave the bank with an information and institutional history gap that can be difficult to fill and at the very least require extensive retraining (see also the Mibanco case).

APS from scratch and then link this to the core database system. A number of IT concerns brought out in the Teba Bank case are presented in the text box to the side.

In addition to supporting lending decisions, scorecards are effectively data management tools. As such, the information that goes into and comes out of a scorecard should be tracked and stored. Data should be stored for clients who are scored but later rejected. Decisions not to follow scorecard policy, often called "overrides," should also be catalogued for use during reviews of scorecard effectiveness. All of this data, including information on loan performance (for example, which loans were bad, how much did the bad loans cost) should be stored for future analysis, including the refreshing or redevelopment of scorecards. Behavioral scorecards in particular need to be refreshed regularly.

Five Tips for Integrating Scorecards in IT Systems

- The programmer needs to understand how the scorecard works. If he or she does not have experience with scorecards, the data model must be very explicit and the card must be tested extensively.
- As scoring can affect data requirements for day-end processing and storage, a knowledgeable database architect may be needed to structure the scoring database and ensure proper data warehousing.
- The scorecard program ideally will be parameterized rather than hard coded, allowing nonprogrammers to modify variables, weights, and cut-off scores.
- Reporting functionality should make it easy for management to generate periodic reports and monitor scorecard performance and the quality of the scorecard loan portfolio.
- The system should avoid any redundant data entry or capture and should protect against data input errors.

3.4.5 LONG-TERM MODEL MANAGEMENT

The scoring software module should generate several standard reports, the most universally useful of which is referred to as the Global Follow-Up Report (Schreiner, 2003). An example of the Global Follow-Up Report from the United Bulgarian Bank case study is presented below in Table 7. This report will indicate the model's effectiveness in correctly assigning risk classifications to borrowers.

TABLE 7: UNITED BANK OF BULGARIA GLOBAL FOLLOW-UP REPORT (ALL LOANS SCORED OCTOBER 2003 - OCTOBER 2005)

			Loans with cases of arrears of 30-59 days			Loans with cases of arrears of 60 days or more		
Final Credit Center Score	**No. of loans**	**% of total**	**No.**	**% of applications in score range**	**% of total applications**	**No.**	**% of applications in score range**	**% of total applications**
175-200	42	1.98%	6	14.29%	0.28%	2	4.76%	0.09%
201-250	378	17.83%	49	12.96%	2.31%	16	4.23%	0.75%
251-300	588	27.74%	45	7.65%	2.12%	13	2.21%	0.61%
301-350	532	25.09%	26	4.89%	1.23%	9	1.69%	0.42%
351-400	364	17.17%	15	4.12%	0.71%	5	1.37%	0.24%
401-450	204	9.62%	4	1.96%	0.19%	0	0.00%	0.00%
451-500	12	0.57%	0	0.00%	0.00%	0	0.00%	0.00%
Total	2,120	100.00%	145	6.84%	6.84%	45	2.12%	2.12%

As shown in Table 7, there is a clear and consistent progression in the concentration of “bad” loans (defined as loans with arrears greater than 60 days) moving from high to low scores (where high scores indicate low risk). For example, only 1.96 percent of loans scoring over 400 went “bad” and no loans between 450 and 500 went bad. “Bads” increase to 2.21 percent of loans scoring between 251 and 300 points, and 4.76 percent of loans scoring 175 and 200 points.

Scorecard management is a long-term process that must live well beyond the initial excitement of scorecard development and implementation. Whether or not data are the driver for scorecard creation, data are the long-term driver of scorecard success. Consistently collecting, storing, and periodically monitoring scorecard data, and also other borrower information, will allow an institution to validate judgmental models, transform judgmental or hybrid models to fully statistical models, refresh and potentially improve predictability of statistical models, and refresh and potentially improve the predictive power of statistical models, or develop models for additional segments.

4. CONCLUSION

As this handbook has illustrated, a scorecard, thoughtfully developed, flexibly implemented, and properly managed can speed loan processing and inform pricing and provisioning, which can help banks and MFIs save costs, reduce subjectivity, and improve risk management. Improved efficiency in the microloan segment will both increase profitability and expand micro-borrowers' access to credit.

APPENDIX A: BANCOSOL, BOLIVIA

1. OVERVIEW

In November 1986, international and Bolivian investors founded PRODEM (Foundation for the Promotion and Development of the Microenterprise/Fundación para la Promoción y el Desarrollo de la Microempresa) as a nongovernmental organization (NGO). PRODEM was created to provide resources to the Bolivian microenterprise sector by offering working capital microloans to groups of three or more individuals dedicated to similar activities, with each individual formally guaranteeing the other's loans. By January 1992, PRODEM had an outstanding loan portfolio of US$4 million and 17,000 outstanding clients. Given this strong growth, and the ever-increasing demand for credit among Bolivian microentrepreneurs, PRODEM's Board of Directors recognized that the legal and financial limitations of NGOs meant that the most promising and viable alternative to meet this demand would be the creation of a commercial bank, to be called Banco Solidario S.A., or BancoSol ("the Bank").

To date, after more than a decade of operations, BancoSol has disbursed more than US$1 billion to more than a million microentrepreneurs. Currently, the Bank has about 74,000 loan clients and an outstanding loan portfolio of US$110 million, as well as US$80 million in deposits from more than 60,000 savings clients. BancoSol has 30 branches in six regions of Bolivia (La Paz, Cochabamba, Santa Cruz, Sucre, Tarija, and Oruro), making it one of the most important financial institutions in the country.

In recent years, Bolivia has experienced a weakening economic environment, aggravated by constant social conflict. At times, the entire economic structure has been threatened by roadblocks and armed conflicts. However, specialized microfinance institutions (MFIs) have continued to grow their loan portfolios, with delinquency levels lower than those seen in the traditional banking sector.

BancoSol has registered profits in recent years, despite turmoil in Bolivia, thanks to its strategic management focused on strengthening the Bank during these adverse times. In terms of BancoSol's core microlending business, improvement strategies are evident in stronger loan policies and a diversified range of products. It has also redesigned its overall loan processes to improve operating efficiency and overall customer service, as well as to improve upon credit risk management practices at the branch level.

THE PROJECT

The credit-scoring project began at BancoSol in early 2001, with the support of ACCION International and an external consulting firm. The overall goal of the project was to implement three different scoring models: first, Collections Scoring and, later, Selection and Segmentation Scoring. The Bank would become the first Bolivian financial institution to incorporate scoring in its loan processes, making it a pioneer in the international microfinance arena.

When the project began, BancoSol had 57,266 loan clients and used traditional methods to evaluate microfinance loan applications, including an exhaustive analysis of both quantitative and qualitative aspects for both new and repeat loan clients, regardless of their risk profile. Loan collection methods were determined based on the amount and numbers of days that payments were past due.

2. THE DRIVERS FOR CREDIT SCORING

BancoSol intended to meet the following objectives when it initiated a credit-scoring project for working capital microenterprise loans:

- Improve customer service by accelerating the loan approval process;
- Standardize policies, processes, and procedures;
- Increase the retention of low-risk clients;
- Maximize efficiency of collection activities;
- Contribute to improved portfolio quality; and
- Increase loan officer productivity.

3. TYPE OF CREDIT SCORING MODEL USED

BancoSol introduced three credit-scoring models:

- **Collections Scoring**. By quantifying risks, the MFI is able to lower recovery costs and increase efficiency.
- **Selection Scoring**. By quantifying information about the potential client's profile and risk factors, the MFI is able to prioritize and personalize the evaluation of new credit applications.
- **Segmentation Scoring.** By classifying existing clients by risk, the MFI is able to improve portfolio quality and overall customer service.

These credit-scoring models, developed by ACCION, facilitate the speedy, consistent, and objective evaluation of a client's creditworthiness. The models were developed using regression analysis to generate a score, which can be used to order a client population based on risk.

ACCION's scoring models allow an MFI to predict the level of risk related to a loan, based on client profile and loan repayment history. Among the characteristics that affect risk, ACCION uses those that are directly related to the client and business profile (such as age, business experience, type of business, ownership of business premises, and so on.), as well as information related to the client's credit history (experience with the institution, number of loans, repayment rate, and so on.). This detailed information about the client allows for the creation of a well-defined risk profile.

4. PROCESS OF ADOPTING CREDIT SCORING

BancoSol implemented credit scoring in five phases:

- Phase I: Analysis and Preparation
- Phase II: Construction of Statistical Model
- Phase III: Development of the Scoring Module
- Phase IV: Testing the Model (Pilot)
- Phase V: Expansion and Transfer

PHASE I: ANALYSIS AND PREPARATION

Phase I consisted of an extensive analysis of BancoSol's client database to identify the necessary variables. While analyzing the database, it was recognized that additional data from existing clients' credit files would be needed, as only partial information was actually being captured in the database. This partial information had been sufficient for credit analysis through credit committees, but would be insufficient to determine the variables required for the statistical model.

In early 2001, BancoSol hired full-time temporary staff to enter the data into the system, demonstrating its full commitment to the project. It took about two months to enter the information, after which the database was analyzed again, the appropriate client population was identified, and all available variables were analyzed. With the completion of this phase, the databases were well structured and it was time to begin the development of the statistical model.

PHASE II: CONSTRUCTION OF THE STATISTICAL MODEL

The process of creating the scorecards began with the statistical analysis of client performance information, both current and historical, for the two years prior to the initiation of the project. At the same time, given that the starting point for modeling is the definition of "Good" and "Bad" clients, a team of staff from both BancoSol and ACCION collaborated on these definitions. Once these basic definitions were determined, development of the models for the three scorecards could begin, and the construction of the statistical model was presented to Bank management in July 2001.

PHASE III: DEVELOPMENT OF THE SCORING MODULE

The main activity of this phase, which began in August 2001, was the review of credit and collection processes, as well as the design and development of the support application for the scorecard tool by the Bank's Systems Department. Functional tests of the application, once development work was completed, proved to be just as important.

To develop the functional specifications of the project, all of BancoSol's existing credit processes, both office- and field-based, needed to be identified and documented. As some inconsistencies between policies and actual practice were identified in this analysis, improvements to the loan processes were made.

As modifications and additional work required to enter all the data into the database were resulting in small delays that began to add up, it was decided that it would be best to create a program that would interface with the Bank's own system and allow the Bank to use the collections scoring model more quickly. Such a program was created, known as the "black box," that automatically calculated and assigned strategies.

The finalized functional specifications document for collections scoring was presented to BancoSol's management team at the beginning of September 2001. Programming was completed by early October 2001, and functional testing was conducted, identifying a few necessary adjustments, which were completed before the official pilot was launched.

The previously mentioned analysis of the credit processes also concluded that the order of some of the subprocess tasks required modifications for selection and segmentation scoring. For example, not all branches were entering data from loan files into the system before credit committee meetings, but rather only after loans were approved. However, for selection and/or segmentation scoring, credit application data needed to be entered into the system from the beginning of the process in order to obtain the score.

A combined functional specifications document for selection and segmentation scoring was generated and finalized in September 2001. However, given that the Bank was focused on collections scoring at that time, the Selection module was not developed and tested until February 2002. The segmentation score module was completed in August 2003.

PHASE IV: PILOT TESTING

Collections Scorecard

Given their proximity to the Bank's headquarters, three branches in La Paz were selected to pilot test the collections scorecard in the fourth quarter of 2001. These branches monitored performance and behavior on a daily basis.

Staff from the pilot branches received both classroom and field-based training. Classroom sessions were primarily focused on raising staff awareness of the benefits of using the scorecard. This was especially important for loan officers, who were traditionally responsible for all collections activities, and scoring would assign some of these activities to third parties (call center, and so on.).

Selection Scorecard

Pilot testing of the selection scorecard began in mid-February 2002. At that time, the Bank's management also decided that the scores would not be decisive in the loan approval decision, meaning that it would be possible to override the decision/strategy suggested by the score. Given this decision, the "forced approval" option, or override of a model rejection, was introduced into the system. The program required the user to record a reason for all such forced approvals. Later forced approvals came to require the authorization of more senior staff.

In March 2004, the Bank hired full-time monitors for the project and formed a Project Coordination Committee with representation from all functional areas, led by ACCION's Resident Advisor. This committee took on all projects activities, with special emphasis on branch activities. It was responsible for supervising, monitoring, and making any required policy changes.

Segmentation Scorecard

The segmentation pilot began on a small scale in March 2004.

PHASE V: EXPANSION AND TRANSFER

As the collections and selection scores were being finalized, BancoSol began to plan for the incremental expansion of scoring to all branches. This expansion phase began with the training of branches that would receive the scoring model first, while the Systems Department was generating the corresponding data for those branches. During the expansion phase, reports were developed to monitor statistical indicators to guarantee the statistical validity of the tools. The reports indicated high levels of reliability in the tools' predictability capacity.

Monitoring reports also revealed that, because of BancoSol's recent expansion into lower-end markets, the scorecard variables and ranges of the score-distribution tables needed some adjustments. As a result, the statistical model and the loan module also needed to be redesigned. Once these modifications were complete, the selection-scoring model was launched in all branches.

5. IMPACT OF CREDIT SCORING

UTILIZATION

BancoSol's uses Selection Scoring in 99 percent of its decisions, scoring from 1,000 to 2,000 loans per month. Most renewals have been evaluated with selection scoring, as the piloting of the segmentation score began only in March 2004. Selection Scoring was used for more than 20 percent of cases by April 2005.

PORTFOLIO QUALITY

Selection Score

The actual use of the selection pre-score is to prioritize client visits by loan officers. Table A-1 illustrates that the behavior of new clients with outstanding loans as expected: "lower-priority" or high-risk clients register a higher arrears rate. In addition, the "highest-priority" clients (A Clients) show an arrears rate of just 2.3 percent, reflecting good risk-based selection.

TABLE A-1: SELECTION PRE-SCORING

Priority	Clients	% Total	Delinquent Clients	% Delinquent clients	Outstanding Portfolio	Portfolio in Arrears	Arrears rate (> 5 days)
C (Low)	5,766	21.8%	963	16.7%	7,734,891	791,490	10.2%
B (Med)	9,899	37.4%	1,047	10.6%	16,408,309	867,659	5.3%
A (High)	10,817	40.8%	528	4.9%	22,810,952	517,278	2.3%
Total	26,482	100.0%	2,538	9.6%	46,954,152	2,176,427	4.6%

For the final selection score, the percentage of delinquent clients, as well as the value of the portfolio in arrears also shows the expected behavior: for clients with a better score, we see lower delinquency. Without considering those C strategy clients whose recommended rejection was overridden and loans were approved (forced approvals), the delinquency rate drops to 4.2 percent, as shown in the bottom shaded row of Table A-2.

TABLE A-2: FINAL SELECTION SCORE

Recommended Action	Clients	% Total	Delinquent Clients	% Delinq. Clients	Portfolio	Portfolio in Arrears	Arrears rate (> 5 days)
C – Rejection	2,819	10.6%	447	15.9%	3,681,112	376,215	10.2%
B – Review	13,509	51.0%	1,517	11.2%	21,703,713	1,267,382	5.8%
A – Approval	10,154	38.3%	574	5.7%	21,569,327	532,829	2.5%
Total	26,482	100.0%	2,538	9.6%	46,954,152	2,176,426	4.6%
Total without C loans	23,663	89.4%	2,091	8.8%	43,273,040	1,800,211	4.2%

Segmentation Score

Within the outstanding portfolio, there are 1,917 credits that have been evaluated with segmentation scoring, and we see, as expected, a much better portfolio quality among these loans (see Table A-3).

TABLE A-3: SEGMENTATION SCORE

Strategy	Clients	% Total	Delinquent Clients	% Delinq. Clients	Portfolio	Delinquent Portfolio	PAR > 5 days
Normal Evaluation	790	41.2%	5	0.6%	1,245,939	2,843	0.2%
Recommend Renewal	692	36.1%	2	0.3%	1,108,856	594	0.1%
Recommend Credit Line	435	22.7%	0	0.0%	700,337	0	0.0%
Total	1,917	100.0%	7	0.4%	3,055,133	3,437	0.1%

EVALUATION OF THE MODEL

To fully evaluate the model, we need to analyze not only client behavior at one point in time (as with the portfolio quality), but also client payment history.

This historical analysis uses what is called the Good and Bad Indicator of good and bad, which classifies clients based on behavior of indicators such as maximum days in arrears and the average days in arrears for credit(s) previously evaluated with scoring. This was the same analysis used when determining the model.

Selection Scoring

Table A-4 illustrates the results of an analysis of clients using both Good and Bad indicators and the overall Selection Score. The analysis shows that the model is functioning well in terms of risk discrimination.

TABLE A-4: SELECTION SCORES WITH GOOD AND BAD INDICATORS

Score	GOOD	%	BAD	%	Disbur.	%	Denied	%	Total	Cumul. %
< 585	110	62.9%	65	37.1%	175	88.4%	23	12%	198	0.6%
586 - 635	647	70.9%	266	29.1%	913	84.1%	172	16%	1085	3.4%
636 - 665	930	69.7%	405	30.3%	1335	84.2%	251	16%	1586	5.0%
666 - 696	1435	71.9%	560	28.1%	1995	83.9%	382	16%	2377	7.4%
697 - 723	1950	76.0%	616	24.0%	2566	85.9%	421	14%	2987	9.3%
724 - 746	2097	77.3%	617	22.7%	2714	85.1%	477	15%	3191	10.0%
747 - 769	2231	79.8%	563	20.2%	2794	85.9%	458	14%	3252	10.2%
770 - 791	2564	81.6%	577	18.4%	3141	84.8%	562	15%	3703	11.6%
792 - 817	2555	81.7%	573	18.3%	3128	87.2%	460	13%	3588	11.2%
818 - 845	2678	84.5%	491	15.5%	3169	87.0%	475	13%	3644	11.4%
846 - 879	2347	85.8%	388	14.2%	2735	89.8%	310	10%	3045	9.5%
880 - 911	1357	88.6%	175	11.4%	1532	90.4%	163	10%	1695	5.3%
> 912	1325	89.4%	157	10.6%	1482	92.3%	124	8%	1606	5.0%
Total	22226	80.3%	5453	19.7%	27679	86.6%	4278	13%	31957	100.0%

Collections Scoring

Figure A-1 and Table A-5 illustrate collections rates by branches in the pilot program since November 2004; in general, we see a significant increase in collections at these branches since scoring was introduced.

FIGURE A-1: AVERAGE COLLECTION RATES AT BRANCHES, 2002–2005

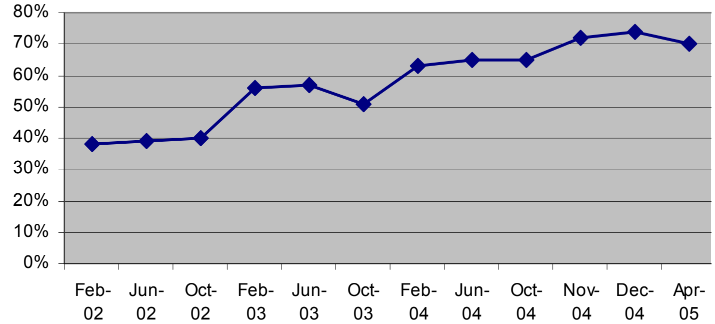

TABLE A-5: COLLECTION RATES BY BRANCH, 2002–2005

Branch	Feb-02	Jun-02	Oct-02	Feb-03	Jun-03	Oct-03	Feb-04	Jun-04	Oct-04	Nov-04	Dec-04	Apr-05	No Scoring
A	50%	49%	53%	61%	61%	54%	68%	66%	61%	69%	74%	70%	49%
B	40%	37%	42%	46%	40%	34%	54%	53%	48%	64%	70%	59%	42%
C	35%	36%	50%	64%	61%	51%	66%	61%	57%	65%	66%	71%	53%
D	56%	53%	53%	63%	52%	47%	63%	63%	62%	73%	78%	73%	57%
E	52%	52%	58%	65%	59%	51%	66%	66%	60%	75%	77%	76%	59%
F	36%	43%	53%	61%	55%	52%	46%	53%	51%	62%	58%	55%	50%
G	39%	37%	37%	46%	57%	57%	66%	72%	72%	72%	74%	72%	52%
H	58%	64%	62%	65%	77%	82%	84%	85%	72%	80%	86%	82%	72%
I	20%	26%	23%	58%	64%	58%	65%	70%	75%	74%	77%	69%	51%
J	55%	53%	47%	54%	71%	64%	63%	66%	76%	76%	79%	75%	59%
K	45%	49%	46%	69%	84%	81%	78%	79%	80%	77%	82%	73%	68%
L	36%	36%	37%	55%	57%	53%	62%	66%	67%	72%	74%	68%	56%
Total:	38%	39%	40%	56%	57%	51%	63%	65%	65%	72%	74%	70%	56%

Table A-6 shows the average collections activities performed by loan officers on a monthly basis, which are conducted in addition to third-party support strategies. On average, the loan officer activities represent 36.9 percent of the total, based on all activities entered into the system. Upon further analysis of the data for loan officers who registered 80 or more collection activities a month, we found that an average of 33.6 percent of their total work time is devoted to collections activities, with each loan officer spending approximately 37 hours per month on collections activities.

TABLE A-6: AVERAGE COLLECTIONS ACTIVITIES

Strategies by Month		Average 2005 #	Average 2005 %
Loan Officer Strategies	Calls	1,370	19.9%
	Visits	5,499	80.1%
Total LO Strategies		6,869	36.9%
Support Strategies		11,740	63.1%
Total Strategies		18,609	100.0%

PREDICTION CAPABILITY

Table A-7 shows that the tool has excellent prediction capabilities, with much higher percentages of clients classified as “Good” with high scores.

TABLE A-7: SCORING WITH GOOD AND BAD INDICATORS

Score	Good		Bad		Total	
	#	%	#	%	#	%
< 10	6	5.0%	115	95.0%	121	0.2%
10 to 24	8	10.1%	71	89.9%	79	0.2%
25 to 76	19	4.8%	377	95.2%	396	0.8%
77 to 353	508	16.9%	2500	83.1%	3008	5.9%
354 to 798	6247	85.0%	1102	15.0%	7349	14.4%
799 to 847	2532	97.4%	68	2.6%	2600	5.1%
848 to 893	676	98.0%	14	2.0%	690	1.4%
894 to 896	1215	99.1%	11	0.9%	1226	2.4%
897 to 939	12909	99.0%	133	1.0%	13042	25.5%
940 to 958	7193	99.7%	24	0.3%	7217	14.1%
> 959	15245	99.4%	85	0.6%	15330	30.0%
Total	46558	91.2%	4500	8.8%	51058	100.0%

CONCLUSION

BancoSol’s experience in microfinance CREDIT SCORING has been a success in many ways. The Bank was able to take advantage of the need to analyze policies and procedures linked to the credit evaluation process that would impact the overall score and vice versa, which resulted in a number of standardized improvements to the credit process. Additionally, the project led BancoSol to recognize the importance of maintaining complete and accurate data on all operations. Such standardizations, as well as streamlining the database and increased use of the credit scores, have meant improved customer service as loan officers have increased productivity and spent less time analyzing every loan. The use of the collections scorecard has also increased the efficiency of BancoSol’s loan recovery efforts, as the Bank has reported increased collections with much less actual recovery tasks. Finally, as illustrated in the above figures and tables, we see that from a technical standpoint, the scoring model has proven to function very well.

APPENDIX B: CAC LEASING SLOVAKIA

1. OVERVIEW/BACKGROUND

CAC Leasing (CAC) commenced business in October 1996, adopting its current name in 1997. It is now wholly owned within the Bank Austria Creditanstalt Leasing (BACA) group.

CAC is the market leader in Slovakia more than 15 percent market share. In December 2002, CAC signed a €15 million loan agreement with the European Bank for Reconstruction and Development (EBRD) in December 2002 to develop its business of leasing to small and medium-sized enterprises (SMEs) in Slovakia as a part of the European Union (EU)/EBRD SME Finance Facility for EU Accession Countries (Facility). Bannock Consulting Ltd. of the United Kingdom (now called DAI Europe) was the consultant selected to implement technical assistance on the assignment.

Historically, the company's leasing assessment reflects a major emphasis on asset value with down payment levels being set to increase cover and reduce risk. One aim of participation in the Facility was to enable the company to move toward greater reliance on cash flow and other financial assessments of customers, particularly by using credit scoring.

Bannock and CAC developed a credit-scoring model for passenger vehicle leasing between May and October 2004. The model was tested over a one-year period and it was rolled out for use company-wide in October 2005.

2. THE DRIVERS FOR CREDIT SCORING

When the consultants started to work with CAC on a credit-scoring model, CAC already was number one in its market, and was a strong competitor in the vehicles segment. Its efficient leasing procedure required a minimum of paperwork for clients that met certain minimum down payment levels. As a result, CAC was able to guarantee fast decision times. CAC's motivation for introducing scoring was to improve its risk assessment of vehicles in order to:

- Decentralize more leasing decisions to the branch level; and
- Bring explicit measures of cash flow into the appraisal of applicants offering lower down payments.

The technical assistance under the Facility provided a stimulus and resources for development of the scoring system.

3. TYPE OF CREDIT SCORING MODEL USED

CAC had a limited set of 20 fields of data on a large number of lease contracts—more than 35,000. This opened up a possibility for statistical modeling, but meant that some factors CAC wanted to consider, such as cash flow, were not available in the historic data set.

This combination of extensive data on a limited set of factors with a strategy designed to introduce new risk measures led the choice of a hybrid model. The consultants used the data set to develop a scorecard using logistic regression. This scorecard contained eight variables and had a Kolmogrov-Smirnov statistic of 34.4 percent, which is considered a reasonably strong model. Using a working group, three variables were removed from the regression scorecard. These were replaced with other variables based on expert judgment of the working group and the modeling expertise of the consultants.

Although scores from the eight-variable regression scorecard could be directly converted to probability of default predictions for each borrower, the hybrid model scores could only rank the borrowers into risk ranges. However, with new data, this hybrid card could be validated and historic, or observed, probability of defaults could be assigned to scores in various score ranges.

4. PROCESS OF ADOPTING CREDIT SCORING

The scorecard was designed by a working group made up of the consultants and a team of experienced leasing professionals from the car leasing, risk management, information technology (IT), and work-out divisions. The consultants performed statistical analysis on the data and presented this analysis the working group. Based on discussion and further testing, the working group adjusted the variables included in the model.

Once the working group agreed on a satisfactory scorecard, the consultants designed a test model in Microsoft Excel. Standard Microsoft Office products are good for model testing because they can perform complex calculations, are easy to modify, and are available on the workstations of most companies.

Training was conducted for a group of salespeople in sales offices located in Bratislava. The training covered the concept of credit scoring, how the model was designed, and the purpose of pilot testing. Specifically, salespeople were told that their evaluation and comments on the scorecard and its perceived benefits or pitfalls in practice was very valuable to the further adaptation and development of the scorecard.

Pilot testing was conducted in parallel with existing procedures, meaning that scores were generated, collected, and saved for each client, but the score was not used in the decision making process. Lease decisions continued to be made according to standard procedure.

In parallel with the pilot testing in branches, the consultants continued to back test the new scorecard on historic cases using a combination of electronic and hard copy files in the head office. Although the original statistical scorecard was validated through out-of-sample testing during the model development phase, the hybrid scorecard, which contained a mix of regression weighted and judgmentally weighted variables, needed to be validated with additional data on the full set of scorecard variables. An additional 300 cases were manually tested by the consultants in the head office.

At the end of the testing period, the consultants compiled the data from the pilot testing with the 300 back-tested cases. The consultants presented their conclusions from this analysis to the working group. Based on both data analysis and anecdotal feedback from the pilot branches, some minor modifications were made to the scorecard and several changes were made into the draft scoring policy.

The scorecard, pilot test results, and the draft scoring policy were presented to the CAC board and representatives of the parent company BACA for approval. The scorecard was approved and CAC drafted an official written scoring policy. Still in its temporary software platform, the vehicle-leasing scorecard was launched company wide in the fourth quarter of 2005. The model is currently being integrated into a new web-based offer generation and lease tracking system that should be completed in the summer of 2006.

5. IMPACT OF CREDIT SCORING

As noted in the opening of this study, CAC was already a market leader in Slovakia. It had a relatively sophisticated IT system, streamlined procedures, and competitive products. Credit scoring offered CAC an opportunity to shape its risk evaluation and continue to decentralize the decision making process for small ticket leases.

Because CAC had an acceptably low-overall bad rate on the portfolio, and because neither the regression weighted scorecard nor the hybrid scorecard had particularly powerful discrimination in the low score ranges, CAC does not use the scorecard to reject any cases. Rather, the scorecard helps speed the approval of more than 60 percent of cases, while requiring the others to go through standard review. The efficiency gain is the time saved on 60 percent of its offers.

Finally, the scorecard is only one piece of the company's larger strategy to automate its offer generation and lease approval systems for standardized products and comprehensively track data for its Basel 2 compliance strategy. The hybrid scorecard scores can be converted into probability of defaults using historical data and default experience and feed into the group's wider Basel 2 strategy.

CAC and the consultants are also working on a scorecard for standard leasing that is judgmental in terms of its development, but has vendor and asset value analysis factors specific to the Slovak market. This card is still undergoing testing in 2006, and will be incorporated into the web-based offer generation software once testing is complete.

6. PARTICULAR LEARNING AREAS OF INTEREST FOR MICROFINANCE INSTITUTIONS

CAC would not normally be described as a microfinance institution (MFI). Instead, it is an example of a commercial leasing company that has embraced scoring as a way to do business more effectively in the micro and small business sector.

The most important lesson MFIs might take from CAC's experience is that hybrid scorecards are an effective answer to the challenge of having extensive data, but not necessarily all of the data required to implement a new strategy or evaluate clients based on the most important risk factors for that segment.

Another lesson from CAC's experience is that model accuracy is important, but thoughtful scoring policy can derive significant benefit from reasonably predictive models. For example, CAC is not using its scorecard to reject clients, since historic data indicates that the company would lose too many profitable clients for each bad client it avoids. So instead, CAC is using the card to automatically approve and thus reduce analysis time on more than half of its borrowers. With the same number of sales people and risk managers, this means that the time saved on rote analysis of very low risk cases can be spent on some combination of additional sales, more thorough analysis of borderline cases, and more thorough analysis of larger—and, in terms of exposure, riskier—contracts.

One final lesson that was not highlighted in the text above but which has been crucial to the success of credit scoring in CAC is management and key staff commitment to the development, implementation, and ongoing improvement of the model. The model development process had equal inputs from CAC and the consultants. Salespeople understand the model, have had a chance to comment on it, and have through this process bought into credit scoring. Management has seen the scorecards' power in estimating risk both in historic and live tests. This organization-wide commitment and involvement in the scoring process is what will continue to provide a range of benefits to CAC's micro-leasing business.

APPENDIX C: CREDIT INDEMNITY

1. OVERVIEW/BACKGROUND

Credit Indemnity was launched in 1978 in Pietermaritzburg (KwaZulu-Natal Province) in South Africa when an estate agent and building contractor saw the demand for extending credit to a market that was not served by the formal financial services sector. The organization had little competition to begin with and the business grew primarily from retained earnings. By 1998, the branch network had increased to 23 branches in KwaZulu-Natal. It was not until after 1998 when the family owned business sold 35 percent of its shares to Nisela (which would later become Theta Investments—part of ABIL) that Credit Indemnity grew more rapidly. The branch network expanded from 23 to 118 branches nationwide and its loan advances increased from R169 million in 1998 to R722 million in 2002. In 2002, Credit Indemnity was absorbed into African Bank Investments Limited (ABIL) as a wholly owned subsidiary and has since been fully operationally integrated into the African Bank business.

For the past three years the ABIL group has focused on consolidating their efforts through optimizing its business model, enhancing its service offering to its clients, re-establishing appropriate growth patterns, and providing its funders and shareholders with satisfactory returns.

The Credit Indemnity brand and branch infrastructure still exists and operates as it did in the past. The Credit Indemnity product/short-term product is a 4-, 6-, 12-, or 18-month loan to salaried individuals, while the African Bank product ranges from 12 to 35 months. The important distinction between the two business models is that the repayment method for Credit Indemnity is mainly cash, while African Bank depends on payroll and debit order strikes to a client's account. For the purpose of this case study, we will focus on the application and behavioral scorecards of the Credit Indemnity/short-term book since scoring has been an integral part of the Credit Indemnity business approach from the start.

There are 125 branches that only sell the 4-, 6-, 12-, and 18-month product and 30 branches that allow customers to choose between the shorter- and longer-term loan products.

The short-term loan book currently has approximately 120,000 active clients with a loan book of R400 million.[1] The average loan size across this loan book is R2,500, but this varies considerably over the different product offerings with average loan sizes varying from approximately R1,200 in the 4-month product to approximately R4,500 in the 18-month product.

2. THE DRIVERS FOR CREDIT SCORING

When Credit Indemnity first started providing 4-month loans, they used a paper-based system to assess loan applications—including an elementary judgmental scorecard with the calculation of the score done manually on paper. Throughout the growth and life of Credit Indemnity, scoring has been used to assess and manage risk. The fact that scoring has been an integral part of Credit Indemnity's approach to business has led to the development of a sophisticated risk management approach.

In 1996/1997 a new custom-built information technology (IT) system was introduced, bringing with it standardization of the application process and growth in the portfolio. The system included an elementary judgmental scorecard and allowed for checking of bureau information. At this point, the application started focusing more on payment profiles. The process was entirely decentralized with the decision-

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1 Subsequent to the absorption of CI into ABIL, CI clients have started to migrate to the longer-term loans traditionally offered by ABIL, hence the decrease in the CI loan book, which is essentially ABIL's short term loan book.

making power resting with the branch manager. A great deal of emphasis was placed on the bureau information despite the fact that the client was being scored on the application scorecard. Managers were allowed to override the scorecard decision in limited instances.

In 1998/1999 Trans Union ITC and Fair Isaac developed a bureau score called Emperica. This score was an additional field that could be accessed during the bureau inquiry. This score enabled the development of a dual score matrix (cross tabulating the Credit Indemnity application score and the Emperica bureau score) thereby improving the application scorecard power. The bureau information improved the quality of decision making.

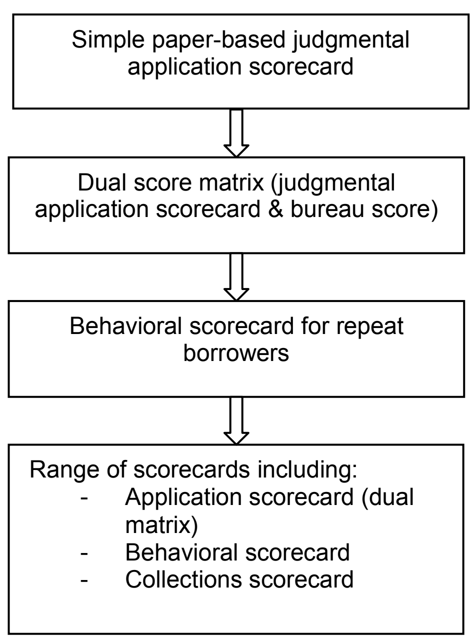
Rapid growth after 1998 led to decreased portfolio quality, necessitating a strong analytical approach to managing risk. With 70 to 80 percent of Credit Indemnity’s applicants being repeat borrowers, a behavioral scorecard was an appropriate mechanism to manage risk. A behavioral scorecard was hence developed with the objective of enabling market segmentation and improving risk management.

The behavioral scorecard was developed with the assistance of PIC Solutions and became the major focus of attention in terms of risk management at Credit Indemnity. While first time applications took approximately 30 minutes to process, repeat borrowers were able to access a loan within 5 minutes using the new behavioral scorecard. The behavioral scorecard also enabled modified, flexible offerings in terms of loan size, loan term, and interest rate based on the risk exposure of the applicant.

3. TYPE OF CREDIT SCORING MODEL USED

Credit Indemnity has progressively advanced through various phases of scorecard development—starting with a paper-based elementary judgmental application scorecard in 1978 to a range of empirically developed scorecards today. Figure C-1 illustrates this process.

FIGURE C-1: PROGRESSION IN SCORECARD DEVELOPMENT



4. PROCESS OF ADOPTING CREDIT SCORING

The application scorecard was not empirically developed. As a result, the most intensive development process that occurred at Credit Indemnity was the development of the behavioral scorecard.

As pointed out already, Credit Indemnity had used a scorecard since inception; hence, the concept was not new to anyone in the organization. Nevertheless, it was still necessary to ensure buy-in across the board, starting at the top. The Exco team and the Credit Committee were very involved in the strategic decision making process throughout the behavioral scorecard development. These forums were valuable since all members had their say, debated issues openly, and then decisions were made. There were significant changes to the way Credit Indemnity did business including, among other things, changing the method of age analysis, changing business rules, and looking at data on a customer level rather than a product level.

- One of the most important tasks to conduct when **developing a scorecard** is documenting every step of the process. (Documentation should include information on basic decisions taken, data sampling, data issues, distribution, steps taken with the data (manipulation), back testing, and so on.) This enables the developer to go back later and identify errors or make necessary changes. The development process consists of:
    - Analysis of the Observation and Performance window data. The Observation window includes application data for a specific period in time (such as 6 months) and the Performance window includes the subsequent performance data for a period (6 to 12 months). This will show whether the application system currently has the ability to sort the applicants (‘goods’ from ‘bads’).
    - Extraction of a data set to carry out data validation and to reconstruct data at a customer level rather than a product level.
    - Logistic regression analysis to determine the significance of the various variables and to determine the parameters of the various bands to be statistically significant.
- The next step is **testing the scorecard using historical data** to demonstrate the impact in practical terms. This testing can be particularly powerful for illustrating to both head office and operational staff that the scorecard can accurately rank order risk.
- **Pilot test the scorecard in a few branches** before full roll out. The pilot test enables you test the roll out of the scorecard on the system, the scorecard itself, and the reactions to the scorecard from both staff and clients. The pilot can be a great success because generally head office tends to test new scorecards in branches where the branch manager understands the scorecard and has bought into the scorecard. Roll out to other branches, where branch management and staff may be less enthusiastic, is the challenge.

The actual scorecard development does not take long (a few months at most), but the implementation of the scorecard is time consuming. Implementation of the scorecard requires:

- Systems development or modifications.
- Training of operational staff; Credit Indemnity carried out intensive training over a period of about a year. They started with training branch managers at head office for three days in a month. The training was not on the variable details, but rather on what a scorecard is, why Credit Indemnity wanted to implement one, the purpose, the value, and so on. After this, head office staff did road shows to all the branches and presented to all branch staff. This included the new business rules. Having completed this

intensive training and providing ongoing support, there were some training-of-trainers exercises and additional branch visits by the trained trainers.

- Securing the required buy-in from staff.
- Ensuring that scorecard data are adequately stored for future analysis (keeping historical data is costly).
- Managing and monitoring the scorecard through developing supportive management information systems (MIS)/reporting systems, and so on.

The cost of development, including expert assistance from consultants, IT development, and indirect labor costs was estimated to be in excess of R2 million. However, it was felt that the payback period of the investment was short, with profitability at Credit Indemnity at least doubling for three years in a row after implementation of the behavioral scorecard (See Table 1).

TABLE 1: EFFICIENCY AND PROFITABILITY FIGURES

	September 2002	September 2003	September 2004
Loans per staff member	177	177	248
After tax profit	R30 million	R56 million	R151.5 million

5. IMPACT OF CREDIT SCORING

The behavioral scorecard has had the largest impact on Credit Indemnity's ability to manage risk, through allowing market segmentation by risk profile. The scorecard enables risk-based pricing, an informed collections strategy that has led to improved efficiency in collections and a flexible product offering that is responsive to Credit Indemnity's risk appetite, the ability for finance to provision successfully according to the various segments and enhancing Credit Indemnity's ability to develop new products.

One of the side benefits of developing the scorecard was analyzing and looking at the data. Credit Indemnity went through a process of redefining various fields and consolidating performance data on a customer level—leaving Credit Indemnity with standardized and easy to use information on their business and clients.

Because of the application and behavioral scorecards and their success, Credit Indemnity and African Bank also have other scorecards in operation (such as a scorecard used for collections that predicts the probability of repayment) and look forward to developing additional scorecards (such as one for fraud management).

Credit Indemnity sees the main advantages of the scorecard in its ability to segment the market, enabling targeting and increasing profitability. This increase in profitability is largely due to the improved quality of the portfolio. There are also some increases in efficiency—a first-time borrower application takes approximately 30 minutes, while a repeat borrower application takes 5 minutes. This is a drastic improvement in efficiency (largely brought about by the reduced necessity to carry out reference checks and employment confirmations).

Table 1 shows the number of loans per loan officer and after tax profit for a period of three years after the behavioral scorecard was employed. Credit Indemnity views scoring as one of the key factors contributing to these efficiency gains, although it would need to do further research to estimate what share of growth in these figures is attributable to credit scoring rather than other factors such as staff rationalization and growth in the loan portfolio.

The application and behavioral scorecards also improved Credit Indemnity's confidence in extending new products. Through improved ability to assess risk, Credit Indemnity started to extend loans of longer terms, hence the development of the product range from purely a 4-month loan to a choice of 4-, 6-, 12-, and 18-month loans. Credit Indemnity was also able to start offering variable interest rates based on risk exposure.

Figure C-2 illustrates how the behavioral scorecard has affected the distribution of sales across the various risk profiles in the scorecard. The 'Diamond' profile represents the lowest-risk group of clients and the 'Ore' profile represents the highest risk group of clients. The figure shows how over time, relatively more loans have been sold to lower risk clients and less loans to higher-risk clients.

FIGURE C-2: SALES DISTRIBUTION FIGURES

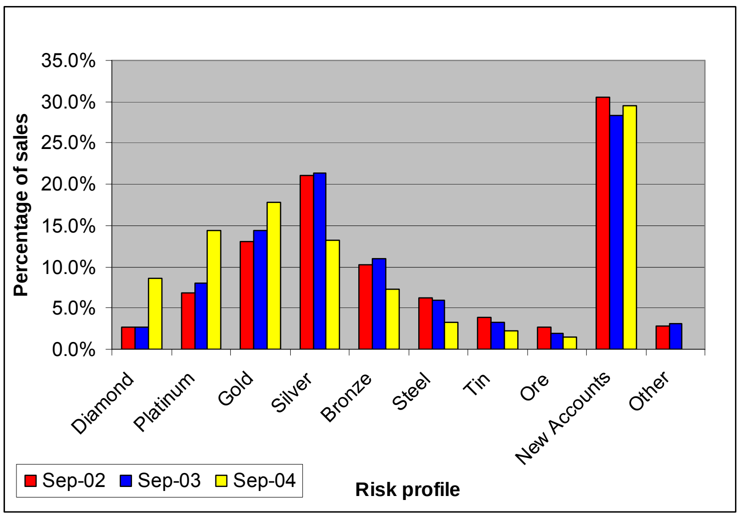
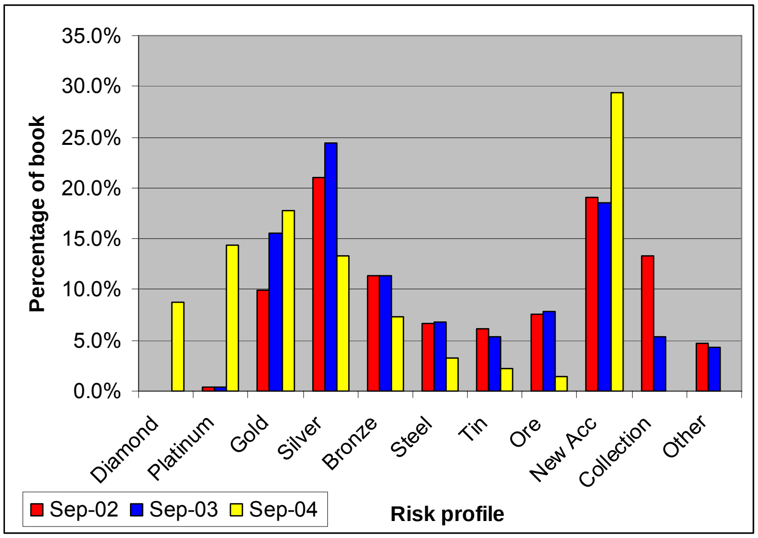


Figure C-3 illustrates the same change in distribution but as a percentage of the loan book value. The third columns in each set show the most recent data on the loan book distribution and illustrate how over time the loan book is shifting positively to lower-risk profile categories.

FIGURE C-3: LOAN BOOK BALANCE DISTRIBUTION



6. PARTICULAR LEARNING AREAS OF INTEREST FOR MICROFINANCE INSTITUTIONS

KEY SUCCESS FACTORS

Some of the key success factors identified within Credit Indemnity are:

- *Staff buy-in.* The Credit Indemnity loan application process allowed for branch managers to override the scorecard decision. Although small numbers of overrides are commonly acceptable, the scorecard becomes invalid if this occurs to frequently due to lack of faith in the scorecards ability to rank order risk or avoiding confrontation with a long-term client. It is important for staff to trust and understand the abilities of the scorecard. This can be achieved over time once performance illustrates the ability of the scorecard to rank order risk.

- *Senior management support.* Senior management at Credit Indemnity saw the strategic value in developing, implementing, and using scorecards as an integral approach to managing risk within Credit Indemnity and African Bank. This is important because credit scoring is resource intensive, there are often major system changes, and developing and implementing a scorecard is a costly exercise.

- *Data.* Staff need to develop a culture/practice of capturing data accurately during the application. This can only be achieved if branch managers buy in to the scorecard. In addition to accurate capturing, IT needs to store historical data including snapshots at specific relevant points in time. Storing large amounts of historical data are costly, but it is especially important in a decentralized operation such as Credit Indemnity.

- *Analytical skills.* Scoring requires specific skills. Although outsourcing some elements of the development of the scorecard is possible, internal capacity of staff is required in order to manage the vendor. Credit scoring should also not be outsourced on a long-term basis since this leads to loss of intellectual property to external parties. In-house analytical skills are vital for the improvement of decision making over time and generation of useful reliable reports for management. In the absence of these skills, the value of this risk management approach is diminished. It is also important to consider succession planning and good documentation so that this intellectual property is kept in-house.

- *Credit policy.* A credit scorecard is only one tool in the toolbox. A credit policy is required in support of the scorecards. The policy should describe how the financial institution can harness the application scorecard to enhance their decision making ability and manage risk better.
- *MIS/useful reporting* is critical to proving the power of the scorecard to skeptics. It is also imperative in interpreting the results correctly. The value of scoring is achieved through segmentation of the loan book for various different analyses and then responding to the results through changes in policy. Without the correct reports, monitoring of the data and the scorecard and responding to observed trends in the market is made difficult if not impossible.
- *Client reaction.* Customer relationship management was an important element of the behavioral scorecard introduction. Clients found it difficult to understand why one month they receive a longer-term product at a lower interest rate while the next time they come into the branch they receive a higher interest rate. It is important to remember that the behavioral scorecard is not about a yes/no decision (because most repeat clients get second loans)—it is about risk exposure and what terms you are prepared to offer to the client.

CHALLENGES

- *Good quality data are* always a challenge—especially due to the cost and ability of the system to store a great deal of historical data and snapshots of data at specific significant points in time, such as when there were policy changes or re-factoring of the scorecard. Data quality at the credit bureau was also a challenge, although this has improved.
- *Convincing senior management and operational staff* of the power of the scorecard. Due to lack of understanding, some people still do not see the value in the scorecard. Building the model is easy in comparison to selling it to the business (illustrating what an impact it can have on business).
- *IT system.* The system was one of the biggest challenges, because interfacing the scorecard into the application and banking systems is uncertain. The scorecard will require revision and changes over time and the system should have the ability to handle this.
- One of the other challenges specific to the behavioral scorecard was the *inconsistent product offerings* made to clients because of the way the behavioral scorecard was structured. Because the scorecard is based on risk exposure, one of the key elements in this score is outstanding loan amount. If a customer has a good repayment history but has a large outstanding amount, he will only be offered a small, short-term loan at higher interest rates than his current loan. A new behavioral scorecard has been developed that attempts to smooth out the score.

OTHER OBSERVATIONS

In addition to the challenges and key success factors summarized above, it is apparent that the impact of a behavioral scorecard is particularly powerful in comparison to that of an application scorecard. It is also easier to “cheat” the system on an application scorecard, as staff eventually figure out which variables to manipulate to get to the answer they want. The biggest impact on institution comes from implementing a behavioral scorecard—as shown in Credit Indemnity’s case. Good credit bureau information is also helpful in strengthening the ability of the scorecard to rank order risk.

APPENDIX D: MIBANCO PERU

1. OVERVIEW/BACKGROUND

The Peruvian microfinance bank called Mibanco ("the Bank") was formally founded with the transformation of the microfinance nongovernmental organization Acción Comunitaria del Perú (ACP) on May 2, 1998. The Bank, which had 13 branches when operations began, was one of the first microfinance institutions (MFIs) in Latin America to implement credit scoring. By the end of 2005, Mibanco had 32 branches located throughout Peru, an outstanding loan portfolio of US$162 million, and more than 125,000 active loan clients. Less than 20 percent of total loans are group loans; the vast majority are individual loans. Mibanco's Credit Scoring Project began in April 2000 with the support of ACCION International and an external consulting firm.[4]

2. THE DRIVERS FOR CREDIT SCORING

Specifically, Mibanco intended to meet the following objectives when it decided to implement credit scoring for working capital microenterprise loans:

- Improve customer service, by accelerating the loan approval process;
- Contribute to the standardization of policies, processes, and procedures as actually used in the field;
- Increase the retention of low-risk clients; and
- Contribute to improved portfolio quality.

3. TYPE OF CREDIT SCORING MODEL USED

The two credit scoring models introduced were:

- **Selection Scoring**. Specifically for new clients. By quantifying information about the potential client's profile and risk factor, the MFI is able to prioritize and personalize the evaluation of new credit applications.
- **Segmentation Scoring.** By classifying existing clients by risk, the MFI is able to improve portfolio quality and overall customer service.

These credit-scoring models, as developed by ACCION, are based on an analytical method that allows for the speedy, trusted, and objective evaluation of the client's creditworthiness. Regression analysis is used to generate a score, which can be used to order a client population based on risk, including both credit history and demographic information. The score becomes a valuable credit analysis tool, minimizing the risk related to the credit operation.

ACCION's scoring model allows an MFI to predict the level of risk related to a loan, based on client profile and loan repayment history. Among the characteristics that affect risk, ACCION uses those that are directly related to the client and business profile (such as age, business experience, type of business, ownership of business premises, and so on), as well as information related to the client's credit history

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[4] ACCION initially partnered with LiSim, a specialized Colombian consulting firm in its credit scoring efforts. ACCION later decided to continue to implement scoring at MFIs without the participation of any outside consultants.

(experience with the institution, number of loans, repayment rate, and so on). This detailed information about the client allows for the creation of a well-defined risk profile.

4. PROCESS OF ADOPTING CREDIT SCORING

Credit Scoring was implemented at Mibanco in five phases:

- Phase I: Analysis and Preparation
- Phase II: Design and Development
- Phase III: Development of the Scoring Module
- Phase IV: Testing the Model (Pilot)
- Phase V: Roll Out

PHASE I: ANALYSIS AND PREPARATION

Phase I consisted of an extensive analysis of Mibanco's client database, and more specifically, an analysis of the sources that would provide the necessary variables. Based on this analysis, it was determined that there was enough information to complete modeling, despite the following challenges:

- Lack of information on rejected clients.
- Client information in the system—as well as information on previously performed character evaluations and financial data—was being overwritten when there were renewals. That is, previously utilized information was erased and updated information was stored. This implied a serious limitation to sampling for the development of the score for new clients, as the most important information would be information on clients and their businesses when first applying for a loan.

PHASE II: DESIGN AND DEVELOPMENT

The process of creating the scorecards began with the statistical analysis of a sample of client performance information, both current and historical, for the two years prior to initiation of the project.

Some important assumptions for the definition of the sample included the following:

- The samples for each of the models consisted exclusively of individual microenterprise clients either applying for their first loan, or renewing a working capital loans.
- Information for each client included in the sample corresponded as closely as possible to the actual moment of disbursement of his or her first loan.
- The construction of the segmentation model was based almost exclusively on approximately two years worth of performance data.

At the same time as the statistical analysis was being performed, the team collaborated on the definitions of "Good" and "Bad" clients, which is the starting point of any good scoring model. The definitions determined by the team in 2000 are still in effect today.

The new client selection score, the first version of which would be based on qualitative client data only, is divided into a pre- and post-score. The pre-score, which is an evaluation of basic client data, initially included 17 variables; adjustments to the model made in 2004 reduced the total number of variables to 13. The post-score, which corresponds to the variables of the evaluation, is composed of 15 variables.

The final score is the sum of the pre- and post-scores; the recommendations resulting from this score are approve the application, reject it, or “normal evaluation.” Normal evaluation is a gray area for which the model in unable to make a recommendation, which alerts the loan officer of the need to conduct a more in-depth analysis before making a final decision.

The segmentation score for renewals has 29 variables, of which 25 are based on the client’s performance with Mibanco. The strategies recommended by this score are Credit Line, Renewal, Normal Evaluation, and Rejection.

PHASE III: DEVELOPMENT OF THE SCORING MODULE

The functional specifications for the incorporation of the tools into Mibanco’s system were prepared by the Bank’s Information Technology (IT) Department in September 2000 and the corresponding work in the system took about six months.

PHASE IV: PILOT TESTING

Based on loan officer productivity and portfolio size, Mibanco selected the Chorrillos branch for pilot testing the scorecards. Testing of the Selection score began in February 2001 and the Segmentation score testing began in May of the same year.

PHASE V: ROLL OUT

During the roll out phase, which began in July 2003, reports were developed to monitor statistical indicators to guarantee the statistical validity of the tools. These reports indicated high levels of reliability in the tools’ predictability capacity. This monitoring also revealed that some variables included in the initial model were not providing the expected results, and in December 2003, a temporary adjustment was made to the model to eliminate those variables that were not functioning properly. The actual modification, which was made to the model in mid-March 2004, incorporated additional quantitative variables from the financial evaluation, and were put into effect in November 2004. To date, the model has required no further adjustments.

Beginning in September 2004, ACCION transferred the responsibility for monitoring reports, including all the underlying Structured Query Language methodology, to Mibanco’s Risk Management Department.

5. IMPACT OF CREDIT SCORING

PORTFOLIO QUALITY

The selection pre-score classifies clients as A, B, or C corresponding to low, medium, or high risk. This pre-score was initially to prioritize client visits, or to identify how client visits should be conducted, as parameters for the loan officer to establish the client’s risk profile. The pre-score uses socio-demographic information provided by the client when he or she first applies for a loan.

Pre-Scores

Table D-1 shows that the clients scored as higher risk (C clients) have a much lower portfolio quality, with a portfolio-at-risk (PAR) over 30 days 5.8 times that of the low risk clients (A clients) and 1.55 times that of the combined A and B clients.

TABLE D-1: PRE-SCORE RESULTS

Pre-Score	Clients	%	Delinquent Clients	%	Portfolio	Past-Due Portfolio	PAR > 30 days
A	12,888	70.4%	596	4.6%	6,772,310	207,272	3.1%
B	4,519	24.7%	564	12.5%	2,321,256	193,150	8.3%
C	911	5.0%	228	25.0%	432,817	76,764	17.7%
Total	18,318	100.0%	1388	7.6%	9,526,383	477,186	5.0%

Final Score

The final score is the sum of the pre-score and the post score, and Table D-2 shows that the scoring system is functioning well. We can see that clients whose score recommended rejection, yet received loans, have a poor quality loan portfolio, with PAR > 30 days of 20.4 percent, while those clients whose score recommended a credit line have a high-quality loan portfolio, with PAR > 30 days of just 2.0 percent.

If these “forced approvals” (of clients whose scores recommended rejection) are not considered, outstanding clients would be reduced by 4.4 percent, but the overall PAR > 30 days would be reduced by 14 percent and the percentage of delinquent clients would be reduced by 9.3 percent.

TABLE D-2: FINAL SCORE RESULTS

Final Score	Clients	% total	Delinquent Clients	% Delinquency	Portfolio	Past-Due Loans	PAR > 30 days
No post score	27	0.1%	3	11.1%	24,365	769	3.2%
Rejection	775	4.2%	175	22.6%	405,745	82,624	20.4%
Normal evaluation	5,554	30.3%	715	12.9%	3,156,213	235,844	7.5%
Recommended approval	8,994	49.1%	427	4.7%	4,665,278	132,346	2.8%
Credit line	2,968	16.2%	68	2.3%	1,274,781	25,604	2.0%
Total	18,318	100.0%	1,388	7.6%	9,526,383	477,186	5.0%
Without forced approvals (recommended rejection)	17,516	95.6%	1,210	6.9%	9,096,272	393,793	4.3%

Segmentation Score

Table D-3 shows that the segmentation score is also functioning well, although here the recommended rejections have a lower PAR than the normal evaluations. This is because there are so few recommended rejections, and those that have received "forced approvals" have demonstrated lower risk in actual operations with Mibanco.

TABLE D-3: SEGMENTATION SCORE

Segmentation Score	Clients	% Total	Delinquent Clients	% Delinq.	Portfolio	Delinquent Balance	PAR > 30 days
Automatic rejection	383	1.2%	46	12.0%	781,232	59,812	7.7%
Normal Evaluation	2,696	8.3%	422	15.7%	5,590,476	516,821	9.2%
Automatic Renewal	9,979	30.6%	477	4.8%	23,503,904	704,616	3.0%
Credit Line	19,514	59.9%	278	1.4%	53,278,175	560,110	1.1%
Total	32,572	100.0%	1,223	3.8%	83,153,787	1,841,360	2.2%

PERCENTAGE OF FORCED APPROVALS

Selection Scoring

In Table D-4, we can see that since Selection scoring began in July 2003, 58.8 percent of clients whose score recommended rejection received loans through forced approvals. During the same period, only 5.4 percent of those clients whose score recommended approval or lines of credit did not receive loans.

TABLE D-4: SELECTION SCORING

Selection Score	Not Disbursed		Disbursed		Total	%
	#	%	#	%		
No post score	17,949	99.8%	39	0.2%	17,988	27.2%
Recommended rejection	1,672	41.2%	2,390	58.8%	4,062	6.1%
Normal evaluation	1,199	5.9%	19,116	94.1%	20,315	30.7%
Recommended approval	1,053	5.4%	18,554	94.6%	19,607	29.7%
Line of credit	226	5.4%	3,923	94.6%	4,149	6.3%
Total	22,099	33.4%	44,022	66.6%	66,121	100.0%

Although the percentage of forced approvals is above the 30 percent maximum acceptable limit for forced approvals established by Mibanco, this is because early on, the score was not being used as a final decision, but rather as input for the loan officer's decision. However, once the model's prediction capabilities were established and the score's recommendation became final, the number of forced approvals has fallen off.

Segmentation Scoring

Since Mibanco launched segmentation scoring in the field in July 2003 through April 2005, 19.8 percent of clients whose score recommended rejections received loans through forced approvals. During the same period, only 4.3 percent of recommended renewals and 2.6 percent of recommended credit lines were not disbursed.

TABLE D-5: SEGMENTATION SCORING RESULTS

Segmentation Score	Not disbursed		Disbursed		Total	%
	#	%	#	%		
Rejection	4,398	80.2%	1,086	19.8%	5,484	6.9%
Normal Evaluation	1,030	6.3%	15,392	93.7%	16,422	20.8%
Renewal	1,225	4.3%	27,209	95.7%	28,434	35.9%
Credit Line	759	2.6%	28,008	97.4%	28,767	36.4%
Total	7,412	9.4%	71,695	90.6%	79,107	100.0%

RESPONSE TIME

Selection Scoring

Table D-6 shows that the weighted average response time for clients evaluated with selection scoring (new clients) since July 2003 is 4.6 days. This is almost half the response time required before Mibanco initiated its scoring strategy, which was close to 8 days.

TABLE D-6: AVERAGE RESPONSE TIME, SELECTION SCORING

Days	# Loans	%	Weighted
0	11,221	22.4%	0
1	8,113	16.2%	0.162188637
2	5,444	10.9%	0.217664228
3	4,375	8.7%	0.262384551
4	3,571	7.1%	0.285554356
5	2,928	5.9%	0.292671225
6	2,534	5.1%	0.303946264
7	2,429	4.9%	0.339910439
8	1,565	3.1%	0.250289872
9	1,110	2.2%	0.199712127
10	841	1.7%	0.168126025
11	772	1.5%	0.169765303
12	579	1.2%	0.138898884
13	560	1.1%	0.145535964
14	588	1.2%	0.16456759
15	360	0.7%	0.107952501
16	266	0.5%	0.085082564
17	249	0.5%	0.084622766
18	223	0.4%	0.080244692
19	182	0.4%	0.069129583
20	198	0.4%	0.079165167
> 20	1,914	3.8%	0.956579105
Total	50,022	100.0%	4.6

Segmentation Scoring

As shown in Table D-7, the weighted average response time for clients evaluated with segmentation scoring (renewals), is down to 2.3 day; this is considered excellent customer service.

Days	# Loans	%	Weighted
0	26014	36.3%	0.0000
1	18943	26.4%	0.2644
2	8456	11.8%	0.2360
3	5170	7.2%	0.2165
4	3402	4.7%	0.1899
5	2229	3.1%	0.1555
6	1560	2.2%	0.1306
7	1256	1.8%	0.1227
8	810	1.1%	0.0904
9	489	0.7%	0.0614
10	411	0.6%	0.0574
11	337	0.5%	0.0517
12	292	0.4%	0.0489
13	243	0.3%	0.0441
14	270	0.4%	0.0528
15	212	0.3%	0.0444
16	173	0.2%	0.0386
17	135	0.2%	0.0320
18	131	0.2%	0.0329
19	119	0.2%	0.0316
20	98	0.1%	0.0274
>20	901	1.3%	0.3772
Total	71651	100.0%	2.3

EVALUATION OF THE MODEL

To fully evaluate the model, we need to analyze client behavior not only at one point in time (as with the portfolio quality), but also client payment history. This historical analysis uses what is called the Good and Bad Indicator of good and bad, which classifies clients based on behavior of indicators such as maximum days in arrears and the average days in arrears for credit(s) previously evaluated with scoring. This was the same analysis used when determining the model.

Selection Scoring

It is expected that a model that is functioning well will have a greater proportion of clients classified as “bad”, with a lower score. Table D-8 shows that the model in use at Mibanco is functioning well, as the percentage of “bad” clients with a lower score is at 32.9 percent while among those with the highest scores, only 6.1 percent are deemed “bad.” In addition, the proportion of rejections classified as “bad” must be taken into account, given that for some reason it was decided not to approve them.

TABLE D-8: SELECTION SCORING WITH GOOD AND BAD INDICATORS

Score	Good		Bad		Disbur.	%	Reject	%	Total	%
	#	%	#	%						
< 675	259	67.1%	127	32.9%	386	83.9%	74	16.1%	460	1.1%
676 - 701	409	72.5%	155	27.5%	564	88.7%	72	11.3%	636	1.5%
702 - 729	927	74.5%	318	25.5%	1245	90.5%	131	9.5%	1376	3.1%
730 - 762	2401	81.0%	562	19.0%	2963	93.8%	196	6.2%	3159	7.2%
763 - 785	2427	81.9%	536	18.1%	2963	94.5%	171	5.5%	3134	7.2%
786 - 806	2702	83.1%	549	16.9%	3251	95.4%	158	4.6%	3409	7.8%
807 - 822	2547	85.5%	433	14.5%	2980	95.8%	132	4.2%	3112	7.1%
823 - 842	3569	85.5%	604	14.5%	4173	96.4%	158	3.6%	4331	9.9%
843 - 859	3374	87.8%	470	12.2%	3844	96.5%	140	3.5%	3984	9.1%
860 - 875	2857	88.6%	369	11.4%	3226	97.2%	92	2.8%	3318	7.6%
876 - 898	3515	90.3%	378	9.7%	3893	97.1%	116	2.9%	4009	9.2%
899 - 924	2993	91.5%	278	8.5%	3271	97.6%	80	2.4%	3351	7.6%
> 924	2366	93.9%	153	6.1%	2519	97.6%	61	2.4%	2580	5.9%
No Data	31	83.8%	6	16.2%	37	0.5%	6911	99.5%	6948	15.9%
Total	30377	86.0%	4938	14.0%	35315	80.6%	8492	19.4%	43807	100.0%

Segmentation Scoring

As shown in Table D-9, the distribution of segmentation scores also shows a strong classification by score ranges. The distribution is not even more extended given the high percentage of rejections of clients with lower scores.

TABLE D-9: SEGMENTATION SCORING WITH GOOD AND BAD INDICATORS

Score	Good		Bad		Disbur.	%	Rejec.	%	Total	%
	#	%	#	%						
< 468	11	84.6%	2	15.4%	13	0.0%	464	97.3%	477	0.9%
469 - 606	109	81.3%	25	18.7%	134	0.3%	1159	89.6%	1293	2.6%
607 - 698	457	82.2%	99	17.8%	556	1.2%	1308	70.2%	1864	3.7%
699 - 766	3307	85.1%	578	14.9%	3885	8.5%	301	7.2%	4186	8.3%
767 - 802	4083	87.6%	576	12.4%	4659	10.2%	184	3.8%	4843	9.6%
803 - 831	4802	90.2%	519	9.8%	5321	11.6%	238	4.3%	5559	11.1%
832 - 855	4691	92.9%	360	7.1%	5051	11.0%	148	2.8%	5199	10.3%
856 - 878	5483	94.6%	316	5.4%	5799	12.6%	163	2.7%	5962	11.9%
879 - 904	6055	95.1%	314	4.9%	6369	13.9%	103	1.6%	6472	12.9%
905 - 935	5717	95.7%	256	4.3%	5973	13.0%	179	2.9%	6152	12.2%
936 - 976	4492	97.2%	128	2.8%	4620	10.1%	91	1.9%	4711	9.4%
> 976	3445	98.5%	52	1.5%	3497	7.6%	35	1.0%	3532	7.0%
Total	42652	93.0%	3225	7.0%	45877	100.0%	4373	8.7%	50250	100.0%

CONCLUSION

Mibanco, one of the very first MFIs in the world to introduce credit scoring into its loan evaluation processes, continues to use the tool to its fullest advantage in the evaluation of microenterprise loan applications. Analysis of the results and use of the scores demonstrate that Mibanco has succeeded in meeting its established objectives of standardizing the application of policies, processes, and procedures, increasing the retention of low-risk clients and improving portfolio quality. A further advantage of the credit-scoring project has been the streamlining of the use of Mibanco’s client database, as the institution has recognized the importance of maintaining complete and accurate data on all operations.

APPENDIX E: TEBA BANK CREDIT SCORING CASE STUDY

1. OVERVIEW/BACKGROUND

Teba Bank evolved from Teba Ltd., a century old recruitment agency and payroll master for the mining sector in South Africa. Teba Bank previously operated as a Savings Fund offering savings and remittance transfer services to mineworkers. In 2000, Teba Bank received their banking license and started operating as a fully licensed savings bank. Credit products were introduced in a joint venture partnership. Initially the credit offering was limited to payroll-backed consumer loans to mineworkers. In the past year, Teba Bank has introduced a range of credit products independently and has grown their loan book from R60 to R190 million. The range includes pension/provident fund-backed housing loans; consumer credit to non-mineworkers[1], mostly in mining towns; consumer credit to mineworkers; loans secured by fixed deposits; a general purpose loan for the informal market; and a business loan for small contractors to the mines (secured by the procurement contract). In addition to the credit offering, Teba Bank offers savings services to mineworkers and the general public, has piloted a debit card (A-card) with several partners, and has a funeral plan for mineworkers, which has recently been made available to the general market. The current value of the savings book is R1.7 billion.

Teba Bank's branch network is unique since it developed around mining towns and more recently in rural areas of the Eastern Cape Province (where many mineworkers originated). They have 22 full-service branches (11 in the Eastern Cape), but the majority of their outlets are on various mines in order to provide mineworkers with financial services. Teba Bank also has agency agreements with Teba Ltd for limited financial services (repayments, cash withdrawals, and deposits) with agency outlets throughout South Africa.

As a licensed bank, Teba Bank is regulated by the South African Reserve Bank, is a voluntary member of the Banking Association and is required to adhere to the Banking and Usury Acts. Teba Bank is also registered with the Micro Finance Regulatory Council (MFRC) in order to provide micro-loans. According to the Usury Act, the regime differs according to the amount of the loan provided by the financial institution: 1) if the loan is under R10,000 and provided by a registered lender, then it falls within the Exemption Notice and the MFRC's jurisdiction and interest rates are not limited; and 2) for loans over R10,000, the Usury Act itself applies and limitations on interest rates are defined from time to time by the Department of Trade and Industry. The current interest rate is capped at 17 percent. A new Consumer Credit Bill is likely to be enacted in the near future, which will encompass all forms of consumer credit below R500,000. This more comprehensive legislation has a strong focus on consumer protection and will have far-reaching consequences across the consumer credit sector.

Due to Teba Bank's unique origins, their traditional market and approach to business is distinctive. However, Teba is increasingly trying to diversify and grow outside of their traditional market. This means that they have to compete directly with many consumer microlenders[2]. Teba Bank's strong social mission, constant aims to develop the communities in which they operate, and rural/ peri-urban branch network differentiates them within this market space.

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1 The target market is the low-income formally or informally employed person in smaller towns and peri-urban areas that surround or are near to their traditional mine based outlets. Bank branches have been opened in some of these towns.

2 The gross portfolio of microloans in South Africa is in excess of R17 billion. There are more than 1,600 registered microlenders in South Africa. Ninety percent of the microloan book is provided by the largest 50 of these lenders (small banks, non-bank financial institutions, and furniture retailers). (Source: MFRC, 2005)

2. THE DRIVERS FOR CREDIT SCORING

In 2002, Teba Bank was awarded a USAID grant to develop a new loan product for a market segment that was currently underserved. Market research was conducted and following a conceptualization workshop, some basic product design and concept testing, it was decided that Teba Bank would develop a savings-backed loan for the informal market. The product would serve clients that do not have a pay-slip and that had saved with Teba Bank or elsewhere for six months or more. It was decided that an application credit scorecard would assist in the loan application decision making for this product. The product and judgmental application scorecard was launched in three branches for a pilot phase in December 2004 and has subsequently been rolled out to all 22 branches. To date, the scorecard has not been validated and does not form part of the decision. Once a sufficient volume of application and performance data has been gathered, the scorecard will be validated and implemented fully.

This product development was the initial reason for the scorecard development, but since then Teba Bank recognizes the importance of incorporating scoring into their risk management approach. The bank sees this as an important element of their strategy to compete in the market.

3. TYPE OF CREDIT SCORING MODEL USED

The scorecard was developed for a new product and a new target market, hence no historical data was available for the scorecard design/development. As such, a judgmental scorecard was developed for Teba Bank by a specialized consultancy. Validation of the scorecard is still to be carried out. Teba Bank also plans to develop additional scorecards for the other products and target markets that they serve. In some cases, it may be possible to develop empirical application scorecards, but it is most likely that the majority will be judgmental since most new products have been launched since May 2005.

4. IMPACT OF CREDIT SCORING

IMPACT ON BUSINESS PROCESSES AND STAFF

The true impact of the scorecard at Teba Bank is yet to be seen since it has not been implemented yet. To date the impact has been focused on the learning that has occurred within Teba Bank around scorecards as an approach to risk management.

The scorecard development has led to the development of strong reporting mechanisms and processes. Reports are easily accessible to the Credit Risk division to monitor risk and to report to the Credit Risk Committee and other forums.

The application process at Teba Bank has always been fully automated, so the addition of scorecard variables to the application interface has had a minor impact on the application process for operational staff.

The Credit Department has developed the internal analytical resources by undergoing training and by recruiting a Credit Risk Analyst with experience in scoring. This places them in a strong position going forward with respect to reaping the benefits of the work they have already carried out in scoring.

5. PARTICULAR LEARNING AREAS OF INTEREST FOR MICROFINANCE INSTITUTIONS

LESSONS LEARNED

Scoring—a new approach to business

Scoring is a strategy that the entire organization needs to understand and buy in to. Adopting this approach to risk management, and your business as a whole, needs to be a conscious choice at a very senior level within the financial institution. This high-level buy-in or strategic vision is necessary due to the investment that is required and the far-reaching consequences of implementing scoring into the business. Scoring will not only influence credit risk management but also it will influence every function within the institution (Finance, Marketing, Information Technology, Operations, and so on). For scoring to be a success, all functions need to understand that this is an organizational strategy and that it will benefit the entire company.

Buy-in and understanding

The benefits of a using scoring as part of your approach to risk management can only be optimized if the entire organization understands the fundamental principles of credit scoring. If scoring is understood by the business, maximum benefits can be achieved—if not, the benefits will be limited since it will not be fully integrated into the business approach. Scoring enables you to understand your customers better, segment your customer according to risk bands, and respond to your market quickly in line with your risk appetite.

Application versus behavioral scorecards

An application scorecard has some benefits in terms of rank ordering risk among first-time applicants, but the real benefits of scoring can be seen more powerfully in a behavioral scorecard. Behavioral scorecards lead to increased efficiency (faster loan applications for repeat borrowers), loyalty programs, pre-approved loans, more targeted marketing due to the ability to segment your portfolio, more accurate provisioning, and competitive pricing according to risk.

CHALLENGES

Teba Bank has faced and is facing many challenges in implementing credit scoring into their business approach. These challenges can be summarized as follows:

- *Data are* one of the most challenging elements of scoring. Data collection, storage, and maintenance are an integral part of successful scoring due to the necessity for consistent, good quality, voluminous data. This is imperative for both the development and maintenance of credit scorecards.
- *IT systems* should either be mature but flexible enough to enable complete integration of the scorecard into the application interface or start from scratch to allow for full integration of the scorecard into the application process and system. Some specific areas to consider when developing a scorecard with reference to the IT system follow:
  - The programmer needs to have had exposure to a credit scorecard before in order to understand the desired end product. It is difficult/ impossible to conceptualize a credit scorecard in operation without having seen it before. The system also needs to be able to handle intensive stress testing.
  - The collection and storage of data requires a great deal of attention. A knowledgeable technical architect is required to structure the databases and to structure the data warehousing.

- Since changes to the scorecard are inevitable, the system needs to be built in a parameterized way rather than hard coded. This will mean that changes to the scorecard can be implemented easily through modifying variables in the parameters rather than changing hard code.
- The integration of the scorecard needs to be ambiguous to the end user—so that the variables are not obvious.
- Reporting and validations/checks need to be carefully developed to enable easy management of the scorecard (such as vintage reports, roll rates, and population stability reports). The true value of the scorecard is limited without the ability/ power to monitor and manage the data.
- The system needs to be streamlined to avoid recapturing of the same variables more than once, such as customer information.
- There can be impacts on day-end processing and these should be considered, such as additional data storage requirements at day ends and behavioral scorecards will need to be updated regularly.

- *Cultures/mindsets.* Changing an institution's approach to business is a huge challenge. In Teba Bank the mindset operationally was to approve credit, based on affordability not risk exposure. It is a major challenge to change this mindset at all levels within the institution and to secure buy-in. In order to secure buy-in, Credit Risk needed to educate the rest of the business on credit risk management and scoring specifically. To achieve this, new skills were brought on board. Without an understanding of the scoring and the impact it can have on your entire business approach, business will not have the vision to envisage behavioral scoring, risk based pricing, improved provisioning, targeted marketing and loyalty programs, and so on. Bringing about this understanding is an immense challenge.
- *New product and new target market.* In hindsight, implementing a credit scorecard for a new product and target market was a challenging way of introducing scorecards to Teba Bank. The learning curve would have been far more reasonable if the product and target market was well known and understood to the bank. In a new market, it takes longer to understand the market and to observe trends. Without known benchmarks, historical data, and an understanding of the market, it is difficult to manage the scorecard.

APPENDIX F: UNITED BULGARIAN BANK, SOFIA, BULGARIA AND LATVIJAS UNIBANKA

1. OVERVIEW

This background summary deals with DAI Europe’s work developing judgmental scorecards for two partner banks participating in the European Union (EU)/European Bank for Reconstruction and Development (EBRD) Small and Medium Enterprise Finance Facility for EU Accession Countries (Facility). In both cases, the banks leveraged participation in the EU/EBRD Facility to strengthen their microlending capacity, with microlending described as loans of up to €30,000.

United Bulgarian Bank (UBB) was incorporated in 1992 after a merger of two Bulgarian banks. The privatization of UBB in 1997 also constituted the first privatization of a large state-owned Bulgarian bank. The bank was bought from National Bank of Greece in 2000. The bank is the third-biggest bank in the country and provides a full range of corporate, small and medium-sized enterprise (SME) and retail banking services. UBB is aided in this task by one of the largest branch networks in the country with more than 130 branches and offices. Approximately half of the loan portfolio consists of retail loans—the size range from as low as €100 up to €100,000.

UBB’s business strategy recognizes the importance of SMEs in the make up of the Bulgarian economy, as well as the sector’s potential for further growth, and regards the SME sector as of strategic importance to UBB’s banking business. Lending to SMEs constitutes a major portion of the bank’s lending business.

The **Latvijas Unibanka** (now SEB Unibanka of Latvia, and further referred to as “Unibanka”) was founded on September 28, 1993, uniting the sections that were not privatized in the reorganization of the Bank of Latvia—21 separate sections of various banks. In the succeeding years, SEB Unibanka has become the leading commercial bank with a wide range of clients in Latvia and stable cooperating partners abroad. The bank has more than 50 branches and client services centers throughout Latvia.

2. THE DRIVERS FOR CREDIT SCORING

Both Unibanka and UBB recognized a need to standardize and streamline the microloan process. In the case of UBB, we worked together to developed five dedicated microloan products. Each of these products has standardized loan terms, including maximum grace periods and equal monthly principal repayments, and fees.

In mid-2000, Unibanka made a strategic decision to focus on SMEs, one of the last, great growth markets in that part of the world. The bank had been the first in its market to introduce a specifically SME product, *Business Package*, a bundle of services targeting start-ups and growing small businesses. Now it wanted to introduce a credit product aimed at the same group, but its existing credit processes were well suited to large corporate lending. Initially, the bank used the same analytical procedures to review all commercial loans, whether for €5,000,000 or €5,000. The microloan scorecard developed under the Facility served as a decision support tool recommending the rejection of the weakest clients, further review for borderline clients, and approval for clients identified as less risky.

In both UBB and Unibanka, the scorecard helped to make the appraisal process more consistent and transparent, providing the following benefits:

- Common risk characteristics for micro clients were captured in one model;
- Approval criteria were standardized throughout the bank;

- Weak applications cold be rejected early in the appraisal process, thus saving time both for the client and the loan officer;
- The scorecard is a tool that guides further analysis of the borrower’s business; and
- Risk is linked to pricing through the score.

Furthermore, in both banks the scorecard was linked to new automated tools for processing microloan applications. In UBB, the scorecard project led into the development of a newly created application processing system (APS), which automates the entire small loan review and documentation process from application to payout.

3. TYPE OF CREDIT SCORING MODEL USED

Both UBB and Unibanka had a history of small business lending, but neither had systematically collected enough historic data on applicant characteristics, financial statements and repayment behavior. In both banks, the judgmental scorecards combined a replication of the banks’ current risk appraisal of borrowers with some new measures designed to better measure some risks particular to micro business, in comparison to corporate borrowers.

Judgmental scorecards of the type developed in UBB and Unibanka assign specific scores to a number of microbusiness borrower characteristics. The specific characteristics are different in each of the cards, but in general comprise elements of business information, such as years in business, type of business, and credit history, with measures of financial strength, not only from historic financial statement indicators, but also from estimations of future cash flow over the requested loan term. In general, the parameters of these judgmental scorecards should present a reasonable measure of both the borrower’s willingness (character related) and ability (financial strength) to repay the obligation.

Judgmental models provide scores that rank borrowers in terms of relative risk, generally with higher scores linked to lower risk, and lower scores linked to higher risk. In data-poor environments, the introduction of judgmental scoring can facilitate the consistent capture of application, financial statement, and repayment information. Over time, this information can be used to weight statistically the judgmental model, or, more likely, redesign it with empirically weighted factors.

4. PROCESS OF ADOPTING CREDIT SCORING

Credit scoring was phased into practice in UBB and Unibanka through a process of back testing and pilot testing. Carefully monitored testing is crucial to the introduction of judgmental scorecards, as a lack of historical data normally precludes validating them with past data, the standard practice for testing statistical models.

Phase One: Testing to Adjust Parameters and Policy Thresholds. In Unibanka, we tested the scorecard on a sample of 50 historic cases, systematically reviewing the scorecard’s sensitivity with various combinations of the indicators for which historic data was not available in the credit files, such as cash flow projections. Another approach, used in UBB, was to test the card with new clients in parallel with the normal approval process. Either of these forms of testing serves the purpose of gauging a card’s granularity, or ability to classify clients into a range of risk levels, as opposed to clustering clients into a few limited ranges.

Phase Two: Pilot Testing in Branches. Pilot testing brings valuable feedback from the front-line lenders and credit committee decision makers. Both Unibanka and UBB tested their scorecards in a number of branches selected based on their strength in SME lending.

The pilot testing began with training provided to lenders in the selected branches. In addition to covering procedural issues, the training highlighted the differences between microbusinesses and larger companies, and explained why scoring is an appropriate tool for quickly evaluating micro-borrowers. The training participants also had a chance to score sample clients and to see first hand the practical benefits the system could bring.

At the initiation of pilot testing, there are many skeptics, particularly the most senior branch lenders who may feel threatened by a new methodology that encroaches on their "territory" as depositories of credit knowledge. Only after testing, these skeptics can come to understand that the scorecard does not supplant their judgment, but is a tool to help sharpen the decision-making skills of less experienced loan officers and draw their attention to borrowers who merit the additional review. Some lenders may never be convinced of the benefits of scoring; this becomes a management issues for the credit risk department—to ensure adherence to credit policy that incorporates a scorecard.

In UBB and Unibanka, the scorecards were tested for several months in Excel-based software. Scores were tracked centrally and local feedback solicited periodically. This information was reviewed by the consultants and management and led to some modifications. After pilot testing, Unibanka made changes to the procedures for using the scoring model as opposed to changes in the scorecard itself. In both banks, some minor technical changes were required to scorecard formulas. Generally, pilot testing leads to minor adjustment rather than major changes.

The technical sophistication of the pilot test scorecard is not essential. The more technically advanced the data input, scoring, and collection, the easier it is to analyze the test data and make adjustments to the scorecard if they are necessary. It is also possible to program the card directly into the bank's core software from the beginning if programming resources are readily and cheaply available in the bank. However, due to the heavy workloads that programmers often face, it may make sense to test the scorecard in a technically simpler user-friendly format such as Excel in which the cost and time of working out bugs is negligible.

Phase Three: Roll Out in Long-Term Software Platform. In UBB and Unibanka, the model was rolled out bank wide while still in the temporary-Excel based platform. Ideally, it would be programmed as a web-based module of the bank's information system even prior to bank-wide roll out. Roll out was accompanied by training program similar to the pilot testing training, but improved on by the feedback from the first pilot training sessions.

In UBB, a completely new web-based APS system was developed under the technical assistance from the Facility and the scorecard was programmed as a module of this system. In Unibanka, the scorecard was programmed as a module in the banks in-house credit underwriting software designed for processing microloans.

The actual software used to integrate scoring into the application processing system is less important than the bank's ability to modify the scorecard independently in the future. We advocate the bank to select the optimal program based on its current systems or those it plans to purchase or develop in the immediate future. The code that we have helped banks to develop under the Facility becomes the sole property of the banks, as long-term sustainability of the models requires that the banks be able to modify them at their own discretion.

Training should be repeated bank-wide any time there are changes to the model or to the policies or procedures guiding its use. In Unibanka, follow up trainings were conducted twice over the two-year technical assistance in connection with changes to the credit policy related to scoring.

Finally, responsibility for monitoring and managing the scoring model should be assigned to bank office staff, not guarded by consultants. In Unibanka, the model was managed by the marketing product manager for the SME segment, while a credit risk manager handled the reporting and risk management at the portfolio level.

5. IMPACT OF CREDIT SCORING

Credit scorecards have improved microlending in both UBB and Unibanka. Some statistics on efficiency related to scoring and accompanying automated processing in UBB are:

- Loan officer time required to prepare a micro loan has been reduced by more than 60 percent;
- Average time to review a microloan has been reduced from 12 hours before scoring was introduced to under 2.5 hours; this saves costs and allows loan officers and credit managers to focus more attention on larger exposures where the potential risk to UBB is greater; and
- The Head Office loan rejection rate has been reduced from over 20 percent, to fewer than 8 percent, demonstrating the scorecard's effectiveness in filtering out weak applications at branch level.

An analysis of the performance of UBB's scorecard demonstrates that it has been effective in ranking risk. As shown in Table F-1, there is a clear and consistent progression in the concentration of "bad" loans, defined as loans with arrears greater than 60 days, moving from high to low scores. For example, only 1.96 percent of loans scoring over 400 points went "bad", while 2.21 percent of loans scoring between 251 – 300 points did, and 4.76 percent of loans scoring 175-200 points did.

TABLE F-1: UBB GLOBAL RISK REPORT

All Loans Scored October 2003 - October 2005								
			Loans with cases of arrears of 30-59 days			Loans with cases of arrears of 60 days or more		
Final Credit Centre Score	No of loans	% of total	No	% of applications in score range	% of total applications	No	% of applications in score range	% of total applications
175-200	42	1.98%	6	14.29%	0.28%	2	4.76%	0.09%
201-250	378	17.83%	49	12.96%	2.31%	16	4.23%	0.75%
251-300	588	27.74%	45	7.65%	2.12%	13	2.21%	0.61%
301-350	532	25.09%	26	4.89%	1.23%	9	1.69%	0.42%
351-400	364	17.17%	15	4.12%	0.71%	5	1.37%	0.24%
401-450	204	9.62%	4	1.96%	0.19%	0	0.00%	0.00%
451-500	12	0.57%	0	0.00%	0.00%	0	0.00%	0.00%
Total	2,120	100.00%	145	6.84%	6.84%	45	2.12%	2.12%

Some other qualitative testimonials of the impact of credit scoring include:

- UBB was able to attract clients by offering an 'instant' evaluation of the loan application. High-scoring applicants are informed that they are approved pending verification of the information supplied, while low-scoring clients are rejected before the client spends time and resources collecting documents and having collateral evaluated.
- By rejecting low-scoring applicants early in the approval process, UBB reduced staff resources spent on proposals that are unlikely to be successful.
- The scorecard in both banks scores key credit risk factors, providing strong guidance and structure for loan proposal preparation. Loan officers are able to write less about a standard set of small business risk factors and produce clearer, more consistent loan proposals. The scores help underwriters quickly understand and focus their analysis on the weak and strong aspects of the loan.
- Both UBB and Unibanka link price to risk as described by the score.
- The score is a powerful risk management tool for monitoring portfolio performance and adjusting lending practices, for example by altering an approval or rejection threshold.

USEFUL LINKS

The Consultative Group to Assist the Poorest: www.cgap.org

Microfinance Risk Management: www.microfinance.com

Women's World Banking: www.swwb.org

ACCION: www.accion.org

DAI Europe: www.dai.com

Fair Isaac: www.fairisaac.com

Fair Isaac Credit Scoring 101: www.ftc.gov/bcp/creditscoring/present/

Experian: www.experian.com

CRIF: www.crif.com

Credit Scoring and Credit Control XI: http://www.crc.man.ed.ac.uk/conference9-abstracts.html

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