Implementing a Comprehensive Credit-Risk-Management System: The Case Study of Hanvit Bank

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In 1997 and 1998, the financial crisis that swept through Asia produced record loan losses throughout the region. Korea experienced especially acute credit problems, because the crisis followed a period of sustained high growth that had stimulated sharp increases in commercial lending. During 1997and 1998, the Korean economy declined appreciably for the first time since 1950, the Korean won depreciated substantially, and financial institutions suffered huge increases in nonperforming loans.

In late 1998, the International Monetary Fund (IMF), the Korean financial regulatory authorities, and the leading Korean financial institutions participated in a memorandum of understanding (MOU) that provided a framework for dealing with the crisis. This MOU called for reforms in many financial practices and in some corporate structures. In particular, the MOU required the leading financial institutions to improve their credit-risk-management practices.

To quickly comply with the MOU's directives, Hanvit Bank, the largest commercial bank in Korea developed an aggressive plan for upgrading its approach to credit-risk management.[1] To carry out the plan, the bank assembled a project team that included the bank's risk-management experts, leading credit-risk consultants, and a major Korean software design and credit-information company. The project involved a thorough overhaul of existing practices with the aim of realizing a modernized, comprehensive, and integrated credit-risk-management system (CRMS).

This case study reviews key components of the CRMS project conducted during 1999 for Hanvit Bank in Korea. The overall project included components devoted to improving the bank's credit-risk business processes, upgrading the analytic decision-support applications, expanding the credit-risk-information sources, and modernizing the technology support. However, our discussion here will focus primarily on development and implementation of the key credit-risk analytic applications. We also review the experience with the CRMS project one year into implementation as a way of gaining insights into the challenges of rolling out such an extensive solution.

A COMPREHENSIVE APPROACH TO CREDIT-RISK MANAGEMENT

Throughout the last 50 years, the Korean economy has enjoyed recurring, strong growth, which has stimulated large increases in commercial lending, especially lending to the large business conglomerates called Chaebols. After the Asian crisis hit, some of the heavily indebted Chaebols defaulted on their loans, creating much of the credit distress faced by the major Korean banks. Given the long history of prosperity, most Korean banks had not seen a need to upgrade their credit-risk-management practices to a level comparable to that of the leading North American and European banks.

With the MOU requiring Hanvit to make sweeping improvements in lending and credit practices, the CRMS project arose as a focal point for comprehensive, bankwide change that was unique by most risk-project standards. Virtually all aspects of credit-information management, analysis, and decision making came under review for substantial upgrading, as Hanvit sought to take a leadership role in the Korean financial sector.

The CRMS project's extensive multiyear objectives included the following:

- developing *advanced analytic applications* facilitating improved financial analysis, credit-risk rating, limit setting, collateral management, loan pricing, and credit-portfolio management;
- redesigning *key business processes* such as credit analysis, loan review, relationship management, consumer credit scoring, and small-business lending;
- improving *credit-risk information* by creating a roughly 1,700-attribute credit-data warehouse.

Since improved analytic modeling stands out as an important starting point for better credit-risk management, in this case study we will focus primarily on that component of the project. We don't mean to downplay the importance of more effective business processes and improved information-management capabilities, which go hand in hand with better modeling. In focusing here on decision-support analytic applications, we mean to illustrate one critical dimension that cuts across all of the components of a comprehensive approach.

For the largest Korean banks, this area stood out as needing perhaps the most upgrading; however, banks in the Asian region are not alone in needing substantially upgraded credit-risk analytics. Even the most sophisticated banks in North America and Europe could use improved decision-support analytics.

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As a final note, in developing the key CRMS applications described below, we needed to account for the effects of the dominant Korean business organizations, the Chaebols. Below we summarize these key analytics and point out the steps taken to recognize the Chaebol organizations.

KEY CRMS ANALYTIC APPLICATIONS

During the CRMS project, new analytic applications were developed that cut across four major components of credit-risk-management: risk ratings, loan pricing, limit setting, and portfolio management. As illustrated in Exhibit 1, these analytic applications support key decisions that range throughout the process of originating, monitoring, and managing credit risk. The custom models described below were designed and implemented to incorporate leading-edge financial theory yet estimated using Korea-specific financial information. The risk-measurement focus will be on key decision metrics that include borrower default, loan loss, loan net-present value (NPV), and credit value at risk (VAR).

DEFAULT MODELING AND RISK-RATING APPROACH

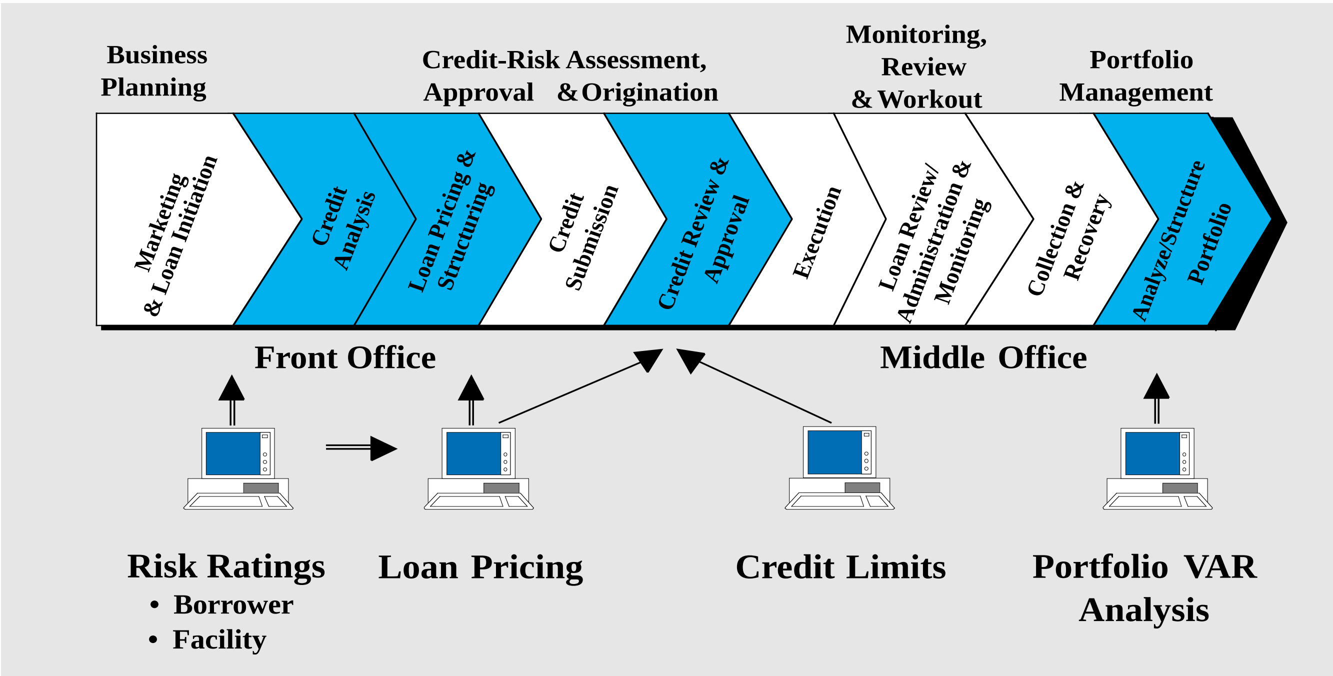
The risk-rating approach developed for Hanvit:

- starts with a *quantitative default model* that provides an initial rating based entirely on financial statement measures of recent performance and indebtedness;
- includes next a *subjective evaluation* of the borrower's current financial standing, which derives from answers to a series of questions on the business outlook, management quality, and risks;
- concludes with the determination of the *final borrower risk rating* as a weighted average of the above components with overrides allowed to correct for inaccuracies.

The risk-rating approach also reviews the collateral and seniority of the credit facility and the effect of any guarantees in establishing a *facility rating*. The facility rating in the CRMS rating approach derives from an estimate of the expected loss rate, whereas the borrower rating emphasized in this discussion relates to an estimated expected default rate (EDR).

The CRMS approach reflects our view that ratings should be quantitative and forward-looking. We also see that subjective factors have a role, particularly in correcting for anomalies in the historical financial measures and

Exhibit 1
Key CRMS Applications



in adjusting for differences between recent performance and future prospects.

The default modeling effort took advantage of key Korean credit-risk databases that:

- classify Korean companies as in default or not in default,
- provide comprehensive financial information on large-corporate and middle-market firms (both public and private with audited financial information).

Over the period 1996 to 1998, about 700 companies were identified as being in default. This represented about 7% of the roughly 10,000 company years of large-corporate and middle-market experience over that period. In the 1998 crisis year, companies in default accounted for more than 10% of that year's sample. This misfortune for the Korean economy provided a bountiful data set for a default model.

We patterned our approach after the Merton model of default and debt valuation.[2] In that model, default occurs when a firm's asset value falls sufficiently below the face value of its debt (see Exhibit 2). By asset value, we mean the expected net present value of future cash flows calculated before deducting debt payments. Analysts usually treat this NPV concept as synonymous with a mark-to-market valuation of assets. Book value may bear a tenuous relation to this basic, economic concept.

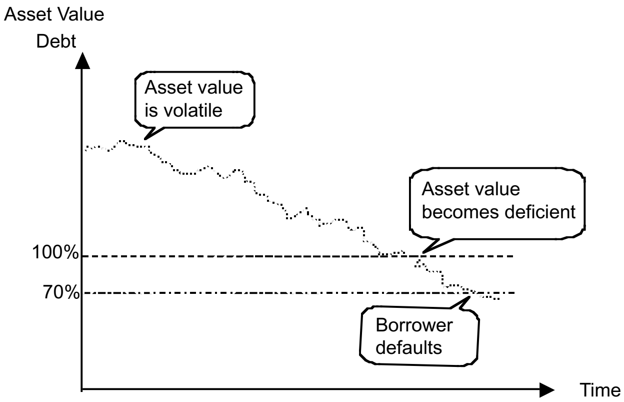
When used in forecasting, the Merton model expresses the probability of default as a function of "default distance." Default distance, broadly speaking, corresponds to leverage—usually measured by the ratio of asset value to debt—divided by volatility. Thus, a highly leveraged firm may have default risk similar to a less leveraged one, if the more leveraged firm has lower volatility. Not surprisingly, we find that the leverage used by volatile, small-capitalization firms generally falls short of that used by stable, large-capitalization firms.

Different assumptions concerning asset volatility produce variations in the formula for default distance. For instance, if asset value *(A)* follows a geometric Brownian-motion process and the face value of debt *(D)* is deterministic, then default distance *(DD)* corresponds to the following:

$$DD = ln(A/D)/\sigma(ln(A)) \qquad (1)$$

Here *ln* denotes the natural logarithm function and σ the standard deviation operator. Alternatively, if asset

EXHIBIT 2
Illustration of Merton Model Default Process



value, A, follows an absolute Brownian motion process, then DD corresponds to the following:

$$DD=(A—D)/\sigma(A) \tag{2}$$

For these particular assumptions on the nature of asset-value risk (that the process is made up of independent Gaussian increments), one can derive closed-form solutions for the default function. While in many applications one obtains adequate approximations by assuming a Gaussian process, this doesn't appear so in default modeling. In predicting default, the tails of the return distribution play a key role, and the observed deviations from normality become important in that range. Thus, those who fit default models often follow KMV's lead of using a DD measure patterned after those defined above in a framework that accommodates a distribution with fatter tails than the normal. In the research described here, we use DD measures in a logistic default function [see (3) below for the simplest case]:

$$EDR = exp(Constant - beta * DD)/(1 + exp(Constant - beta * DD)) \tag{3}$$

Here EDR denotes the expected default rate, exp the exponential function, Constant a constant term, and *beta* the coefficient of DD.

In initial tests of this approach, we fit such a model for Korean firms with listed equity. In this case, we derived DD from data on stock prices and indebtedness. Specifically, we estimated asset value as the sum of the market value of equity plus the book value of debt. This model fit the default experience of public Korean companies quite well.

While this model based on stock prices worked well, it provided *expected default-rate* (EDR) estimates for only a small subset of the bank's large-corporate and middle-market customers. Thus, we faced a challenge of finding proxy measures for asset value and thus extending the approach to all of the bank's potential commercial borrowers.

After much experimentation, we chose two proxy measures derived from financial data that together explained defaults almost as well as market-value default distance. We call these measures "cash flow default distance" *(CFDD)* and "balance sheet default distance" *(BSDD)*. We define these indicators as below:

$$CFDD = (GCF—INTEXP)/\sigma(GCF) \tag{4}$$

$$BSDD = ln((E + D)/D)/\sigma(ln(E + D)) \tag{5}$$

Here GCF denotes gross cash flow (EBITDA) [earnings before interest expense, taxes, depreciation, and amortization], $INTEXP$ interest expense, and E the book value of equity. We used five years of historical data in computing the standard deviations in the above formulas. Under particular assumptions, such as that expected interest expense rises at the trend growth rate of asset value, simple algebra shows that these indicators have a relation to the market-value default-distance measure (see the following illustration):

$$\frac{A-D}{\sigma(A-D)} = \frac{\dfrac{\overline{GCF} - INTEXP}{r-g}}{\sigma\left[\dfrac{\overline{GCF} - INTEXP}{r-g}\right]} \approx m\frac{\overline{GCF} - INTEXP}{\sigma(GCF - INTEXP)} \tag{6}$$

After some trials, we fit a default model of the following form:

$$EDF = \exp(const - b \cdot CFDD - c \cdot BSDD) / (1 + \exp(const - b \cdot CFDD - c \cdot BSDD)) \tag{7}$$

In the final model, we included separate constant terms for the individual years 1996, 1997, and 1998. In forecasting EDRs for 1999 and beyond, we averaged these yearly constant terms, with the 1996 value receiving half the total weight. We put twice the usual emphasis on 1996 as a way of eliminating the bias inherent in an estimation sample dominated by the unexpectedly high Korean default experience during the 1997 to 1998 period. Using spot checks with a number of companies with public equity, we found that the double weighting of 1996 reconciled rather well in 1999 with stock-market-based EDRs.

Also, for companies that were members of a large Chaebol, we used *CFDD* and *BSDD* measures that blended the values for the individual borrower with those for the overall Chaebol organization. We decided to experiment with such blended variables after reviewing studies indicating that Chaebols often subsidize their weaker members. The use of Chaebol default-distance values improved the fit of the model and allowed the approach to reflect the important influence of this type of business organization in Korea.

The EDR value from the default model determines an initial risk rating. The analyst then provides scores reflecting a subjective evaluation of the borrower's financial prospects along several qualitative dimensions. In this second step, the approach resembles the full ratings process of many institutions that rely entirely on subjective assessments. A second estimate of the risk rating combines the default-model result with the overall subjective assessment. As a final step, the approach allows for overriding the composite second-stage rating as a way of correcting for inaccuracies in the financial data or for accounting for any late-breaking changes in the borrower's situation.

CREDIT-PRICING APPROACH

Following the establishment of a risk rating, we see proper pricing as the next and culminating step in originating loans intelligently. Assuming the existence of effective portfolio management, one can argue that an institution should originate any NPV (expected) positive loan and avoid any NPV negative loan. Thus, the valuation of a loan becomes a key decision point in approval or denial. Further, one would like to see the pricing tool used in more ways than as a passive barometer. One would like to see loan officers use it as a tool facilitating negotiation of a larger number of NPV-positive deals. Applied in this way, the model could help boost both aggregate loan value and volume.

We now describe the approach to pricing commercial loans that we developed as part of the CRMS project.[3] Under this approach, the pricing tool computes the NPV of a loan's expected, credit-risk-adjusted cash flows. By *credit-risk-adjusted*, we mean that the cash flows at each possible, future ratings state include a deduction for the fair value of credit insurance covering one-period credit risk at that state.[4] This insurance premium will vary with the credit grade, increasing for lower (higher-risk) grades. It may also vary depending on the remaining maturity of the loan. Following this adjustment, the cash flows become risk free, from a credit perspective. Hence, we discount the credit-risk-adjusted cash flows using forward values for the risk-free, commercial lending rate.

We see proper pricing as the culminating step in originating loans intelligently.

The NPV of the loan represents the mathematical expectation, or probability-weighted sum, of all of the possible, future, discounted cash flows. We determine the probabilities associated with cash flows at each of the future ratings states using ratings-transition matrixes. In the CRMS project, we derived the transition matrix from the results of the default modeling discussed above. The ratings results over 1996 to 1998 gave us two years of ratings-transition experience.

Loans remain outstanding, creating credit exposure, only at the nondefault states.[5] Thus, in consolidating future cash flows in the CRMS pricing model, we enumerate only those states. The calculations still allow for the cash flow consequences of default. The credit premiums charged at the various nondefault states account for this.

Prepayment as well as ratings transitions can affect the probabilities of future, state-dependent cash flows. However, at this time in Korea, most loans have short tenors and prepayments aren't common. Thus, the present version of the model ignores the possibility of prepayment-related attrition.

Model Inputs and Outputs

We illustrate the basic inputs and outputs of the pricing model below. In its use as a loan-valuation tool, the analyst enters the borrower risk rating and descriptions of facility structure and pricing and, then, based on assumptions characterizing credit risk and other considerations, the pricing algorithm calculates an NPV (Exhibit 3).

EXHIBIT 3

Model Flow in Determining NPV

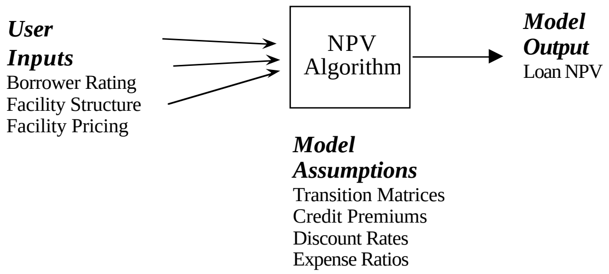
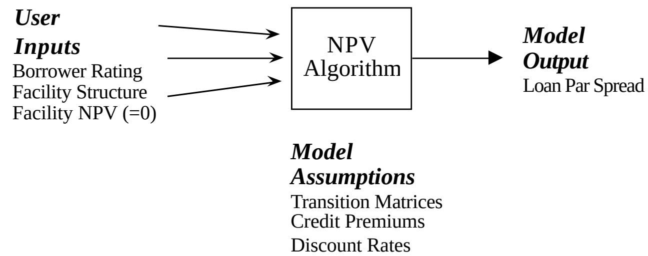


EXHIBIT 4

Model Flow in Determining a Par Spread



Alternatively, one may use the model in determining pricing at which the loan provides a particular NPV value, usually set to zero. In this case, the loan's NPV is an input and the par spread (or drawn and undrawn spreads for revolvers) is the output (Exhibit 4). The par (total) spread calculated by the model provides for bank costs as well as credit risk. The par *credit* spread refers to the portion of the total spread needed to cover credit risk.

NPV Algorithm

The core, NPV algorithm includes three basic steps that involve:

- computing cash flows net of the implicit credit-insurance premium at each of the future possible risk grades and time points;
- weighting the ratings- and time-dependent cash flows by the probabilities of reaching each risk grade at each time point;
- discounting and summing the probability-weighted cash flows.

The remaining components of the CRMS pricing tool basically handle the input and output of information, including loan descriptions and modeling assumptions.

Calibrating the Model

The proper calibration of the pricing model presented one of the greatest challenges. This calibration included notably:

- estimating par credit spreads for different risk grades from the comparatively undeveloped Korean bond market,
- determining the operating costs incurred by the bank in originating and servicing loans,
- assessing recovery rates for defaulting Korean loans.

For this effort we used bond market data in estimating competitive credit premiums. The operating costs came from rough internal estimates. The recovery rates came from the collateral model that used data provided by an insurance company specializing in distressed loans. In each case to support calibration, we needed to create filtering and smoothing procedures to extract plausible parameters from the noisy data.

CREDIT-LIMITS APPROACH

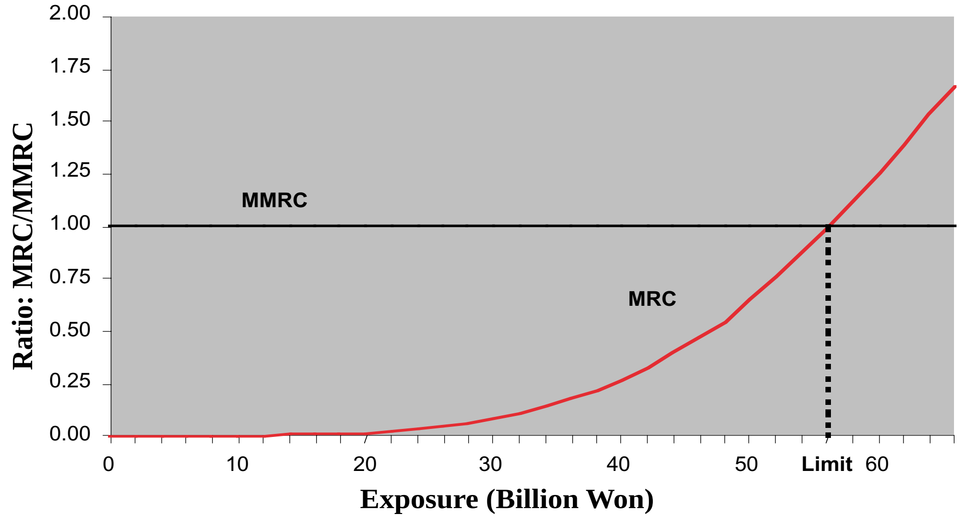
In the CRMS project, we developed two approaches to determining credit limits. To start, we created a procedure that estimated the level at which additional lending would, in theory, push the borrower into default. Under this approach, we analyzed the lender in isolation from other bank credit exposures. The approach provided an estimate of probably the highest limit that the bank would consider.

Alternatively, we developed a procedure that considered not only the borrower's credit status but also the borrower's correlation with other exposures. This method assumes that a borrower's limit corresponds to the first point at which *additional* credit exposure would make more than a maximum allowed contribution to portfolio risk. This maximum, *marginal* contribution would be set by credit policy, guided perhaps by regulatory limits. We consider this alternative, more complex limits approach here.

This approach implies that the borrower's size, risk rating, types of credit facilities, and correlation with the bank's entire portfolio will affect the limit.

EXHIBIT 5

Limit Determination Using Logistic Default Model



Thus, limits will be lower for smaller, higher-risk borrowers, who post little collateral and are highly correlated with the bank. Portfolio risk considerations motivate this approach. The rules described here deal only with limiting risk. A full portfolio-management approach would also consider the returns from the different borrowers.

One could use a credit value-at-risk model in measuring a borrower's total and marginal contribution to portfolio risk. But this probably would prove too cumbersome to apply on a case-by-case basis. Also, few banks have credit VAR systems sophisticated enough for an accurate assessment of limits. As an alternative to a full marginal VAR analysis, we developed a computationally feasible method for approximating the limits that would arise from a state-of-the-art VAR analysis.

Experiments with VAR systems suggest that one can approximate the credit-portfolio-risk contribution of a borrower with the following formula (8):

$$RC = EDR\_WT \times LIED\_WT \times CORR\_WT \times EXPOSURE \quad (8)$$

With the assistance of a pricing model, one could use the following, closer approximation:

$$RC = SPREAD\_WT \times CORR\_WT \times EXPOSURE \quad (9)$$

In (9) we define:

- *RC* as the estimated contribution to portfolio risk;
- *EDR_WT* a weight proportional to the borrower's EDR;
- *LIED_WT* a weight proportional to the loss in event of default rate typical of the borrower's credit facilities;
- *SPREAD_WT* a weight proportional to the par credit spread typical of the borrower's facilities;
- *CORR_WT* a weight proportional to the borrower's correlation with the portfolio;
- *EXPOSURE* the nominal exposure adjusting for loan equivalency but not the above weights.

To get the marginal risk contribution, we compute the change in (8) or (9) with respect to indebtedness:

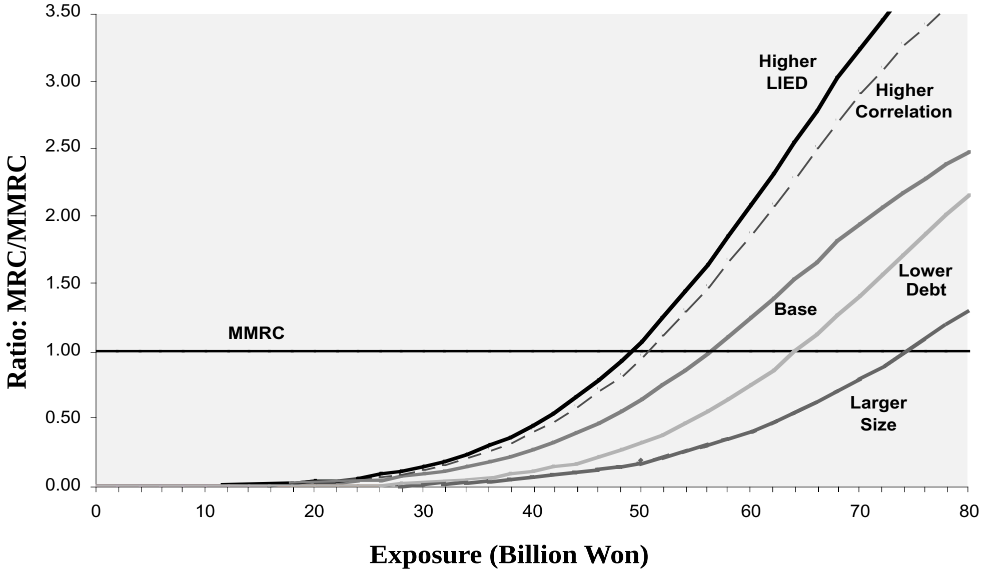
$$MRC = \Delta RC / \Delta D \quad (10)$$

Here *MRC* denotes the marginal-risk contribution, Δ change, and *D* total indebtedness of the borrower.

Setting Limits Using a Maximum Marginal-Risk-Contribution Threshold

Under the approach here, one determines a borrower's credit limit by finding the point at which *MRC* reaches a ceiling (*MMRC*) set by policy (Exhibit 5).

EXHIBIT 6
Illustration of Limit Sensitivity for Logistic Default Model



$$\textit{Limit} = \textit{EXPOSURE at which } \Delta RC/\Delta D = MMRC \qquad (11)$$

The position of the MRC curve and thus the debt limit depends on a company's size (debt capacity), indebtedness to others, correlation with the bank, and facility structures (loss in event of default) (Exhibit 6).

Determining the Maximum Marginal Contribution to Portfolio Risk

To make the above approach operational, one must establish a threshold for the marginal-risk contribution. In a full, portfolio risk/return analysis, one might set the threshold depending on the return associated with a borrower's loans.

Putting pricing aside, one might determine the *MMRC* from regulatory limits. In this case, one would select an extremely large borrower with the highest risk grade in an industry with a low correlation with the bank's overall portfolio. One would further assume that that borrower's entire indebtedness was with the bank. One then would solve for the *MRC* value corresponding to the regulatory limit on credit exposure to a single borrower (Exhibit 7). That *MRC* would represent the *MMRC* threshold to be used in determining limits for all borrowers.

This limits approach presented here restricts the *MRC* of a borrower to a level consistent with regulatory guidelines. Under this method, the limit depends on a borrower's size, risk rating, correlation with the entire bank, and indebtedness to other creditors.

CREDIT VAR APPROACH

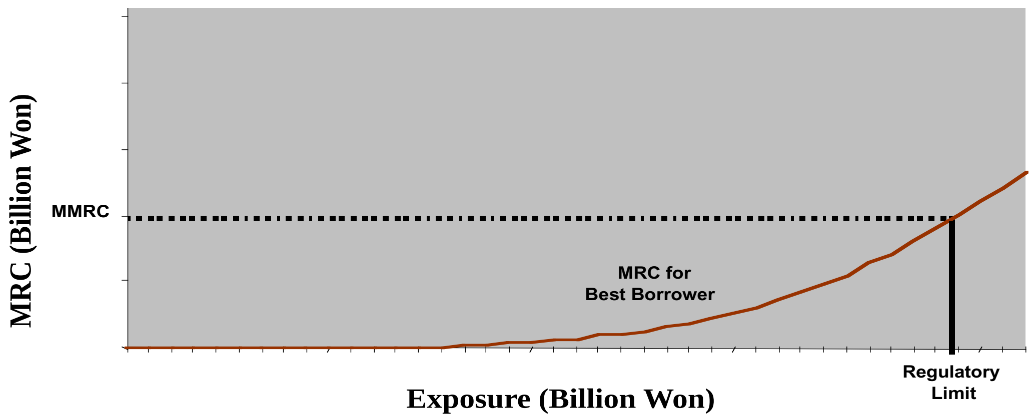
In the CRMS project, we developed a credit VAR model involving six-month, single-step simulations. The model has a basic framework similar to that of most of the credit-VAR applications offered by vendors. However, the model goes beyond those applications in:

- incorporating extremely detailed tables for revaluing debt upon ratings change or default;
- accounting for correlation arising from the Chaebol business organizations as well as from industry sources;
- including equity as well as debt as a source of credit VAR.[6]

The detailed revaluation tables control for tenor, credit-line utilization, and the average LIED rate. We used the CRMS pricing model in calculating these tables.

The VAR model assumes that the i^{th} borrower's migrations to default or to nondefault ratings derive from a continuous indicator of *change* in the borrower's credit strength, $y(i)$. We assume that this index $y(i)$ combines two

EXHIBIT 7
Establishing the MRC Threshold



kinds of standard-normal random effects: *z(j)*, systematic factors that the borrower shares with others, and *u(i)*, idiosyncratic influences unique to the i^{th} borrower.[7] We write this as below:

$$y(i) = \sqrt{\rho(i)} \sum_j w(i,j) z(j) + \sqrt{1-\rho(i)}\, u(i) \qquad (12)$$

Here in (12) ρ(i) denotes the fraction of the variance of y(i) arising from systematic factors and w^2(i, j) the share of systematic variance arising from the jth factor. Thus $\sum_j w^2(ij) = 1$. The systematic factors include industry and large Chaebol effects. In the CRMS model, we use company size in determining ρ(i) and line-of-business sales and asset data as well as Chaebol information in determining the weights w(i, j). Correlation among borrowers arises at this point through the exposure of different borrowers to common industry and Chaebol effects.

To determine changes in the values of credit exposures, we first transform each index *y(i)* into its corresponding discrete risk rating. For the i^{th} obligor in the credit state *g(i, 0)* at the beginning of the six-month simulation period, we obtain the credit rating at the end of the period *g(i)*, as follows:

$$g(i) = \begin{cases} g_1 & \text{if } y(i) > b(2, g(i,0)) \\ . & \\ g_n & \text{if } b(n+1, g(i,0)) < y(i) \le b(n, g(i,0)) \\ . & \\ D & \text{if } y(i) < b(D, g(i,0)) \end{cases} \qquad (13)$$

Here $g_n \in \{g_1, \ldots, D\}$ denote the discrete risk grades, with D representing default. We get the thresholds *b(n, g)* that determine the ratings bins from the six-month transition matrix. In particular,

$$b(n, g) = \Phi^{-1}\left(\sum_{k=1}^{n} p(g, g_k)\right) \qquad (14)$$

Here Φ^{-1} denotes the inverse normal probability function, and the variables $p(g, g_k)$ represent the unconditional probabilities of moving from risk grade g to g_k over six months. We may also illustrate this process of determining the ratings thresholds (Exhibit 8).

Having determined a simulated rating (or default), we look up the simulated end-of-period value of the credit obligation in the appropriate table derived from the pricing model.

For equity, we used a simple approach to revaluation. Based on direct analysis of the volatility of a company's stock price or on an average value for companies of similar size, we assume that the equity value per share would change as follows:

$$\Delta(\ln(E(i))) = r(i) + \sigma(i) y(i) \qquad (15)$$

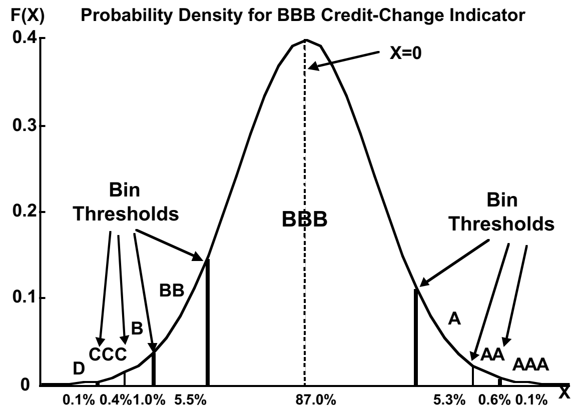
Here *E(i)* denotes the share price for the ith obligor, *r(i)* the expected equity return for companies comparable to obligor *i*, and $\sigma(i)$ the 6-month volatility of equity in that class.

Given this framework, the estimation of VAR involves:

- drawing several runs of the systematic factors *z(j)* from an appropriate multivariate, normal distri-

EXHIBIT 8

Credit Metrics™ Framework for Determining Ratings Bin Thresholds*



*See, "CreditMetrics: The Benchmark for Understanding Credit Risk"(technical document, J.P. Morgan, New York, 1997).

bution and the idiosyncratic factors *u(i)* from independent normal distributions,

- calculating the values of *y(i)* and *g(i)* for each simulation run,
- looking up in the proper revaluation tables the simulated values for each debt exposure within each simulation run,
- using the simple formula to revalue equity exposures within each simulation,
- summing exposure values within each simulation and tabulating the valuation results across all of the simulations, thereby producing the overall VAR distribution and various component distributions.

IMPLEMENTATION CHALLENGES IN THE FIRST YEAR AND SUGGESTED SOLUTIONS

We review now some implementation challenges encountered by Hanvit Bank in the first year of using the CRMS system. In revisiting the CRMS project one year later, we expected to find implementation incomplete. The changes being made were extensive and, from the start, we foresaw a multiyear implementation involving continuing knowledge transfer and learning by doing. Here, we focus on the four key decision-support applications highlighted above: *risk rating, pricing, limits,* and *credit VAR*. In some cases, Hanvit needed to make minor adjustments to resolve unforeseen problems. In other cases, the bank may need to upgrade functionality so as to satisfy evolving regulatory requirements. Finally, some of the implementation issues reflect a need for ongoing communication of the features of the new systems.

ADAPTING THE RATINGS SYSTEM

As a central feature of the loan approval process, the new ratings system has been used more extensively than any other CRMS component. It comes as no surprise, therefore, that Hanvit has found need to fine-tune the ratings system more than the other CRMS capabilities. The system requires added features to deal with exceptional cases, noisy and missing data, and general calibration.

Handling Exceptional Cases

Early on in testing the quantitative scoring part of the ratings model, bank employees discovered that the results appeared overly favorable for companies already in workout. Further research revealed that many of the workout companies had received concessions on interest and principal due, and this relief distorted measures of cash flow relative to debt service and asset value relative to debt. This suggests a simple solution. The rating system should classify all companies in workout due to nonpayment of interest or principal as "in default," the lowest quality rating grade. The scoring model and the rest of the usual ratings approach would apply only to companies not already in default. To implement this change, one needs to screen for companies in workout.

Filtering Noisy Data and Imputing Missing Data

As noted above, the quantitative scoring model estimates a borrower's annual default probability based largely on measures of balance sheet and cash flow "default distance." To derive these indicators for a company, one must estimate the annual volatility of gross cash flow and of book asset value. In both cases, we use five annual observations in calculating volatility from historical financial results. This seems to provide the right balance between sampling error and coverage. Using fewer observations would make the volatility estimates too noisy. Requiring more would cause many companies to fall short of the scoring model's data requirements.

This compromise doesn't work well in every case, however. In using the ratings system, Hanvit employees have observed that, often when they override the scoring model, one or both of the volatility estimates has an extremely high or low value. This indicates that one needs to filter the volatility measures obtained by direct calculation.

One could use instrumental variable techniques as the filtering procedure. In this case, one applies statistical regression to the overall sample of calculated volatility measures in determining equations that predict volatility on the basis of relevant variables observed with small error such as company size and industry composition. One then uses these equations in adjusting the directly calculated measures of cash flow and asset volatility, if those measures fall outside a chosen range of reliability. For example, as a possible filtering rule, one could compare the calculated value with a two-standard-deviation prediction interval. Then, if the calculated value fell outside that range, one would replace it with the value at the closest end of the interval. Of course, one might use other filtering rules involving weighted averages of calculated and predicted values.

Early tests demonstrate that such filtering mostly eliminates discrepancies between the scoring results and the final ratings in those cases of judgmental overrides.

The prediction equations also offer a way of dealing with low coverage of comparatively new companies. Bank employees want to extend use of the scoring model to companies with a financial history of at least two years but less than the five years set as the standard for computing volatility. To make this possible, one could use the volatility equations explained above in imputing values for companies with too few observations for direct calculation. In effect, one would impute volatility for a new company based on the average volatility value calculated for older companies with the same size and industry composition.

This approach has two apparent problems. To start, older and newer companies with the same size and industry composition may differ in volatility if age itself affects stability. Further, new companies typically are smaller than older ones. Thus, the sample of similarly sized older companies may be small.

One might address some of these concerns by testing the imputation method as part of the default-model estimation. In this test, one would calculate cash flow and balance sheet default distance using the predicted volatility measures in place of the directly calculated ones. One then would fit the default model a second time and determine the loss in explanatory power. This would quantify the risk inherent in the imputation process. Note, however, that the use of filtered data could actually improve the model's predictive power.

Evaluating the General Calibration of the System

Recall that we used a somewhat arbitrary reweighting of the separate yearly results in calibrating the default model. We reweight, giving the 1996 results double the normal emphasis, so as to reduce the bias inherent in a sample dominated by the 1997-98 Korean economic crisis. Some bank staff members have suggested that we reexamine this calibration method. We could compare the current calibration with that implied by a Merton-type model based on current equity prices. This might suggest a more accurate and objective way of establishing *future* expected default rates.

We could make the comparison using KMV default rates.[8] Alternatively, we could use the Merton-type model estimated during the development project in computing default rates. In either case, for Korean companies with listed equity, we would compare these other estimates of default rates with those from the current scoring model. Any systematic deviation could motivate a better calibration. For example, suppose the average default rate from the equity-based model fell short of the average from the scoring model by 20 bps. Then, we might consider adjusting down the constant term in the scoring model by that amount.

MAKING THE PRICING MODEL MORE USEFUL

To this point, lenders at Hanvit haven't used the pricing model as a routine part of loan administration. This may reflect unfamiliarity or unease with the concept of value-based lending. The risk management group has continued to experiment with the pricing model, although, they have had difficulty updating the model's calibration to market data on an ongoing basis.

Expanding Awareness of Value-Based Lending

Lenders at the bank still often think of approved loans being priced basically the same using standard rates. They view the pricing model, therefore, much more as a calculator for determining those standard rates than as a tool for helping relationship managers negotiate the pricing and other terms of individual loan agreements. Under this later view, the pricing model helps determine not the reference rate but the spread relative to the reference rate that along with the other loan features delivers the highest, possible value to the bank. This involves decentralized negotiation of the best possible, customized loan contracts, including both price and loan structure. We call this "value-based lending."[9]

For Hanvit to use the pricing model to full advantage, bank executives must become comfortable with and bank staff familiar with value-based lending. At that point the model would receive wider use, and relationship managers would uncover more implementation problems to be solved by modifying the application.

Making Calibration Simpler

The risk-management staff reports having difficulty calibrating the pricing model to more current data. The model was set initially to reconcile broadly with spreads over AAA yields observed in the nascent Korean bond market in late 1999. After collecting the bond-yield data at that time and using the default rates of the scoring model, we grouped the yields according to each issuer's annual default rate and the issue's remaining time to maturity. After removing the highest and lowest values, we formed averages for each bin and constructed spreads by deducting indicative AAA yields. We next smoothed the raw spread data by fitting an equation of the following form:

$$spread = ELR + ULR \doteq LIED \cdot EDR + \rho \cdot LIED \cdot \sqrt{EDR(1 - EDR)} \qquad (16)$$

Here *ELR* denotes the expected loss rate, *ULR* the unexpected loss rate (pure risk premium), *LIED* the loss in event of default rate, *EDR* the annual average default rate, and ρ a parameter to estimate. This formula assumes that one can approximate the par spread rather accurately as a sum of two components: the expected annual loss rate and a term proportional to the loss rate annual standard deviation. The second term includes a general factor ρ, the one parameter that we estimate in fitting to market spreads. As the shortest time to maturity with a substantial sample, we use three-year bonds in this smoothing and in the rest of the calibration steps.

In calibrating the pricing model, we use this formula in determining par spreads for each risk grade. Take, for example, a risk grade with an annual default rate of 50 basis points (bps). Then, assuming a value of 0.15 for ρ and 60% for *LIED*, we get a par credit spread for this risk grade as follows:

$$spread = 0.600 \cdot 0.005 + 0.15 \cdot 0.600 \cdot \sqrt{0.005(1 - 0.005)} \doteq 0.0093 \qquad (17)$$

In the pricing model, such spreads determine the implicit costs of self-insuring against credit loss at each quarterly time step and possible risk grade over the life of the loan. In computing a loan's NPV, the model deducts the implicit insurance premium at each possible risk grade at each future date and averages the net cash flows over all of these nodes using a transition matrix for determining the probabilities. This neglects some fine points, such as the difference in risk between a one-year grade-3 loan and the first year of a five-year grade-3 loan. However, many of the bank's loans have one-year tenor and most of the rest two- or three-year tenors, so this simplification does little harm.

To update the calibration, one must gather current data on bond spreads, re-estimate the formula (17), and compute a standard spread for each risk grade in the manner just described. The grouping and averaging of the bond yields involve routine database procedures. The smoothing of the spreads involves an existing regression procedure. The bank's biggest challenge lies in creating easy access to the best available data on bond yields. Given the immaturity of the Korean bond market and the volatility of the Korean economy, the bank probably needs to review the pricing model's calibration at least quarterly.

INCREASING TRANSPARENCY OF THE FULL FUNCTIONALITY LIMITS MODULE

So far, Hanvit hasn't used the full functionality of the limits module. The bank instead has used the simplified version that limits lending to the point at which increased debt would create theoretical bankruptcy. In an advanced economy, such a high lending limit would seem reckless. In Korea, where lenders provide much of the capital to fuel the expansion of volatile growth firms, comparatively lenient limits may make some sense.

In any case, the system now being used focuses entirely on the financial status of the borrower in isolation. It doesn't consider whether additional lending to a company enhances or diminishes diversification in the bank's overall portfolio of exposures.

The limits module with full functionality includes this added layer of sophistication. Reflecting the view that limits should constrain *incremental* lending where it adds more than an agreed-upon threshold amount of risk to the bank's portfolio, the full-limits module considers both portfolio concentration and the effect of increased debt on the borrower's creditworthiness.

The full-functionality module applies a formula that approximates the marginal VAR of an additional small amount of lending to the borrower. We use an approximation so as to avoid going to the VAR model in making routine limits checks. In terms of implementation, the full functionality of the limits module was quite sophisticated relative to the bank's experience; the CRMS project team is still experimenting with the approach and has not started to use this module directly.

In this case, we need to communicate better the advantages of the unused functionality of the limits system. The bank then may make a more informed decision on the way it wants to manage limits. It could now, for example, choose to discard the approximate marginal VAR formula and instead integrate the credit-VAR model into the limits process.

ENHANCING THE CREDIT-VAR MODEL

The credit-VAR system developed for Hanvit includes several advanced features. It provides for distinct treatment of equity, bonds, derivatives, loans, and payment guarantees. For all classes of debt, it applies highly detailed factors determining the value change upon borrower upgrade or downgrade. These detailed factors differ depending on the instrument's tenor, utilization, and LIED rate. Finally, its correlation structure recognizes shared risks related not only to industries but also to affiliation with a Chaebol.

In trials of the credit-VAR module thus far, here are some of the implementation issues that the staff faced.

Adding Calibration Portfolios to VAR Runs

VAR models involve complicated structures that draw on disparate information sources. One must test the model and its calibration by comparing the simulation results with the risk characteristics of actual portfolios.

To conduct this testing, we've added diversified portfolios of hypothetical high-yield bonds, leveraged loans, and equities to the VAR runs. We compare the simulated returns and variances of these portfolios with the same statistics for Korean stock indexes and U.S. high-yield-bond and leveraged-loan indexes. In the future, if Korean bond and loan indexes appear, we would use those benchmarks in calibrating the VAR model.

Initial tests revealed that the simulated equity returns matched the external benchmark almost exactly. The simulated bond and loan-index variances fell slightly below those of the external benchmarks. Thus, the bank may need to make small, systematic upward revisions to its assumptions governing the shares of company creditworthiness that derive from systematic factors.

Discovering a Need for Added Functionality

The financial regulatory agency in Korea asks that banks calculate VAR over an annual time frame and determine loan reserves so as to cover anticipated losses over one year. The VAR model could provide both sets of figures if it were run over a one-year horizon.

The current VAR model simulates outcomes over a single, six-month period. We selected six months so as to avoid the problem of forecasting the bank's reinvestment of funds provided by maturing loans. In ignoring reinvestment, the model implicitly assumes that the creditor places the proceeds from maturing loans into risk-free assets.

Many of the bank's loans have a one-year term. Most of the rest have two- or three-year tenors. In a six-month analysis, therefore, one probably underestimates risk only a little by ignoring the reinvestment problem. In a longer-term analysis, however, the underestimate would become large. Thus, in estimating VAR over more than a six-month horizon, one can hardly ignore the reinvestment issue.

The bank can solve this problem by establishing plausible rules for reinvestments of principal from maturing loans and of recoveries of principal from defaulting loans. In addition, the bank might upgrade its VAR model to a multistep simulation tool.[10]

One possible reinvestment rule derives from the bank's studies of credit-line usage. These studies show that the bank grants tighter credit lines to lower-rated (higher-risk) borrowers.

The reinvestment rule could assume that the bank continues to do business with its current customers and those customers will need the same amount of credit. If a customer stays at the same credit grade, one assumes that the bank renews the loan with no change. However, if a customer falls to a lower-quality credit rating, one assumes that the bank will renew the loan with a tighter commitment limit. If the customer rises to a better credit rating, one assumes that the bank will renew the loan with a more generous commitment limit. The bank may use its studies of credit-line usage in determining the extent of the tightening or loosening of the commitment limit upon loan renewal.

In the case of default proceeds, one probably would not assume reinvestment with the same customer. In this case, one might assume that the bank loans the money to a pool of hypothetical average new customers. The bank might look at recent new customers in determining the composition of this pool.

The multistep VAR procedure could run at a quarterly or monthly frequency. Assume that quarterly proves sufficient. In this case, the model would run a series of simulations, each involving several quarterly periods. At the end of each quarter in a simulation, the model would account for defaults and loan renewals and apply the reinvestment rule in keeping the bank fully invested over the full simulation horizon. We would then determine VAR from the range of values obtained across all of the multiquarter simulations at the specified time horizon. Indeed, from a single simulation set, we could get VAR for many different time horizons including one year.

One also could derive an expected amount of loan losses over one year. In this case, one would merely keep track of defaults and losses in the simulation runs and sum the default losses over a year in each simulation. To get the expected value over a one-year horizon, one would average the one-year loss totals from all of the simulation runs.

In closing this section, we note that our discussion assumes that the Korean regulators want banks to hold capital today to cover the portfolio losses the might occur over the next year on both existing exposures and on new exposures originated during the coming year. Instead, the regulators may want banks to hold capital today to cover potential losses only on the current book of exposures. In this case, we would not include reinvestment as part of the multistep simulation.

PROSPECTS FOR MOVING FORWARD

The potential for continued economic instability in Korea presents a dilemma. To engage in banking, Korean banks must bear risks much greater than those assumed by their counterparts in developed nations. To be secure with those risks, the banks need abundant capital. But capital is scarce in Korea.

A risk-management system may deliver its greatest benefits in good times by preventing an institution from taking uncompensated, high risks in advance of a possible economic decline.

To get out of this trap, Korean banks need a thriving Korean economy. The best risk-management system can do little to prevent the demise of capital-poor banks in an economic crisis. Indeed, in such a situation, the risk-management system may in effect advise exit from the business, which is what may happen anyway if the institution fails.

Ironically, then, a risk-management system may deliver its greatest benefits in good times by preventing an institution from taking uncompensated, high risks in advance of a possible economic decline. So assuming that the Korean economy achieves reasonable growth over the next few years, Hanvit needs to continue to use the new CRMS.

Hanvit then needs to understand that when the pricing model recommends a higher spread, that when the limits system advises restraint, and that when the VAR model suggests moderating exposure in growth areas, the risk-management system is preparing the institution for the next possible economic decline. Further, to get the best signals from CRMS, the bank needs to support ongoing training and assessment of the model outputs, keep the system in tune, continue to calibrate to new data, and add new functionality in response to the demands of a dynamic lending and regulatory environment.

SUMMARY

The Asian crisis and the associated regulatory response forced many of the largest Korean banks to revamp their lending operations and improve their risk-management activities. The CRMS project at Hanvit Bank described in this Korean case study involved an extensive overhaul of most of the key components of credit-risk management. The CRMS included development of improved business processes and better information-technology solutions. Above all, however, the project focused on creating integrated, best-of-breed analytic applications that would enable the bank to measure credit risk more accurately, to price loans more appropriately, and to manage credit portfolios more intelligently.

Hanvit chose to roll out the new capabilities on an accelerated schedule, without the benefit of extensive and expensive acceptance testing. Revisiting the project one year later, we find that the bank has mostly implemented the highest-priority component, a new risk-rating system. The bank has been slower in using the pricing, limits, and portfolio-management modules, with which it is still experimenting. To move ahead, the bank now needs to develop some practical approaches to filtering selected credit data, calibrating the credit models, and training bank staff in the use of the new applications. Also, in response to new regulatory requirements, the bank needs to upgrade its credit-VAR application to support multistep simulations.

While this case study focused on the largest Korean bank, all banks around the world face, in varying degrees, the same credit-risk challenges. With the Bank for International Settlements (BIS) about to provide banks with a detailed framework for using internal models for managing credit risk, some of the largest North American and European banks could find it advantageous to consider aspects of this "Korean approach" to integrated credit-risk management.

ENDNOTES

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The views and opinions are those of the authors and do not necessarily represent the views and opinions of Algorithmics Incorporated.

[1]This project was carried out in 1999 in Korea for Hanvit Bank, while Forest and Aguais were members of the KPMG Consulting-Risk Solutions Group. Hanvit Bank was formed at the end of 1998 by the merger of Commercial Bank of Korea and Hanil Bank. The general methods described here represent approaches to advanced credit-risk modeling developed over more than 12 years of research on this subject.

[2]The approach implemented here is patterned after the approach initially developed by the KMV Corporation to assess expected default behavior. See, P. Crosbie, "Modeling default risk," working paper, revised, KMV Corporation, January 1999.

[3]The credit-pricing application developed for Hanvit is a simplified version of the pricing models outlined in A. K. Ginzburg, J. Maloney, and R. Wilner, "Debt rating migration and the valuation of commercial loans," Citibank Portfolio Strategies Group report, December 1994, and S. D. Aguais and T. Santomero, "Incorporating new fixed income approaches into commercial loan valuation," *Journal of Lending and Credit Risk Management* 80, no. 6(1998): 58-65. For a more recent discussion see, S. Aguais and L. Forest, "The future of risk-adjusted credit pricing in financial institutions," *The RMA Journal* (November 2000): 26-31.

[4]This doesn't imply that the creditor actually obtains credit insurance, which is rarely done. However, the creditor must either insure away the risk or self-insure by holding capital. In either case, the economic costs are the same, which are usually referred to as "unexpected losses." See, B. Belkin, L. Forest, S. Aguais and S Suchower, "Expect the unexpected," *Risk Magazine* (November 1998): 34-39, for a discussion of the credit-risk insurance premium approach.

[5]We're abstracting here from the risks involved in collection.

[6]When defaults or downgrades occur, the related equity values typically fall much more than the debt values. Thus, one would underestimate the risk posed by movements in systematic credit factors, if one were to exclude equity from the simulations for banks with substantial equity holdings. In the recent case of Korea, many of these equity holdings resulted from credit restructurings and should therefore not be confused with traded equity. It was for this reason that this type of non-traded equity was included in the credit VAR simulations.

[7]The approach to modeling shared, systematic factors in credit-VAR models follows on work described in B. Belkin, S. J. Suchower, and L. Forest, "The effect of systematic credit risk on loan portfolios and loan pricing," *CreditMetrics Monitor* (April 1998): 17-28, and, B. Belkin, S. J. Suchower, and L. Forest, "A one parameter representation of credit risk and transition matrices," *CreditMetrics Monitor* (October 1998): 46-56.

[8]KMV Corporation's products provide expected default frequencies (EDF™) for both public and private companies.

[9]For a discussion of the trade-off inherent in structuring loan contracts see, Aguais, S. D., L Forest, S. Krishnamorthy, and T. Mueller, 1998, "Creating value from both loan structure and price," *Commercial Lending Review*, 13(2):13-24.

[10]For an example of a multi-step credit-VAR approach see, I. Iscoe, A. Kreinin, and D. Rosen, "An integrated market and credit risk portfolio model, *Algo Research Quarterly*, 2, no. 3(1999): 21-37.