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CORPORATE CREDIT SCORING MODELS: APPROACHES AND STANDARDS FOR SUCCESSFUL IMPLEMENTATION

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Abstract

A number of banks have recently undertaken a reassessment of their credit-lending process. The banks' endeavors coincided with the efforts of a small, but growing number of vendors who have developed systems to assess both public and private corporations. The purpose of this article is to define the qualities of a carefully developed and rigorously tested credit modeling system for assessing the attractiveness of lending opportunities. We identify and discuss several types of credit evaluation systems and their relative importance. These systems are classified as primary ("ground up" or "firm-intrinsic" approach) and supplementary ("top-down" or "firm capital market") approaches. The crucial step in evaluating any of these systems is the thorough testing of the results and the establishment of rigorous standards for acceptance. In addition to these standards, we discuss the role that an acceptable credit system can play as the link between individual loan assessment and logically derived estimates of expected loss rates and loan pricing criteria.

I. Introduction

In the July, 1994 issue of the **Journal of Commercial Bank Lending**, P. Henry Mueller's article, "Credit Policy: The Anchor of the Credit Culture" posits that:

- *"The convulsions that followed the excesses of the 1980s stemmed from the breakdown of standards and disciplines, which in turn, undermined systems and cultures."*
- *"If a credit system is not properly supervised, the marketing and profit center initiatives... invite conflict of interest, flawed judgments, and an erosion of the bank's credit ethic."*
- *"attempts at credit risk management are fruitless if a bank's credit culture lacks needed disciplines."*
- *"For a bank, credit policy is like an anchor from which a boat swings with wind and tide. While the boat's position shifts with changing conditions, the anchor keeps it from drifting. So too, can a strong credit policy keep a bank tied to the bedrock of basic credit standards."*

Mr. Mueller is eloquent in identifying many of commercial lending's most important problems. These include subjectivity (lack of detached judgment), short-term horizons (poor recollection of the bank's past lending mistakes), breakdown of basic credit standards, and lack of independent supervision. In short, the lack of "needed disciplines." We are less sanguine than Mr. Mueller that any amount of "trying harder" will improve the credit culture without the introduction of additional quality control tools.

Most commercial lending institutions have an internal credit rating system which plays an integral role in their overall lending process. Indeed, many institutions are now reassessing their systems in view of the dismal performance of past techniques, particularly in the 1990-1992 period in the United States and Australia and the 1992-1994 period in Europe and parts of Asia.

As reported by Wuffli and Hunt (1993), existing credit rating approaches often reflect the subjective preferences of account officers and their superiors rather than the underlying credit risks of the client. Such systems are often applied selectively by different branches of the same bank. This results in a rating for a client which differs according to who is performing the analysis. In addition, many internal rating approaches yield a fuzzy, ordinal risk ranking of potential and existing customers, without a clear and objective indication of the expected loss function associated with the rating given. For example, a rating of 2 in a 9-grade rating system is deemed to be superior to a 3 and worse than a 1, but contains no analytical guidelines to assist account officers, central credit departments and senior bank management in assessing expected losses and the pricing of loans. Finally, banks have become very interested in whether or not a form of modern portfolio analysis can be legitimately and effectively applied to bank portfolios, as well as the view that a loan can be analyzed as a "security", to be bought and sold in a manner similar to what equity portfolio managers practice.[1] In summary, doubts about the consistency of

[1]See, for example, McAllister and Mingo (1994) for a recent summary of banking industry practice in loan portfolio risk management.

subjective credit ratings, a desire for more precise mathematical "definitions" of credit ratings, and issues associated with portfolio analysis have marshalled a great deal of interest in objective, reproducible credit rating models.

As a result of these conditions, a number of banks have recently undertaken a reassessment of their credit-lending process. The banks' endeavors coincided with the efforts of a small, but growing number of vendors who have developed systems to assess both public and private corporations.[2] The purpose of this article is to define the qualities of a carefully developed and rigorously tested credit modeling system for assessing the attractiveness of lending opportunities. We identify and discuss several types of credit evaluation systems and their relative importance. These systems are classified as primary ("ground up" or "firm-intrinsic") and supplementary ("top-down" or "firm capital market") approaches. The crucial step in evaluating any of these systems is the thorough testing of the results and the establishment of rigorous standards for acceptance. In addition to these standards, we discuss the role that an acceptable credit system can play as the link between individual loan assessment and logically derived estimates of expected loss rates and loan pricing criteria.

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[2]While these models are not revolutionary, see Altman (1970), they are being scrutinized for practical implementation like never before.

Primary Credit Anchor: The Firm-Intrinsic Approach

The first tool needed is a standardized way of measuring the inherent or "intrinsic" risk of the borrower. This tool is the anchor that is fundamentally sound and grounded in history, is uninfluenced by fads, measures the risk of default (or loss), and produces consistent results across time and for a wide range of borrowers. The anchor should serve credit policy as a common credit language and quality control feedback mechanism. The bank should use the system as a yardstick to further investigate borrowers that don't "measure up." The bank must act when the yardstick's warnings cannot be reconciled with respect to a well conceived bank strategy or explained by other information.

A firm-intrinsic credit model is one that uses specific information about a company, primarily its financial statements. Measures of profitability, liquidity, and capital structure are usually important components of a firm-intrinsic model. Capital market prices and evaluations can be used in tandem with financial statements to further enhance the effectiveness of such models. These indicators are combined into a single measure of corporate vulnerability called a credit score. The objective of a firm-intrinsic credit model is to estimate the similarity of any individual company to hundreds of other companies that have compromised their creditors. The firm-intrinsic approach provides the benchmarks and feedback needed for rational credit grading and loan pricing. Perhaps the most prominent model of the firm-intrinsic type is the ZETA® credit scoring method (Hoboken, New Jersey).

In our opinion, the firm-intrinsic approach provides the best anchor for stabilizing the credit culture because it is rooted in accounting fundamentals and time-honored, rigorously tested principles of credit analysis. As such, it provides the best method for measuring a borrower's intrinsic, largely undiversifiable risk. If enough data exists for empirical validation, the risk can be quantified in terms of an estimate of the probability of default.

Many published models are built by a process that resembles cooking a stew. Variables or ratios are thrown into a "pot" and "stirred about" until they seem to predict something in a test sample. Most creators of firm-intrinsic models have done minimal testing of their products. This article stresses the importance of an objective and well tested anchor.

- *"Objective" means some form of statistical or mechanical process that produces a rating which is independent of human opinion. Mechanical rating systems are usually referred to as "models."*

- *"Well tested" is a many faceted concept. Some tests are associated with setting up a credit modeling system while others are associated with using and maintaining one over time. Creating a model requires a period of intense testing for a relatively short period of time. However, using and maintaining a model requires a continuing commitment to a variety of tests and support activities.*

Do all firm-intrinsic models have equal validity? Not any more than all bankers have equal ability to rate credits. Three of the most important aspects of testing any credit rating system are:

1. Sensitivity of ratings to real changes in credit quality.

2. Lead time with respect to recognized real changes in quality.

3. Stability of ratings where no real change has occurred.

These issues apply as much to existing subjective rating systems as to objective models. Perhaps one of the biggest problems for bank systems is that they are too slow to recognize real changes. For good reasons, banks wish to avoid false alarms in ratings. Lowering a rating can have negative consequences for a relationship with a borrower. There is a tendency to give the customer the benefit of the doubt, to wait and see if it can work things out on its own. Unfortunately, the reluctance to recognize the truth about a borrower can lead to problems if real deterioration takes place. Therefore, choosing a credit model for an anchor should involve a series of tests:

#1 The Clear-Definition-of-Risk Test

The first step is understanding what the model measures. As noted above, any credit system should be sensitive to *real change* in credit quality. This is why most models use conditions such as bankrupt/non-bankrupt or default/non-default as the testing criterion. Less useful, but still relevant, are models which are designed to classify companies into bond ratings or bank loan grades. A criterion such as bankruptcy/non-bankruptcy is preferable because the classifications are less subjective than ratings. Bankruptcy is a fact! A bond rating or loan grade is a subjective opinion; leading rating agencies often do not agree with each other on a surprisingly large number of cases. And, we know that bankers often disagree as to the "appropriate" risk grade. Models that are designed to duplicate "expert opinion" accept highly subjective decision criteria.

#2 The Model-Development Test

The process of model development involves statistical testing in some, but not all, cases. Many statistical techniques are available, but the actual technique is less important than the definition of risk and the care with which explanatory variables are defined, the data collected and the model is tested.

There are a number of aspects of performance measurement. With respect to the typical measurement criterion of bankruptcy/non-bankruptcy, performance is usually measured in terms of error rates -- typically Type I and II errors. Type I errors occur when the model classifies (or "predicts") bankrupt companies as non-bankrupt. Type II errors occur when the model classifies non-bankrupt companies as bankrupt. Error rates assume a single cutoff point and a simple decision rule: accept all companies with scores above the cutoff point and reject all companies with scores below the cutoff point. Error rate measurement is generally intended to evaluate the sensitivity of ratings to real credit quality changes. But there is more to performance measurement than this, even in the testing stage.[3]

Development Sample - This is the sample used to develop a model. The information from this sample is used to define the relationships between the model's variables. The statistical methodology involved creates variable weights or other relationships that allow maximum separation of bankrupt and non-bankrupt companies. The methodology provides a "cutoff" point (or other decision rule) that would achieve the maximum separation between the two groups. It also reports the model's Type I and Type II "error" rates. While development sample accuracy plays a part in the building of a model, it tells users *nothing* about how a model will perform and may be based on unrealistic assumptions about the costs of errors.

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[3]Should a bank feel it necessary to begin from scratch in its ground-up model development, there are a number of additional considerations. The process begins by developing financial and capital market data of individual firms comprising clearly identifiable, unambiguous groupings (e.g., bankrupt vs. non-bankrupt, default vs. non-default, etc.). The variables used to establish the credit model are primarily financial ratios derived from financial statements at various points prior to the credit-event. These ratios can be supplemented by capital market data such as stock and bond prices and their resultant equity and debt values. The firm specific variables are then rigorously analyzed by statistical methodologies such as parametric discriminant, logit or probit classification techniques, non-parametric methods such as recursive partitioning analysis or expert systems such as neural networks. These techniques, with the exception of the last one, all have the important quality that they are essentially transparent to the analyst, can be understood, rigorously analyzed, tested, and compared with existing techniques.

Univariate ratio studies evolved from early works in the 1930's and 1940's and were popularized in the modern financial literature by Beaver (1967, 1968). Multivariate approaches using discriminant analysis are found in the first works of Altman (1968), Orgler (1970), Deakin (1972) and finally improved upon by Altman, Haldeman, Narayanan (1977). Altman's 1968 Z-Score model has become the standard comparison in the literature while the Altman et al ZETA® approach is another standard amongst practitioners and also by scholars (e.g., by Scott [1981]). Works using logit-regression models can be found (Zmijewski [1984]), Ohlson (1980) as well as other similar parametric techniques. Frydman, Altman and Kao (1985) used recursive partitioning analysis, and in the former case, compared results to discriminant techniques. And a number of recent efforts, e.g., Coats and Fant (1993) and Altman, Marco and Varetto (1994) have attempted to model the firm distress process using the non-transparent, black-box, neural network approach.

Holdout Sample - The second aspect of performance is how the model and its cutoff or decision criterion works with companies that were "held-out" of the original test. The errors reported on the hold-out test are much more representative of a model's expected performance than are the development, or training sample, error rates.

Lead Time - The next aspect of performance is how far in advance of bankruptcy the bankrupt companies were correctly identified. For each year prior to bankruptcy, the more bankrupt companies falling below the cutoff point, the better. Most studies try to report Type I or Type II error rates for 3-5 years. Once again, hold-out sample error rates are more representative of true performance than development sample rates.

Another question regarding "lead time" is from what period of time prior to distress should the original model be trained or developed. Advocates of the most recent data prior to distress, including this writer, argue that the samples of sick and healthy firms will be most dissimilar at this point and a "true" profile of such firms can be established. Advocates of more distant training samples (e.g., Deakin, 1972) argue that if the model is still accurate based on more distant data, it will likely be a more effective early warning indicator. There is no clear, correct answer to this question but we have encountered ambiguities in the more distant approach when a 3-year prior training classifies a truly distressed firm as distressed, for example, and a less distant model (e.g., 2-year) gives the same firm a healthier classification.

Range of Scale - The real world of credit seldom presents a clear accept/reject situation. The credit culture requires assignment of the borrower to one of several (usually about 7 to 9) credit grades. Each of these credit grades can be considered as representing a different cutoff rule. For example, "Accept 1 through 5, reject 6 through 9." These decision rules each have a different set of Type I and Type II errors. Understanding the success of a credit model over the whole range of credit scale is quite important, but few models will have enough data to assess these error rates. It requires accumulating enough information about non-bankrupt and eventually bankrupt companies in each credit grade for a number of years before bankruptcy.

Summary - The Model Development Test is really a series of fairly well established procedures designed to understand the efficiency of a model. The decision about which model to accept is usually a matter of accepting the one which is most accurate and robustly versatile.

#3 The Test-of-Time

Most creators of new models are understandably "excited" about them. Even if a thorough statistical job has been done, however, all "predictions" made by the model are done in hindsight. An important quality of a credit model is its ability to hold up over time, in good business climates as well as bad. Conditions are always changing with respect to the factors that influence measures of performance of a model (accounting, macroeconomics, stock market P/E ratios, inflation, etc.). A good model should perform well although conditions change. But performance should be verified and validated on a continuous basis. Validation tests take advantage of predictions that the model has made "subsequent" to its initial development. The kinds of tests required are similar to model development tests in that they are intended to measure changes in credit quality and the lead time with respect to recognition of real changes.

There is no need for a model's coefficients to be changed or "re-estimated" if the re-estimated coefficients can't do better on independent hold-outs than on the original model's observations. But, there should be a rigorous program to keep track of bankrupt and defaulting borrowers and to monitor the success rate of an existing model. It requires a considerable amount of data and testing to analyze error rates, develop probability of bankruptcy (or loss) functions and instill confidence in the anchor of the bank's credit culture. The results of development and hold-out testing are usually only a starting point. Model building rarely involves enough data to fully understand a model. As a model seasons and is exposed to new companies and new economic scenarios, it can be evaluated in a way that is more valid than in laboratory hold-out testing. In essence, "the truth is in the eating of the pudding", not in the making of the model or how elegant the mathematics.

A credit model should probably not even be considered if it has not been tested with at least several hundreds companies over a ten year test period. With the passage of ten or fifteen years, a model can make "ex-ante" predictions for many thousands of companies, particularly if it is applicable to privately held entities. Predictions can be compared with performance and this performance can be compared with other credit measures (such as bank rankings or bond ratings). Data is eventually rich enough to allow estimation of loss functions and perhaps even the timing (mortality) of the loss. Such experience allows much more confidence in the meaning of credit ratings. Unfortunately, this requires that a model be developed at least 5-10 years prior to the prediction tests.

#4 The Stability Test

A legitimate concern about mechanical, objective rating systems is whether they are <u>too</u> volatile. Do they change when, in fact, no fundamental change has occurred in the company? Some do. "Noise" results when there are short-term, dramatic fluctuations in credit ratings even though no fundamental change has occurred.

Even more important than in academic research, minimizing "noise" is critical for practical application. Random fluctuations undermine credibility in the pricing and credit approval process. Noise serves no productive role in ongoing credit relationships. Many kinds of information can be associated with credit problems. Some information predicts trouble well. Other information predicts trouble even when it does not occur. The ideal model changes only when the underlying facts about a company also change. A volatile model can change even though the underlying facts don't. Testing for unwanted volatility should be a critical part of the acceptance process.

#5 The Public/Private Test

Due to practical considerations, most model builders' efforts are limited to public companies because of easy access to data. Public company databases are usually more reliable and more extensive than those developed for private companies. This allows for more rigorous initial testing. The Public/Private test is necessary to assure that classification or predictive results for private and public companies are comparable. Hence, it is important to eventually test a public-firm-derived model on private entities.

#6 The Probability-of-Failure Test

The credit scoring model should allow users to associate a probability of failure estimate with each credit rating category. The probability estimates should be based on at least ten years of actual experience regarding ratings and defaults. Actuarial techniques are needed to estimate the probability of failure and the uncertainty (volatility) in the estimate associated with a credit score. For a description of how these estimates may be achieved see the articles by Altman (1989 and 1993) and the applications adopted by Moody's (Lucas and Lonski, 1991) and Standard & Poor's (1991). These procedures and their results are now common standards used in stress test measures by the rating agencies in their evaluations, such as for the appropriate over-collateralization of structured finance instruments.

#7 The Recognition Test

A good indicator of a model's efficiency is whether its ratings have credibility in the financial community. Building a model is not difficult. We have seen hundreds of models developed by regulators, banks, insurance companies, students and academics. Most have been abandoned or ignored. Only a few have been able to stand up to the light of public scrutiny and fewer still have been <u>used</u> and not abandoned by regulators and financial institutions. This is really the heart of the matter -- has the model "earned its stripes?"

#8 The Support Test

Whether a model is developed internally or purchased from a vendor, there are a host of support and implementation issues that have nothing to do with model building. The "model" should be treated as a major system. Installation involves integration with loan accounting systems, data base spreadsheets and report writing software. It involves establishing procedures, systems design, ongoing training of bank personnel and for action on warnings to avoid defaults. A good system should have the flexibility to adapt to changes in the type of information it captures.

Successful implementation requires a strong, although not necessarily large, support staff with a variety of skills:

> ***Credit and Finance*** *-- The basis of a model is the underlying experience of the builders in credit and financial analysis. The model should be built from the ground up by those who understand the variables utilized.*
>
> ***Statistics*** *-- Objectivity is assured by strict application of statistical principals. Continuing application of those principals amounts to quality control.*
>
> ***Actuarial*** *-- Actuarial methods provide the tools to translate credit information into risk-based pricing and portfolio management information.*
>
> ***Systems and Programming*** *-- Experience in installation problems can save endless frustration when implementing credit systems.*

#9 The Pilot Test

The pilot test should be the litmus test for accepting a model. It should be performed on a bank's own data based on 5 to 10 years of information. It should be designed to measure the three previously identified key aspects of risk measurement.

1. Sensitivity to real changes, i.e., known credit problems.
2. Stability in the absence of real changes.
3. Lead time in recognizing changes.

It must also compare model performance with bank performance in each area.

Test samples must be carefully selected so that:

- Large company performance can be compared with small company performance.

- Public companies can be compared with private companies.
- Sufficient defaulted loans are included.
- The range of grades is covered.

If a bank has 7 grades, each grade must have adequate representation in the sample -- at least 20 observations for each grade. Some of these data targets can't be reached because the bank simply does not have enough examples of borrowers in very high or very low grades. The important point is that a substantial investment in bank effort is necessary to effect a realistic test of a credit model, and these are the dimensions that must be tested. Of course, if banks cooperate in a form of a consortium, which includes sharing data, the likelihood of meaningful data representation will be significantly enhanced.

In a proper pilot test, if there is a rating differential between that of a quantitative model and the internal rating system, it should not be viewed negatively. It should prompt, however, a careful examination of the differential by an independent credit group. Questions that are relevant are, for example, was the difference in ratings caused by a secondary source of repayment or guarantee and, if so, was the credit rating of the guarantor sufficiently different from the borrower to warrant the difference? Or, was the collateral adequate to provide a recovery that was close to the bank's exposure on the loan?

Of course, good models should anticipate credit problems which are either unrecognized by the lender or not sufficiently criticized to warrant closer scrutiny. If a model is really effective, it will motivate a reassessment of the loan and perhaps trigger a change in the credit grade by the bank early enough to avoid losses.

One common outcome of a pilot-test which must be avoided is simply to select a model which is most closest in its credit grading to lender opinions. At the same time, a model is suspect if a large proportion of its credit gradings are significantly different from the professional assessment of practitioners at the bank.

Banks that wish to build their own models should understand that the process of developing the kind of information and experience outlined in Tests 1 through 8 could take several years. Pilot testing is a step that presumes the model building phase is over and that some reasonable track record has been established. Commercially developed models have solved many problems that new model builders will not be able to anticipate.

Supplemental Systems: Smoothing Out the Waves

While the primary system is concerned with measuring the intrinsic, undiversifiable, or expected risk, it is also desirable to measure the potentially diversifiable risk. The anchor system, if properly designed, should also serve as a measure of diversifiable risk. The primary, firm-intrinsic approach does this by quantifying the inter-period variation in underlying default (or loss) rates.

Two other approaches claim utility for smoothing out the waves. They are the firm-capital market approach and the firm-econometric approach.

Firm-Capital Market Approach

Building upon the works of Sharpe (1972) and more importantly the option pricing, contingent claims framework of Merton (1973) and others, some models attempt to use the information content of capital market movements to assess the financial vulnerability of firms. Indeed, these models rely almost exclusively on capital market information and firm obligations to assess risk. The key information is considered to be the level and volatility of stock prices. Perhaps the most prominent example of the capital market approach is the KMV Corporation model (San Francisco, CA.

From a positive standpoint, measures of the level and the volatility of stock prices have been shown to be helpful early warning indicators. It is well known that the level of share price as a measure of the firm's equity value is a helpful risk indicator (e.g., see Fisher [1959], Beaver [1968], Altman [1968] and Altman, et al [1977]). To the extent that share price changes reflect the market's change in expected future performance, volatility is again a helpful indicator. An alternative approach uses option-pricing theory, whereby the volatility of share price and its level are used as an estimate of a firm's distribution of asset values. The different values of the assets are utilized to estimate the probability of a firm's becoming insolvent. Since the volatility of the stock price is assumed to be inextricably related to the volatility of the asset's value, it is posited to be a key concept in estimating expected default.

The problem with using measures of volatility as proxies for default is the attendant volatility of the resulting risk measure itself. The practitioner should be wary of any credit scoring approach which swings dramatically in its overall assessment of the firm's health. Usually, however, a multivariate statistical approach will not produce highly volatile scores from period to period since share price or earnings variability are but one of many indicators. On the other hand, a model which assumes market efficiency and is heavily based on the level of volatility of the current share price will quite likely lead to volatile changes in overall scores and probabilities of insolvency. To the best of our knowledge, banks that have employed rating systems which give volatile results have not retained these systems beyond a few years. The challenge then is to produce a market-based model that is not unnecessarily volatile. If inter-temporal changes in the credit scores seem random, user confidence will be undermined.

One of the key appeals of market price volatility as a measure of risk is that there is continuous market price data for public firms, i.e., the data will be timely. For firms that are privately held, however, not only is the information efficiency assumption violated, there is <u>no</u> share price data. To get around this shortcoming, vendors have had to "gerry-rig" what amounts to firm-intrinsic risk rating systems to make private firms fit into the "efficient market" framework. In essence, they are saying, *if* this firm were public, and *if* all relevant information about it were efficiently disseminated, it would behave like certain other firms which are public. Basing default estimates for private companies on the correlation of similar public firms' equity prices is questionable. The "efficient market" assumption presumed by this approach is severely strained when it is applied to private companies.

A second possible appeal of this approach is that it attempts to apply the mean-variance analytical ideas from modern portfolio theory to C&I loan portfolios. Correlations of stock price movements in companies are used to deduce correlations in risk between industries which are, in turn, used to manage the C&I portfolio. The trick then is to simply "diversify" the portfolio by lending to industries that have opposite cycles. If industry A does well when industry B does poorly, and vice/versa, then lending to both will result in less risk (fluctuation in earnings) for the bank. The practical problem for this approach is that both intra- and inter-industry correlations have never been demonstrated to be stable, especially with respect to less functions. A study by the Bank of England (Davis [1993]) confirms this problem with the possible exception of one industry.

Firm-Econometric Approach

While corporate bankruptcy and/or default is basically a micro-economic event, it is obvious that macro-economic conditions add to or lessen the financial stress that firms operate under. Such variables as economic growth, inflation, interest rates, capital market activity, financial institutions, health, and business formations, among others, can and do contribute both to the firm's ability to survive as well as borrower's willingness to support an ailing company. Indeed, Altman (1983) attempted to exploit macro-economic factors in explaining the overall Dun and Bradstreet "Failure-Rate" of US companies. And, models such as DRI's junk-bond failure rate (Wyss, Probyn and de Angelis, 1989) utilize macro-economic and industry-level forecast scenarios on existing firm balance sheets in order to predict future defaults. By aggregating individual firm defaults under various scenarios, an overall bond default rate was reached. In essence, econometric models help to determine probability distributions of firm insolvency. The deterministic variables are macro-economic factors instead of the security valuation concepts of the firm-capital market approach.

An approach which combines the firm-intrinsic methodology, discussed above, with macro-economic, exogenous "shocks" was first proposed by Bennett (1984) and amplified by Chirinko and Guill (1992). This idea takes the firm specific credit rating and then adjusts that rating based on one or more major economic shock scenarios. For example, it assesses the revised rating of all loans if the price of oil per barrel increases by ten percentage points or local real estate values fall by 20%, etc. Both individual and multiple shocks can be simulated with the expected correlation of the shocks becoming relevant as the number of shocks increases. Used creatively, this approach can require senior bank management to specify a tolerance level for the proportion of loans that can be equal to or below a certain level in the risk rating system. It also puts a premium on loans whose change in rating are not highly correlated with the shocks, i.e., negative or low covariance.

This approach requires a considerable faith in the ability of econometricians to model complex relationships between industries and between nations. It lacks the simplicity and convenience of measuring covariances of readily available stock prices. The firm-econometric approach requires a great deal of data and the relationships of economic data between industries need to be shown to be relatively stable -- a questionable combination.

Concluding Remarks

We have tried to identify the key ingredients for an effective credit scoring system. Ultimately, the successfully implemented system will probably contain attributes which lead to accurate assessments and are understood by a variety of individuals who have both a firm-fundamental and a capital market perspective. To be successfully implemented over time, the system must be credible to and accepted by both senior management and the field troops, including loan officers and credit analysts. While the link between the analytical elements of the scoring system is critical, one should not underestimate the comfort factor of a well tested and transparent system to those who will eventually be asked to act upon its signals.

Any model must prove its merit to a group of individuals who are basically skeptical about a system that will improve upon their professional judgments. We feel that the firm-intrinsic approach stands the best chance to be accepted by the various constituents mentioned above. It has proven to be accurate, objective and also understandable to key individuals.

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