INTERNAL CREDIT RISK RATING MODEL

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ABSTRACT

INTERNAL CREDIT RISK
RATING SYSTEM

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The Internal Ratings Based (IRB) approach for capital determination is one of the cornerstones in the proposed revision of the Basel Committee rules for bank regulation. This paper discusses two of the primary motivating influences on the recent development of internal credit scoring models for bank, i.e., the important implications of Basel 2's proposed capital requirements on credit assets and the enormous amounts and rates of defaults. The development of internal credit risk rating system by more prominent credit scoring techniques, Z-Score along with qualitative technique, are reviewed. Finally, both models are assessed with respect to default probabilities. Altman Z-Score model for Asian emerging market obligations is used to contrast estimates across model specifications. Determine the credit rating for blue chip companies like OGDC, PTCL, PSO and HUBCO with their sector analysis. Credit risk rating model is designed by qualitative and quantitative analysis; well same weights are applied for both the analysis in the model.

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GLOSSARY

Basel II	Basel II Capital Accord
IRRS	Internal Risk Rating System
CAR	Capital Adequacy Ratio
IRB	Advanced Internal Ratings Based Approach for
CR	Credit risk
OR	Obligor Rating
FR	Facility Rating
EDP	Exposure Default Probability
LGD	Loss Given Default
M	Maturity
PD	Probability of Default
RWA	Risk Weighted Assets
RAROC	Risk Adjusted Return of Capital
EC	Economic Capital
VaR	Value at Risk
CVaR	Credit Value at Risk

DM	Default Mode
UL	Unexpected Loss
EL	Expected Loss
EAD	Exposure at Default
EDF	Exposure Default Frequency
RR	Risk Rating
UGD	Usage Given Default

Chapter 1

INTRODUCTION

In this chapter I explore the traditional and prevalent approach to credit risk assessment the "internal risk rating" system. Most internal risk rating systems are based on both quantitative and qualitative evaluation. The final decision is based on many different attributes, but usually it is not based on using a formal model those knows how to weight all the attributes in some optimal way. In essence, the internal risk rating systems are based on general considerations and on experience, and not on mathematical modeling. They cannot, therefore, be regarded as precise tools. Their usage clearly relies on the judgment of the rating evaluators.

Internal rating systems are usually applied to non-financial corporations, as special approaches are employed for banks and other financial institutions. Companies and instruments are classified into discrete rating categories that correspond to the expected loss, which represent the combined estimate of the likelihood of the company failing to pay its obligations and the subsequent loss in the event of default.

In the first section I show how an internal risk rating systems of a bank can be organised in order to rate creditors systematically. Ratings generally apply to obligors and loan for which underwriting and structuring require judgment. They are produced for business and institutional loans and counterparties on the derivatives transactions, not for consumer's loan. Credit decisions for small lending exposures are primary based on credit scoring techniques while the rating system we propose in this chapter is based on the extensive experience of the commercial bank, other bank may have some what different systems, but most are similar in nature. In the following three sections, the detail of the rating process and other considerations are described.

We suggest adopting a two tier rating system. First, an *obligor rating* that can be easily mapped to a default probability bucket, a *facility rating* that determines the loss parameters in case of default, such as (i) "Loss Given Default" (LGD), which depends on the seniority of the facility in the quality of the guarantees and collateral, and (ii) "Usage Given Default", (UGD) for loan commitments, which depends on the nature of the commitment and the rating history of the borrower.

The main problem faced by banks is obtaining information about companies that have not issued traded debt instrument. The data about these companies are of unproven quality and are therefore less reliable, and it can be a challenge to extract the minimum required information in order to improve the allocation of credit.

The credit analyst in a bank or a rating agency must take into consideration many attributes of a firm: financial as well as managerial, quantitative as well as qualitative. The analysts must ascertain the financial health of the firm, and determine if earnings and cash flows are sufficient to cover the debt obligations. The analysts would also want to analyze the quality of the assets of the firm and the liquidity position of the firm. The analysts should also be concerned by the quality of the management and try to discover any unfavorable aspects of the borrower's management.

In addition the analysts must take into account the features in the industry to which the potential client belongs, and the status of the client with in its industry the effects of macro-economics events on the firm and its industry should also be considered, as well as the country risk of the borrower. Combined industry and country factors can be assisted to calculate the correlation between assets for the purpose of calculating portfolio effects.

The environment of the borrower that the credit analysts must assess in order to determine the credit worthiness of the borrower and, thus, the interest spread that the bank should charge. A major consideration in providing the loan is the existence of the collateral, or otherwise of a loan guarantor, and the quality of the guarantee. The issue of guarantee is especially important to banks providing loans to small and medium-sized companies that cannot offer sufficient collateral.

When the objective is to allocate economic capital, monitor loans, and establish loan reserves, the point-in-time approach is more appropriate. The credit horizon of these decisions is usually one year, and the rating decision is based on the borrower's current and most likely future outlook over the credit horizon. Point-in-time rating is more responsive to change in the status of the obligor, and therefore more appropriate to monitor a credit. At the same time, point-in-time ratings are supposed to be updated frequently to stay current. This approach is also consistent with the use of rating as an input to a credit portfolio model, such as Credit Metrics based on the credit migration methodology. Credit risk models required specifying the credit horizon, usually one year; an each rating is mapped to a default probability bucket.

INTRODUCTION TO INTERNAL RATING SYSTEMS

We begin by looking more closely at an internal risk rating system (IRRS). A typical IRRS will assign both an obligor rating to each borrower (or group of borrowers), and a facility rating to each available facility. A risk rating (RR) is design to depict the *risk of loss* in a credit facility[1]. A robust risk rating system should offer a carefully designed, structured, and documented series of steps for the assessment of each rating.

The goal is to generate accurate and consistent risk rating, yet also to allow professional judgment to significantly influence a rating whenever appropriate. The expected loss (EL) is the product of an exposure (say US$100) multiplied by the probability of default (PD) (say 2%) of an obligor (or borrower) and loss given default (LGD) (say 50%), in any specific credit facility in this example, the EL is US$100*0.02*0.50=US$ 1. A typical risk rating methodology initially assigns an obligor rating that identifies the expected PD by that borrower (or group) in repaying its obligations in the normal course of business. Risk ratings quantify the quality of individual facilities, credits, and portfolios. If RR is accurately and consistently applied, then they provide a common understanding of risk.

Levels and allow for active portfolio management. An IRRS also provides the initial basis for capital charges used in the various pricing models. It can also assist in establishing loan reserves. The IRRS can be used to rate credit risks in most of the major corporate and commercial sectors, but it is unlikely to cover all business sectors.[2]

This paper primarily discusses a model developed by the author over 30 years ago, the so-called Z-Score model, and its relevance to these recent developments. In doing so, we will provide some updated material on the Z-Score model's tests and applications over time as well as some modifications for greater applicability.

The major theme of this paper is that the assignment of appropriate default probabilities on corporate credit assets is a three-step process involving from the development of:

(1) Credit scoring models,

(2) Capital market risk equivalents - - usually bond ratings, and

(3) Assignment of PD[3] and possibly LGDs on the credit portfolio.

Our emphasis will be on step 1 and how the Z-Score model, (Altman, 1968), has become the prototype model for one of the three primary structures for determining PDs

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[1]*The risk of loss is a very general notion since it can be described in several distinct dimensions. For example, it in relation to the expected loss dimension, the unexpected loss (economic capital) dimension.*

[2]*A typical IRRS generally excludes banks, agriculture, public finance and other identified groups.*

[3]*Some might argue that a statistical methodology can combine steps (1) and (2) where the output from (1) automatically provides estimates of PD. This is one of the reasons that many "modelers" of late and major consulting firms prefer the logit-regression approach, rather than the discriminant model that this author prefers.*

Chapter 2

CREDIT ASSESMENT MODELS

A best-practice approach to segmentation and defined the data requirements for credit assessment in each segment. Besides the creation of a complete, high-quality data set, the method selected for processing data and generating credit assessments has an especially significant effect on the quality of a rating system.

This chapter begins with a presentation of the credit assessment models commonly used in the market, with attention to the general way in which they function and to their application in practice. This presentation is not meant to imply that all of the models presented can be considered best-practice approaches.

In addition to these "pure models", we frequently encounter combinations of heuristic methods and the other two model types in practice. The models as well as the corresponding hybrid forms are described in the sections below. The models described here are primarily used to rate borrowers. In principle, however, the architectures described can also be used to generate transaction ratings.

Heuristic Models

Heuristic models attempt to gain insights methodically on the basis of previous experience. This experience is rooted in:

— Subjective practical experience and observations

— Conjectured business interrelationships

— Business theories related to specific aspects.

In credit assessment, therefore, these models constitute an attempt to use experience in the lending business to make statements as to the future creditworthiness of a borrower. The quality of heuristic models thus depends on how accurately they depict the subjective experience of credit experts. Therefore, not only the factors relevant to creditworthiness are determined heuristically, but their influence and weight in overall assessments are also based on subjective experience. In the development of these rating models, the factors used do not undergo statistical validation and optimization.

In practice, heuristic models are often grouped under the heading of expert systems. In this document, however, the term is only used for a specific class of heuristic systems.

Qualitative Systems

In qualitative systems, the information categories relevant to creditworthiness are also defined on the basis of credit experts' experience. However, in contrast to classic rating questionnaires, qualitative systems do not assign a fixed number of points to each specific factor value. Instead, the individual information categories have to be evaluated in qualitative terms by the customer service representative or clerk using a predefined scale. This is possible with the help of a grading system or ordinal values (e.g. "good," "medium," "poor"). The individual grades or assessments are combined to yield an overall assessment. These individual assessment components are also weighted on the basis of subjective experience. Frequently, these systems also use equal weighting.

In order to ensure that all of the users have the same understanding of assessments in individual areas, a qualitative system must be accompanied by a user's manual. Such manuals contain verbal descriptions for each information category relevant to creditworthiness and for each category in the rating scale in order to explain the requirements a borrower has to fulfill in order to receive a certain rating.
In practice, credit institutions have used these procedures frequently, especially in the corporate customer segment.

Quantitative Criteria	Economic situation	Overall assets situation Annual financial statements
	Cust. relationship / account mgmt.	Customer account management Customer transparency/information behavior
Qualitative Criteria	Future company development	Development since last financial statements Enterprise planning Income planning/future debt service capacity Special company risks
	Market/industry	Development of market/industry Cyclical dependence Customer/supplier structure Export/import risks Intensity of competition Products/range Service level
	Management	Management Accounting/management accounting

Hybrid Forms

In practice, the models described in the previous sections are only rarely used in their pure forms. Rather, heuristic models are generally combined with one of the two other model types (statistical models or causal models). This approach can generally be seen as favorable, as the various approaches complement each other well. For example, the advantages of statistical and causal models lie in their objectivity and generally higher classification performance in comparison to heuristic models. However, statistical and causal models can only process a limited number of creditworthiness factors. Without the inclusion of credit experts knowledge in the form of heuristic modules, important information on the borrower's creditworthiness would be lost in individual cases. In addition, not all statistical models are capable of processing qualitative information directly (as is the case with discriminant analysis, for example), or they require a large amount of data in order to function properly (e.g. logistic regression); these data are frequently unavailable in banks. In order to obtain a complete picture of the borrower's creditworthiness in such cases, it thus makes sense to assess qualitative data using a supplementary heuristic model.

This heuristic component also involves credit experts more heavily in the rating process than in the case of automated credit assessment using a statistical or causal model, meaning that combining models will also serve to increase user acceptance.

In the sections below, three different architectures for the combination of these model types are presented.

C h a p t e r 3

CREDIT SCORING MODELS

Almost all of the statistical credit scoring models that are in use today are variations on a similar theme. They involve the combination of a set of quantifiable financial indicators of firm performance with, perhaps, a small number of additional variables that attempt to capture some qualitative elements of the credit process. While this paper will concentrate on the quantitative measures, mainly financial ratios and capital market values, one should not underestimate the importance of qualitative measures in the process.[4] Starting in the 1980's, some sophisticated practitioners, and certainly many academicians, had been moving toward the possible elimination of ratio analysis as an analytical technique in assessing firm performance. Theorists have downgraded arbitrary rules of thumb (such as company ratio comparisons) widely used by practitioners. Since attacks on the relevance on ratio analysis emanate from many esteemed members of the scholarly world, does this mean that ratio analysis is limited to the world of "nuts and bolts?" Or, has the significance of such an approach been unattractively garbed and therefore unfairly handicapped? Can we bridge the gap, rather than sever the link, between traditional ratio analysis and the more rigorous statistical techniques that have become popular among academicians? Along with our primary interest, credit risk assessment and financial distress prediction, we are also concerned with an assessment of ratio analysis as an analytical technique.

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[4] *Practitioners have reported that these so-called qualitative elements, that involve judgment on the part of the risk officer, can provide as much as 30-50% of the explanatory power of the scoring model.*

Traditional Ratio Analysis

The detection of company operating and financial difficulties is a subject which has been particularly amenable to analysis with financial ratios. Prior to the development of quantitative measures of company performance, agencies had been established to supply a qualitative type of information assessing the credit-worthiness of particular merchants. Formal aggregate studies concerned with portents of business failure were evident in the 1930's, (see Altman [1968] for several references). Classic works in the area of ratio analysis and bankruptcy classification were performed by Beaver [1967, 1968]. His univariate analysis of a number of bankruptcy predictors set the stage for the multivariate attempts, by this author and others, which followed. Beaver found that a number of indicators could discriminate between matched samples of failed and non failed firms for as long as five years prior to failure. However, he questioned the use of multivariate analysis, although a discussant recommended attempting this procedure. The Z-Score model, developed by this author at the same time (1966) that Beaver was working on his own thesis, did just that. A subsequent study by Deakin [1972] utilized the same 14 variables that Beaver analyzed, but he applied them within a series of multivariate discriminant models.

The aforementioned studies imply a definite potential of ratios as predictors of bankruptcy. In general, ratios measuring profitability, liquidity, and solvency seemed to prevail as the most significant indicators. The order of their importance is not clear since almost every study cited a different ratio as being the most effective indication of impending problems. Although these works established certain important generalizations regarding the performance and trends of particular measurements, the adaptation of the results for assessing bankruptcy potential of firms, both theoretically and practically, is questionable. In almost every case, the methodology was essentially univariate in nature and emphasis was placed on individual signals of impending problems. Ratio analysis presented in this fashion is susceptible to faulty interpretation and is potentially confusing. For instance, a firm with a poor profitability and/or solvency record may be regarded as a potential bankrupt. However, because of its above average liquidity, the situation may not be considered serious. The potential ambiguity as to the relative performance of several firms is clearly evident. The crux of the shortcomings inherent in any univariate analysis lies therein. An appropriate extension of the previously cited studies, therefore, is to build upon their findings and to combine several measures into a meaningful predictive model. In so doing, the highlights of ratio analysis as an analytical technique will be emphasized rather than minimized. The questions are:

(1) Which ratios are most important in detecting credit risk problems?

(2) What weights should be attached to those selected ratios, and

(3) How should the weights is objectively established.

Discriminant Analysis

After careful consideration of the nature of the problem and of the purpose of this analysis, we chose multiple discriminant analysis (MDA) as the appropriate statistical technique. Although not as popular as regression analysis, MDA had been utilized in a variety of disciplines since its first application in 1930's. During those earlier years, MDA was used mainly in the biological and behavioral sciences. After the late 1960's, this technique became increasingly popular in the practical business world as well as in academia (see Altman, Avery, Eisenbeis and Sinkey, [1981]). MDA is a statistical technique used to classify an observation into one of several a *priori* groupings dependent upon the observation's individual characteristics. It is used primarily to classify/or make predictions in problems where the dependent variable appears in qualitative from, for example, male or female, bankrupt or non bankrupt therefore, the first step is to establish explicit group classifications. The number of original groups can be two or more. Some analysts refer to discriminant analysis as "multiple" only when the number of groups exceeds two. After the groups are established, data are collected for the objects in the groups; MDA in its most simple form attempt to derive a linear combination of these characteristics that "best" discriminates between the groups. If a particular object, for instance, a corporation, has characteristics (financial ratios) that can be quantified for all of the companies in the analysis, the MDA determines a set of discriminant coefficients.

When these coefficients are applied to the actual ratios, a basis for classification into one of the mutually exclusive groupings exists. The MDA technique has the advantage of considering an entire profile of characteristics common to the relevant firms, as well as the interaction of these properties. A univariate study, on the other hand, can only consider the measurements used for group assignments one at a time. Another advantage of MDA is the reduction of the analyst's space dimensionally, that is, from the number of different independent variables to G-1 dimension(s), where G equals the number of original *a priori* groups. The distressed classification and prediction analysis is concerned with two groups, consisting of bankrupt and non bankrupt firms. Therefore, the analysis is transformed into its simplest form: one dimension. The discriminant function, of the form $Z = V1X1 + V2X2 + VnXn$ transforms the individual variable values to a single discriminant score, or Z value, which is then used to classify the object where:

V1, V2, ... Vn = discriminant coefficients, and

X1, X2, ... Xn = independent variables

When utilizing a comprehensive list of financial ratios in assessing a firm's bankruptcy potential, there is reason to believe that some of the measurements will have a high degree of correlation or collinearity with each other. In my opinion, this aspect is not necessarily serious in discriminant analysis and it usually motivates careful selection of the predictive variables (ratios). It also has the advantage of potentially yielding a model with a relatively small number of selected measurements that convey a great deal of information. This information might very well indicate differences among groups, but whether or not these differences are significant and meaningful is a more important aspect of the analysis.

Perhaps the primary advantage of MDA in dealing with classification problems is the potential of analyzing the entire variable profile of the object simultaneously rather than sequentially examining its individual characteristics. Just as linear and integer programming have improved upon traditional techniques in capital budgeting, the MDA approach to traditional ratio analysis has the potential to reformulate the problem correctly. Specifically, combinations of ratios can be analyzed together in order to remove possible ambiguities and misclassifications observed in earlier traditional ratio studies. Critics of discriminant analysis point out that most, if not all, financial models using this technique violates several statistical requirements including multivariate normality and independence of the explanatory variables. While valid concerns, my experience has shown that careful bounding of certain extreme value ratios will usually mitigate the normality problem and tests for the models' robustness over time will determine if the independence violation is serious or not.

Variable Selection

After the initial groups were defined and firms selected, balance sheet and income statement data were collected. Because of the large number of variables that are potentially significant indicators of corporate problems, a list of 22 potentially helpful variables (ratios) were compiled for evaluation. The variables are classified into five standard ratio categories, including liquidity, profitability, leverage, solvency, and activity. The ratios were chosen on the basis of their popularity in the literature and their potential relevancy to the study, and there were a few "new" ratios in this analysis. From the original list of 22 variables, five were selected as doing the best overall job together in the prediction of corporate bankruptcy. The contribution of the entire profile is evaluated and, since this process is essentially iterative, there is no claim regarding the optimality of the resulting discriminant function.

In order to arrive at a final profile of variables, the following procedures were utilized: [5]

(1) Observation of the statistical significance of various alternative functions, including determination of the relative contributions of each independent variable;

(2) Evaluation of intercorrelations among the relevant variables;

(3) Observation of the predictive accuracy of the various profiles; and

(4) Judgment of the analyst.

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[5] *Subsequent versions of discriminant model software include step-wise methods which self-select the variables that either enter (forward stepwise) or are excluded (backward) from the final variable profile. Our experience with these techniques is, while helpful, do not always result in superior classification and prediction results.*

Chapter 4

THE Z SCORE MODEL

The Z-Score Model

$$Z = 1.2\,X_1 + 1.4\,X_2 + 3.3\,X_3 + 0.6\,X_4 + 1.0\,X_5$$

X_1 = working capital/total assets,
X_2 = retained earnings/total assets,
X_3 = earnings before interest and taxes/total assets,
X_4 = market value equity/book value of total liabilities,
X_5 = sales/total assets, and
Z = overall Index or Score

Note that the model does not contain a constant (Y-intercept) term. This is due to the particular software utilized and, as a result, the relevant cutoff score between the two groups is not zero. Many statistical software programs have a constant term which standardizes the cutoff score at zero if the sample sizes of the two groups are equal.

X_1, Working Capital/Total Asset (WC/TA)

The working capital/total assets ratio, frequently found in studies of corporate problems, is a measure of the net liquid assets of the firm relative to the total capitalization. Working capital is defined as the difference between current assets and current liabilities. Liquidity and size characteristics are explicitly considered. Ordinarily, a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets.[6] Two other liquidity ratios tested were the current ratio and the quick ratio. These were found to be less helpful and subject to perverse trends for some failing firms. In all cases, tangible assets, not including intangibles, are used.

X_2, Retained Earnings/Total Assets (RE/TA)

Retained earning (RE) is the term used to describe the account that reports the total amount of reinvested earnings and/or losses of a firm over its entire life. The account is also referred to as earned surplus. It is conceivable that a bias would be created by a substantial reorganization or stock dividend and appropriate readjustments should, in the event of this happening, be made to the accounts. This measure of cumulative profitability over time is what we referred to earlier as a "new" ratio. The age of a firm and its use of leverage are implicitly considered in this ratio. For example, a relatively young firm will probably show a low retained earnings/total assets (RE/TA) ratio because it has not had time to build up its cumulative profits. Therefore, it may be argued that the young firm is somewhat discriminated against in this analysis, and its chance of being classified as bankrupt is relatively higher than that of another older firm, *ceteris paribus*. But, this is precisely the situation in the real world. The incidence of failure is much higher in a firm's earlier years [40–50% of all firms that fail do so in the first five years of their existence (Dun & Bradstreet, annual statistics)].

In addition, the RE/TA ratio measures the leverage of a firm. Those firms with high RE, relative to TA, have financed their assets through retention of profits and have not utilized as much debt. This ratio highlights either the use of internally generated funds for growth (low risk capital) or OPM (other people's money) - higher risk capital.

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[6] *It is true, however, that this ratio, indeed all liquidity measures using short term assets, can be misleading in that the ratio can be growing just when a firm is about to fail. This fact highlights the problems of univariate measures of performance.*

X_3, Earnings before Interest and Taxes/Total Assets (EBIT/TA)

This ratio is a measure of the true productivity of the firm's assets, independent of any tax or leverage factors. Since a firm's ultimate existence is based on the earning power of its assets, this ratio appears to be particularly appropriate for studies dealing with credit risk. Furthermore, insolvency in a bankrupt sense occurs when the total liabilities exceed a fair valuation of the firm's assets with value determined by the earning power of the assets.

X_4, Market Value of Equity/Book Value of Total Liabilities (MVE/TL)

Equity is measured by the combined market value of all shares of stock, preferred and common, while liabilities include both current and long term. The measure shows how much the firm's assets can decline in value (measured by market value of equity plus debt) before the liabilities exceed the assets and the firm becomes insolvent. We discussed this "comparison" long before the advent of the KMV approach (discussed below) and before Merton [1974] put these relationships into an option-theoretic approach to value corporate risky debt. KMV used Merton's work to springboard into their now commonly used credit risk measure - the Expected Default Frequency (EDF). This ratio adds a market value dimension that most other failure studies did not consider. At a later point, we will substitute the book value of net worth for the market value in order to derive a discriminant function for privately held firms (Z') and for non manufacturers (Z").

X_5, Sales/Total Assets (S/TA)

The capital-turnover ratio is a standard financial ratio illustrating the sales generating ability of the firm's assets. It is one measure of management's capacity in dealing with competitive conditions. This final ratio is unique because it is the least significant ratio on an individual basis and on a univariate statistical significance test, it would not have appeared at all. However, because of its relationship to other variables in the model, the sales/total assets (S/TA) ratio ranks high in its contribution to the overall discriminating ability of the model. Still, there is a wide variation among industries and across countries in asset turnover and we will specify an alternative model (Z''), without X_5, at a later point. Variable means were measured at one financial statement prior to bankruptcy and the resulting F-statistics were observed; variables X_1 through X_4 are all significant at the 0.001 level, indicating extremely significant differences in these variables among groups.

Variable X_5 does not show a significant difference between groups and the reason for its inclusion in the variable profile is not apparent as yet. On a strictly univariate level, all of the ratios indicate higher values for the non bankrupt firms. Also, all of the discriminant coefficients display positive signs, which is what one would expect. Therefore, the greater a firms distress potential, the lower its discriminant score. While it was clear that four of the five variables displayed significant differences between groups, the importance of MDA is its ability to separate groups using multivariate measures. Once the values of the discriminant coefficients are estimated, it is possible to calculate discriminant scores for each observation in the samples, or any firm, and to assign the observations to one of the groups based on this score. The essence of the procedure is to compare the profile of an individual firm with that of the alternative groupings. The comparisons are measured by either a chi-square value, or similar test, and group assignments are made based upon the relative proximity of the firms' score to the various group centroids (means).

A Further Revision – Adapting the Model for Emerging Markets

The next modification of the Z-Score model analyzed the characteristics and accuracy of a model without X5 - sales/total assets. We do this in order to minimize the potential industry effect that is more likely to take place when such an industry-sensitive variable as asset turnover is included. In addition, we have used this model to assess the financial health have applied this enhanced Z" Score model to emerging markets corporate, specifically Asian firms. The book value of equity was used for X4 in this case. The classification results are identical to the revised five-variable model (Z'Score). The new Z'' Score model is:

$$Z'' = 6.56 (X1) + 3.26 (X2) + 6.72 (X3) + 1.05 (X4)$$

Where Z''-Scores below 1.10 indicate a distressed condition. All of the coefficients for variables X1 to X4 are changed as are the group means and cutoff scores. This particular model is also useful within an industry where the type of financing of assets differs greatly among firms and important adjustments, like lease capitalization, are not made. In the emerging market (EM) model, we added a constant term of +3.25 so as to standardize the scores with a score of zero (0) equated to a D (default) rated bond. See Panel E for the average of emerging market rating equivalents of this newer, emerging Market (EM)-Score model.

Emerging Market Score	
Emerging Market Rating	**Average EM Score**
AAA	**6.40**
AA	**5.65**
A	**4.95**
BBB	**4.75**
BB	**4.50**
B	**2.95**
CCC	**1.75**
D	**0**

C h a p t e r 5

VALIDATION OF INTERNAL RISK RATING

The rating result generated for a specific customer can change over time. This is due to the fact that a customer has to be re-rated regularly both before and after the conclusion of a credit agreement due to regulatory requirements and the need to ensure the regular and current monitoring of credit risk from a business perspective. In line with best business practices, the requirements arising from Basel II call for ratings to be renewed regularly (at least on an annual basis); this is to be carried at even shorter intervals in the case of noticeably higher risk. This information can be used to improve risk classification and to validate rating models.

In addition to the exact assignment of default probabilities to the individual rating classes (a process which is first performed only for a defined time horizon of 12 months), it is also possible to determine how the rating will change in the future for longer-term credit facilities. The transition matrices specific to each rating model indicate the probability of transition for current ratings (listed in columns) to the various rating classes (listed in rows) during a specified time period. In practice, time periods of one or more years are generally used for this purpose.

This section only presents the methodical fundamentals involved in determining transition matrices. Their application, for example in risk-based pricing, is not covered in this document.

The One-Year Transition Matrix

In order to calculate the transition matrix for a time horizon of one year, it is necessary to identify the rating results for all customers rated in the existing data set and to list these results over a 12-month period. Using this data, all observed changes between rating classes are counted and compiled in a table. Gives an example of such a matrix

	AAA	AA	A	BBB	BB	B	CCC
AAA	90.81%	0.70%	0.09%	0.02%	0.03%	0.01%	0.21%
AA	8.15%	90.64%	2.27%	0.33%	0.14%	0.11%	0.23%
A	0.68%	7.79%	91.05%	5.95%	0.67%	0.24%	0.35%
BBB	0.12%	0.64%	5.52%	86.93%	7.73%	0.43%	1.30%
BB	0.09%	0.06%	0.74%	5.30%	80.53%	6.48%	2.38%
B	0.08%	0.14%	0.26%	1.17%	8.84%	83.46%	11.24%
CCC	0.04%	0.02%	0.01%	0.12%	1.00%	4.07%	64.50%
Default	0.03%	0.01%	0.06%	0.18%	1.06%	5.20%	19.79%

With regard to the time interval between consecutive customer ratings, it is necessary define a margin of tolerance for the actual time interval between rating results for, as the actual intervals will only rarely be exactly one year. In this context, it is necessary to ensure that the average time interval for the rating pairs determined matches the time horizon for which the transition matrix is defined. At the same time, the range of time intervals around this average should not be so large that a valid transition matrix cannot be calculated. The range of time intervals considered valid for calculating a transition matrix should also be consistent with the bank's in-house guidelines for assessing whether customer re-ratings are up to date and performed regularly.

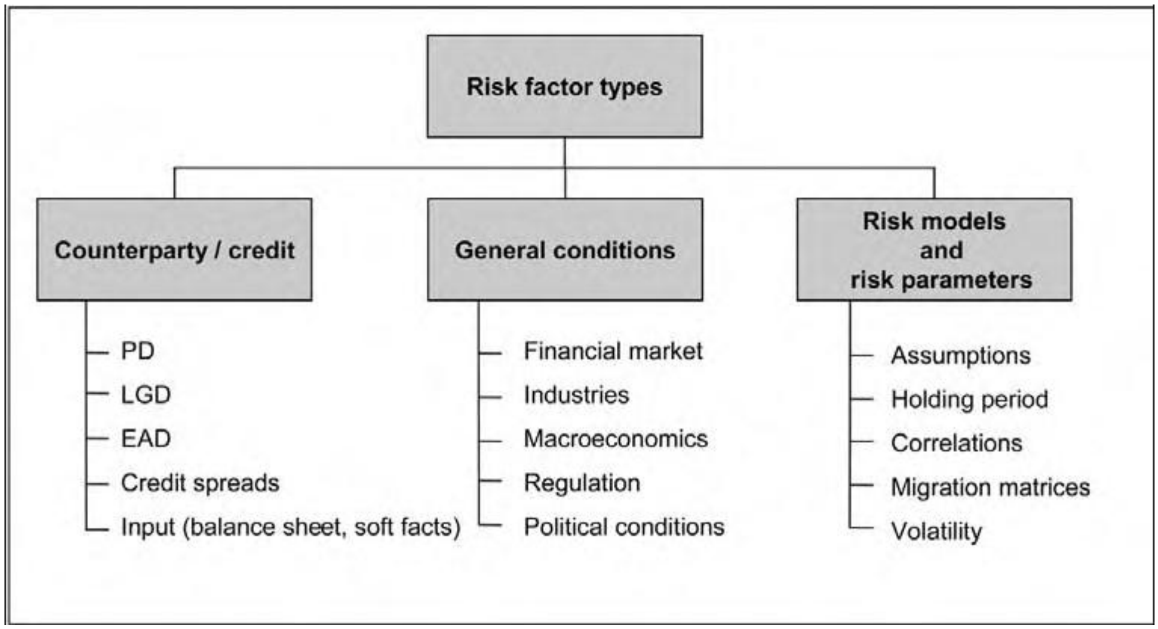
Actual credit defaults are frequently listed as a separate class (i.e. in their own column). This makes sense insofar as a default describes the transition of a rated borrower to the "defaulted loans" class.

Frequently cases will accumulate along the main diagonal of the matrix. These cases represent borrowers which did not migrate from their original rating class over the time horizon observed. The other borrowers form a band around the main diagonal, which becomes less dense with increasing distance from the diagonal. This concentration around the main diagonal correlates with the number of existing rating classes as well as the stability of the rating procedure.

The more rating classes a model uses, the more frequently rating classes will change and the lower the concentration along the main diagonal will be. The same applies in the case of decreasing stability in the rating procedure. In order to calculate transition probabilities, it is necessary to convert the absolute numbers into percentages (row probabilities). The resulting probabilities indicate the fraction of cases in a given class which actually remained in their original class. The transition probabilities of each row including the default probability of each class in the last column should add up to 100%.

Especially with a small number of observations per matrix field, the empirical transition matrix derived in this manner will show inconsistencies. Inconsistencies refer to situations where large steps in ratings are more probable than smaller steps in the same direction for a given rating class, or where the probability of ending up in a certain rating class is more probable for more remote rating classes than for adjacent classes. In the transition matrix, inconsistencies manifest themselves as probabilities which do not decrease monotonically as they move away from the main diagonal of the matrix. Under the assumption that a valid rating model is used, this is not plausible. Inconsistencies can be removed by smoothing the transition matrix. Smoothing refers to optimizing the probabilities of individual cells without violating the constraint that the probabilities in a row must add up to 100%. As a rule, smoothing should only affect cell values at the edges of the transition matrix, which are not statistically significant due to their low absolute transition frequencies. In the process of smoothing the matrix, it is necessary to ensure that the resulting default probabilities in the individual classes match the default probabilities from the calibration.

The Credit Portfolio and Other General Condition



Counterparty-based and credit facility-based risk factors: These scenarios can be realized with relative ease by estimating credit losses after modeling a change in PD and/or LGD/EAD. The methods of modeling stress tests include the following

Examples:

— Downgrading all borrowers by one rating class

— Increasing default probabilities by a certain percentage

— Increasing LGD by a certain percentage

— Increasing EAD by a certain percentage for variable credit products (justification: customers are likely to utilize credit lines more heavily in crisis situations, for example)

— Assumption of negative credit spread developments (e.g. parallel shifts in term structures of interest rates) for bonds

— Modeling of input factors (e.g. balance sheet indicators)

The approaches listed above can also be combined with one another as desired in order to generate stress tests of varying severity. With regard to general conditions, examples might include stress tests for specific industries or regions. Such tests might involve the following:

— Downgrading all borrowers in one or more crisis-affected industries

— Downgrading all borrowers in one or more crisis-affected regions

Macroeconomic risk factors include interest rates, exchange rates, etc. These factors should undergo stress-testing especially when the bank uses them as the basis for credit risk models which estimate PD or credit losses. If the bank uses models, these stress tests are to be performed by adjusting the parameters and then recalculating credit losses.

Examples include:

- — Unfavorable changes (increases/decreases, depending on portfolio composition) in the underlying interest rate by a certain number of basis points
- — Unfavorable changes (increases/decreases, depending on portfolio composition) in crucial exchange rates by a certain percentage

If the bank uses risk models (such as credit portfolio models or credit pricing models), it is necessary to perform stress tests which show whether the assumptions underlying the risk models will also be fulfilled in crisis situations. Only then will the models be able to provide the appropriate guidance in crisis situations as well.

RESULTS

Internal credit risk ratings are utilised by many sophisticated banks to summarise the risk of individual credit exposures, and are increasingly incorporated into various banking functions, including operational applications (such as determining loan approval requirements) and risk management and analysis (including analysis of pricing and profitability as well as internal capital allocation).

Internal ratings may also cover a much broader range of borrowers, providing assessments of the credit quality of individuals and small-to-medium sized companies through credit scoring, and assessment of larger non-rated borrowers through detailed analysis. internal ratings-based approach also shares certain similarities with credit risk models in terms of its reliance on banks' internal credit assessments, and in its conceptual measures of risk; as such, it could also provide incentives for banks to further refine credit risk management techniques, paving the way for a transition towards full credit risk models in the future.

In this thesis the credit risk rating of different companies and the assigning a risk grade for the purpose is to check the stability, solvency and to identify the overall level of risk associated with the capital structure, so long as the risk rating structure and assignment procedure provide a meaningful and consistent identification of the risk. These rating can also provide a valuable reference point for assessing degree of the trade-off among various loan terms and characteristics and, in particular, in determining appropriate loan pricing.

CONCLUSION

The internal risk rating system methodology presented in this thesis provides a disciplined framework to be followed with appropriate guidelines. The framework includes consideration of all the relevant risk factors in assessing the credit quality of an obligor and the loss in the event of default for a facility. The assessment of the PD and LGD is the critical element in the loan adjustication process. As the economic environment changes and the fortune of the obligor evolve, this assessment needs to be reviewed and updated in order to keep these rating current. The rule is to be updating these ratings whenever a credit event occurs, or a change in the risk of the obligor is perceived. In any event, at a minimum the risk rating should be reviewed at least once a year in conjunction with the annual review of each loan.

The new Basel Capital Accord (Basel Committee on Banking Supervision, 1999), also referred to as Basel II, has explicitly recognised that, in the future, an internal risk rating-based system could prove useful to banks in their calculation of the minimum required regulatory capital. Basel II offers a menu of approaches to measure credit risk: the standardized approach, which is an improved version of the current 1988 Accord, and the internal rating-based (IRB) approach with two variants, the foundation and the advanced approaches, the later applying to the most sophisticated banks. Under the IRB approach, banks will be allowed to use their own regulators of the bank's internal risk rating system, and the validation of the key risk parameters such as the PD for each rating category, the LGD and EAD for loan commitments.

The is no single definition of what constitutes a good IRRS, Basel II has not yet given any clear guideline on the characteristics of an IRRS eligible to the IRB approach. But there are some common features to advanced IRRS:

- An IRRS must have the appropriate level of granularity. The number of grades should be such that there is not too much concentration of obligors in one category. While more than fewer granularities are recommended, the bank should develop a calibration methodology that allows the differentiation in a meaningful way between the credit qualities of two consecutive grades.
- An IRRS should be a two-tier rating system with an OR that estimates the EDP and FR that represent the LGD.
- An IRRS should be part of a robust information system, which tracks historical default and loss experience. This information should be used for periodic recalibration and back-testing of the IRRS.
- An IRRS must be applied consistently throughout the bank. The requires a well documented process as well as systematic training of the raters to avoid inconsistencies.

APPENDIX

Rating Definition

A best rating is an independent option, based on a comprehensive quantitative and qualitative evaluation, of a company's balance sheet strength, operating performance and business profile. Ratings are not a warranty of a company's ability to meet its ongoing financial obligations.

	Rating	Descriptor	Definition
Investment Grade	**AAA**	Exceptional	Assigned to issues, where the issuer has, in our opinion, an exceptional ability to meet the term of the obligation.
	AA	Very Strong	Assigned to issues, where the issuer has, in our opinion, a very strong ability to meet the term of the obligation.
	A	Strong	Assigned to issues, where the issuer has, in our opinion, a strong ability to meet the term of the obligation.
	BBB	Adequate	Assigned to issues, where the issuer has, in our opinion, an adequate ability to meet the term of the obligation; however, is more susceptible to change in economic or other conditions.
Non-Investment Grade	**BB**	Speculative	Assigned to issues, where the issuer has, in our opinion, speculative credit characteristics, generally due to moderate margin of principle and interest payment protection and vulnerability to economic changes.
	B	Very speculative	Assigned to issues, where the issuer has, in our opinion, very speculative credit characteristics, generally due to modest margin of principle and interest payment protection and vulnerability to economic changes.
	CCC	Extremely speculative	Assigned to issues, where the issuer has, in our opinion, extremely speculative credit characteristics, generally due to minimal margin of principle and interest payment protection and vulnerability to economic changes.
	D	In Default	In default on payment of principle, interest or other terms and conditions. The rating also is utilized when bankruptcy petition, or similar action, has been filled

Qualitative analysis

Management Review

- Management Record
- Management qualification
- Policies and procedure
- Future Planning

Industry Comparison

- Industry Behavior
- Compliance
- Perfect Competition
- Sales Growth

Assumption

- Altman emerging market Z-Score model are used to determine the credit risk rating.

- The qualitative analysis is judged on the basis of sector facts and information.

- Credit rating model is assessed by qualitative and quantitative analysis. 50% weights are assigned by qualitative and 50% are assigned by quantitative analysis.

Data

The data have been taken from financial statement of OGDC, PSO, PTCL and HUBCO and sector information is also taken from State Bank of Pakistan.

Financial Highlight of OGDC

Analysis of financial ratios

Leverage ratio	**31.19**
Debt equity ratio	**31.19**
Total assets/Total liabilities	**420.59**
Gearing ratio	**0.00**
Retained earnings/Total assets	**0.31**
Current ratio	**246.45**
ROE	**41.73**
ROS	**59.45**
Sales as a % of total assets	**53.51**
Working capital / total assets	**0.35**
EBIT/total assets	**0.37**
Market value of equity / total liabilities	**3.21**
Sales / total assets	**0.54**

Value of Z-Score (OGDC)	**9.13**

Qualitative analysis on OGDC

Management Review (60%)	**Score**	**Weights per criteria**
Management has a clear track record and hasn't defaulted.	10	5%
Management holds graduation degree on an average in the field of business and business management.	7	3.5%
Management planning for future projects	7	3.5%
Highly standard system and procedure will define with certification.	9	4.5%
Management team is experienced with in the related industry.	8	4%
Industry Comparison (40%)	**Score**	**Weights per criteria**
High growth rate and good stability in the industry.	8	4%
Partially compliant with the implementation of the international charter.	6	3%
Stability during economic downturn to inject the capital requirement.	8	4%
Established market share in the stock exchange.	9	4.5%
The effect of trade environment, including trade agreements that that an impact on the industry.	8	4%

Financial Highlight of PSO

Analysis of financial ratios

Leverage ratio	**193.71**
Debt equity ratio	**193.71**
Total assets/Total liabilities	**151.63**
Gearing ratio	**0.35**
Retained earnings/Total assets	**0.58**
Current ratio	**132.03**
ROE	**38.50**
ROS	**2.90**
Sales as a % of total assets	**452.09**
Working capital / total assets	**0.21**
EBIT/total assets	**0.18**
Market value of equity / total liabilities	**0.52**
Sales / total assets	**4.52**

Value of Z-Score (PSO)	**6.05**

Qualitative analysis on PSO

Management Review (60%)	Score	Weights
○ Management has a clear track record and hasn't defaulted.	9	4%
○ Management holds graduation degree on an average in the field of business and business management.	7	3.5%
○ Management planning for future projects	8	4%
○ Highly standard system and procedure will define with certification.	8	4%
○ Management team is experienced with in the related industry.	7	3.5%
Industry Comparison (40%)	**Score**	**Weights**
○ High growth rate and good stability in the industry.	8	4%
○ Partially compliant with the implementation of the international charter.	6	3%
○ Stability during economic downturn to inject the capital requirement.	8	4%
○ Established market share in the stock exchange.	9	4.5%
○ The effect of trade environment, including trade agreements that that an impact on the industry.	8	4%

Financial Highlight of HUBCO

Analysis of financial ratios

Leverage ratio	**126.81**
Debt equity ratio	**126.81**
Total assets/Total liabilities	**178.86**
Gearing ratio	**51.38**
Retained earnings/Total assets	**0.54**
Current ratio	**367.37**
ROE	**22.81**
ROS	**32.44**
Sales as a % of total assets	**31.00**
Working capital / total assets	**0.25**
EBIT/total assets	**0.16**
Market value of equity / total liabilities	**0.79**
Sales / total assets	**0.31**

Value of Z-Score (HUBCO)	**5.26**

Qualitative analysis on HUBCO

Management Review (60%)	Score	Weights
○ Management has a clear track record and hasn't defaulted.	8	4%
○ Management holds graduation degree on an average in the field of business and business management.	7	3.5%
○ Management planning for future projects	8	4%
○ Highly standard system and procedure will define with certification.	8	4%
○ Management team is experienced with in the related industry.	7	3.5%
Industry Comparison (40%)	**Score**	**Weights**
○ High growth rate and good stability in the industry.	8	4%
○ Partially compliant with the implementation of the international charter.	6	3%
○ Stability during economic downturn to inject the capital requirement.	8	4%
○ Established market share in the stock exchange.	9	4.5%
○ The effect of trade environment, including trade agreements that that an impact on the industry.	8	4%

Financial Highlight of PTCL

Analysis of financial ratios

Leverage ratio	**88.31**
Debt equity ratio	**88.31**
Total assets/Total liabilities	**213.24**
Gearing ratio	**24.97**
Retained earnings/Total assets	**0.36**
Current ratio	**342.21**
ROE	**24.94**
ROS	**30.11**
Sales as a % of total assets	**0.02**
Working capital / total assets	**0.23**
EBIT/total assets	**1.13**
Market value of equity / total liabilities	**0.44**
Sales / total assets	**0.02**

Value of Z-Score (PTCL)	**4.97**

Qualitative analysis on PTCL

Management Review (60%)	Score	Weights
○ Management has a clear track record and hasn't defaulted.	8	4%
○ Management holds graduation degree on an average in the field of business and business management.	6	3%
○ Management planning for future projects	6	3%
○ Highly standard system and procedure will define with certification.	6	3%
○ Management team is experienced with in the related industry.	7	3.5%
Industry Comparison (40%)	**Score**	**Weights**
○ High growth rate and good stability in the industry.	7	3.5%
○ Partially compliant with the implementation of the international charter.	6	3%
○ Stability during economic downturn to inject the capital requirement.	7	3.5%
○ Established market share in the stock exchange.	8	4%
○ The effect of trade environment, including trade agreements that that an impact on the industry.	7	3.5%

Emerging Market Score	
Emerging Market Rating	**Average EM Score**
AAA	**6.40**
AA	**5.65**
A	**4.95**
BBB	**4.75**
BB	**4.50**
B	**2.95**
CCC	**1.75**
D	**0**

FINAL GRADING BENCHMARCKS

QUANTITATIVE	RATING	RISK RATING RANGE
6.40 = 47%	**AAA**	85-----------100
5.65 = 43%	**AA**	75-----------84
4.95 = 38%	**A**	65-----------74
4.75 = 33%	**BBB**	55-----------64
4.50 = 27%	**BB**	51-----------54
2.95 = 23%	**B**	45-----------50
1.75 = 20%	**CCC**	41-----------44
0 = 0%	**D**	UPTO 40

INTERNAL CREDIT RISK RATING

COMPANY NAME	FINAL CREDIT RATING		
	QUALITATIVE	QUANTITATIVE	CREDIT RATING
OGDC	40%	47%	87%
PSO	39%	43%	82%
HUBCO	38%	38%	76%
PTCL	34%	38%	72%

COMPANY NAME	CREDIT RATING
OGDC	**AAA**
PSO	**AA**
HUBCO	**AA**
PTCL	**A**

Sector Information

	Average	Max	Min	Quartile 1	Median	Quartile 3
Net Working Capital (Rs.M)	466.79	10,760.45	-4,738.63	-6.30	123.23	498.37
Current Ratio (x)	2.19	112.48	0.28	0.97	1.77	1.56
Solvency (x)	1.24	4.49	0.20	0.66	1.50	1.55
Debt Leverage (x)	2.83	25.93	0.00	0.79	2.44	3.40
Book Value (Rs.)	33.15	166.88	10.11	17.14	34.60	42.84
Revenue per Share (Rs.)	225.42	2,222.47	0.35	22.87	66.29	269.34
Gross Profit Margin (%)	27.04	87.86	0.67	8.50	38.28	41.33
Times Interest Earned (x)	112.94	6,864.85	-	2.00	5.36	11.14
Fin Charges/Total Revenue (%)	6.49	35.18	-	0.47	5.41	10.94
Fin Charges/Total Expense (%)	39.24	498.50	-	9.04	40.88	63.13
Net Profit Margin (%)	12.42	43.89	0.20	2.39	13.59	20.73
Earnings per Share (Rs.)	20.22	92.41	0.01	8.46	20.06	24.36
Dividend / Net Profit (%)	48.44	468.42	-	16.35	65.66	66.61
Dividends per Share (Rs.)	3.46	35.00	-	0.50	3.00	4.00
Return on Investment (%)	7.66	29.22	0.07	3.64	9.51	10.76
Return on Equity (%)	20.85	88.97	0.07	11.37	27.39	28.33

Transport & Communication						
	Average	Max	Min	Quartile 1	Median	Quartile 3
Net Working Capital (Rs.M)	-872.56	1,966.47	-16,208.77	-182.44	21.27	69.89
Current Ratio (x)	1.37	3.73	0.47	0.94	1.01	1.59
Solvency (x)	1.29	8.20	0.15	0.67	1.14	1.36
Debt Leverage (x)	3.45	73.96	0.24	0.74	1.03	1.78
Book Value (Rs.)	15.87	32.24	0.84	11.52	13.90	22.31
Revenue per Share (Rs.)	25.94	71.55	7.23	11.34	21.80	29.05
Gross Profit Margin (%)	85.79	100.00	12.77	100.00	100.00	100.00
Times Interest Earned (x)	13.14	80.67	1.18	1.98	6.16	13.69
Fin Charges/Total Revenue (%)	4.03	19.87	0.21	1.87	2.89	4.97
Fin Charges/Total Expense (%)	8.37	58.91	0.22	2.24	5.02	10.89
Net Profit Margin (%)	15.10	36.47	0.25	3.90	13.15	24.07
Earnings per Share (Rs.)	5.47	12.13	0.71	3.39	5.22	6.90
Dividend / Net Profit (%)	26.39	200.54	-	-	-	49.71
Dividends per Share (Rs.)	0.62	2.40	-	-	-	1.25
Return on Investment (%)	7.32	17.65	0.22	2.75	8.45	10.98
Return on Equity (%)	25.67	328.66	0.75	5.80	15.50	22.20

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