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INSOLVENCY PREDICTION FOR PROPERTY-LIABILITY INSURERS:
NEW STATISTICAL MEASURES AND THE EFFECTS OF
ALTERNATIVE ACCOUNTING PRACTICES

DISSERTATION

Presented in Partial Fulfillment of the Requirements for
the Degree Doctor of Philosophy in the Graduate
School of The Ohio State University

By
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****
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1983

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To my wife Edna
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CHAPTER I
INTRODUCTION

Statement of the Problem

Approximately one hundred eighty formal insolvent property-liability (P-L) insurers were listed by A M. Best [30] during the period Jan. 1971-Dec. 1980, including about eighty firms that were listed as "voluntary-retirement" firms. There were more than 2900 P-L insurers in the U.S. at the end of 1980. The average annual failure rate was about .6 percent during the 1970s. Liabilities to policyholders of about 1 billion $ were involved in these insolvencies. Several of these cases would be eliminated if it were possible to detect these insolvencies in advance. This overall record demonstrates why it is in the public interest to identify those firms in potential financial distress as early as possible.

Monitoring solvency is one of the primary functions of insurance industry regulation. In order to monitor solvency (and for other purposes) a special accounting procedure, the Statutory Accounting Principles (SAP), has been developed. Regulators consider the SAP as a better method for monitoring solvency than other accounting procedures. However, they have almost never attempted to determine empirically which accounting method may be the best for monitoring and predicting insolvencies. Regulators argue consistently that SAP is preferred for monitoring solvency. The growing concern by insurance
regulators about insurance company insolvencies has been given top priority by the National Association of Insurance Commissioners (NAIC). In the 1981 annual meeting the president of the NAIC announced the formation of blue-ribbon committee to study the problem of monitoring the surveillance and solvency in the insurance industry [86].

The issue of insurers' solvency is considered a primary area of concern by insurance regulators, because they are concerned with protecting policyholders in their states. At least four other groups are concerned about the financial solvency of P-L insurers: 1) policyholders, 2) owners (stockholders) and potential investors, 3) agents, and 4) other companies and the general public. Distress prediction models may be very important tools for these groups. Detecting financial distress as early as possible can avoid losses to consumers and producers resulting from insurer insolvencies. The early detection can serve the primary objective of the regulatory bodies, and can maintain premium tax revenue for the various states. Assessments paid to guaranty funds are offset against premium taxes in many states.

The two main tools that have been designed to examine whether or not insurance companies are financially sound are: the A.M. Best's ratings (BR) [29, 30], and the NAIC-Insurance Regulatory Information System (IRIS) [121].

Extensive research over those two methods has been published during the last fifteen years. Although Denenberg [44] concludes

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1 The A.M. Best ratings and the NAIC-IRIS will be explained in Chapter IV. The IRIS was known as the Early Warning System.
that Best's rating was an effective tool for avoiding delinquent insurance companies; Breslin, Troxel, Anderson and Bachman [34, p. 269] indicate that the "Best's rating system is not meant to disclose differences among insurers." Hershbarger [74] concludes that Best's ratings are not sufficiently discriminating. Thornton and Meador [155] conclude that the NAIC (IRIS) system does not discriminate adequately between troubled and sound companies. Hershbarger [73] finds that the system falls short of predictability expectations.

Univariate financial ratios as well as multidiscriminant analysis of these ratios have been examined in several studies, but the results have not been satisfactory, especially for early prediction. Trieschmann and Pinches [156], the Aetna research [12] and others have used financial ratios as variables for predicting insolvencies among P-L insurers. The results with univariate ratios were not satisfactory [130]. Better predictions were found by applying multidiscriminant analysis to financial ratios, but the results either fell short of expectations for early prediction [12, 73], or the issue of early prediction was not examined [156].

Objectives and Needs for the Study

The proposed research applies new methods to predict insolvencies among property-liability (P-L) insurers. Methods developed as part of the research should help regulators to monitor solvency and should allow prediction of insolvency earlier than methods currently in use. The new methods measure the financial status of the P-L insurers by employing newly developed stability measures. The proposed research
differs from past studies in that it uses these stability measures instead of direct tests on insurer financial ratios. The predictive power of these stability measures is compared with that of financial ratios. Generally, the stability measures are found to be superior.

This research formulates methods for predicting corporate failure and for testing hypotheses empirically. The primary purpose of the study is to formulate new models\(^2\) for predicting failed property and liability (P-L) insurers. The results may indicate what models and variables are important in the empirical research. Stability and sensitivity measures are introduced and their purpose is to improve predictions of failures among P-L insurers. The performance of the new model will be examined and compared under different accounting procedures.

This study compares four different accounting procedures to determine how they affect the predictive power of both the stability measures and the previously-used tests using financial ratios. Empirical evidence on the relative merits of these accounting procedures as they affect the prediction of insolvency are presented. Regulators use statutory accounting principles (SAP) as the method for monitoring

---

\(^2\)The words model, method, and measures will be used interchangeably. A more strict definition may emphasize the word method rather than model. However, since the decomposition measures (DM) formulate stability process over time, they might consider a model which can be used as a method of prediction. Moreover, several probabilistic issues will be considered for the purpose of prediction of insolvencies.
solvency rather than other accounting methods. One major objective of this research is to analyze which accounting method (SAP, Generally Accepted Accounting Principles (GAAP), and others) may be the best procedure for monitoring and predicting insolvencies.

The study determines what needs to be known, why it needs to be known, and then designs the research accordingly. The objectives of this research are four:

1) The study constructs univariate models that may be used to predict insolvencies among insurers. The new models are: the Decomposition Measures (DM), and stability of financial ratios over time. The research examines the profitability and risk for each insurer as it is measured by the stability of financial earnings. New univariate models are compared in order to find which model is the most efficient\(^3\) one. The new methods are compared with existing methods (e.g., Best, NAIC-IRIS) to determine whether the new models are better and more efficient models than the old ones.

2) Multivariate models have been considered more efficient for predicting failures in several industries.\(^4\) Previous research concludes that multivariate models are superior to univariate models.

\(^3\)Better, superior, or efficient goals are defined as an attempt to predict insolvencies as accurately and as early as possible (e.g., identifying insolvent insurers three years prior to insolvency). Accurate may be interpreted as more reliable prediction (less type I and II errors).

\(^4\)Several industries were presented by Altman [3,5] Meyer and Pifer [115], and Sinkey [142]. In the P-L insurance industry multivariate models were considered by Trieschmann and Pinches [156] and Hershbarger [73].
This study examines whether or not the indices (variables) that are constructed by the univariate models could have better results when they are being used in multivariate analyses.

Multivariate Discriminant Analysis (MDA) is the common tool which has been used to predict failures of firms. Zero-one multiregression models have also been used. Extensive research has used financial ratios as variables in the predictive models.\(^5\) However, this study differs from the past research in that it uses stability measures instead of direct tests on financial ratios.

A theoretical foundation for probabilistic prediction of insolvency in the P-L insurance industry will be underlined, and recent probabilistic models will be analyzed. A linear probability model as well as probit and logit models will be considered. However, classification and discriminant methods will be applied.

The practical implications of the models will be emphasized, since these models can be used by regulators and others. The models also may demonstrate a quick-screening process which may discriminate between potentially solvent and insolvent insurers. Furthermore, only a few financial items are necessary for the stability measures. Trieschmann and Pinches [156] used about 100 financial items to derive a final set of six predictive ratios. The NAIC-IRIS has used at least 50 items [121], while the AIA (Aetna) system [12] has used about 300

\(^5\) E.g., see Altman [1], Horrigan [80], Beaver [21,22], etc.
items. The new methods may be less costly than the old methods, by decreasing the cost of information processing.

3) The study examines the effect of different accounting procedures on the ability of new and existing models to predict insolvencies.

A discussion of financial accounting procedures (SAP vs. GAAP) and literature is closely related to the prediction and identification of insurers' distress. The study examines the main differences between the two accounting methods, and measures how these two different methods may influence the prediction models. For the same purpose the market value of assets, and modified statutory accounting will also be employed.

4) Finally, the fourth objective is to measure and classify insolvencies among insurers. Classifications and measurement problems will be identified and discussed. The causes of insolvency and the main attributes of insolvent P-L insurers are disclosed and discussed. Classification of insolvent and solvent insurers, as well as measurement of the phenomenon of insolvency may create many problems. The study discusses when and how insurers become insolvent. The research also surveys possible methods of measurement of insolvency, but a complete classification may not be possible.

Because there is no perfect measurement of insolvency, the classification process is somewhat arbitrary. Technically, under a set of

---

Trieschmann and Pinches [156] started the research with about 70 variables (financial ratios) and the AIA (Aetna) model started with 150 ratios [12].
criteria a company might be "insolvent" at one point of time and if it is not declared insolvent by court or voluntarily retired, it may become a "solvent" company later. This situation demonstrates the difficulties concerning the identification and classification of insolvent companies. The study here on this topic is a preliminary one, but it may serve as a basis for further research.

**Scope and Limitations**

This study concentrates on developing and examining stability models for predicting insolvent insurers, and on related accounting issues. First, the study addresses accounting figures under Statutory Accounting Principles (SAP) with conventional modification for underwriting profits. Second, the study modifies the figures in accordance with the GAAP and other procedures. Stability of profits will be examined over time with and without investment income gain or loss.

To a large extent, the models may have application to life companies, other financial institutions and other industries. However, no empirical examination or detailed discussion is presented for organizations other than the P-L insurance industry.

Although some information is available for 150 insolvent P-L insurers (about 80% of the total failures during 1971-1980), due to lack of data most small insolvent mutual insurers will not be

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7 Problems and issues in the statutory accounting system of P-L insurers are described in Chapter VII and Appendix A.
More complete data are available for about 90 insolvent P-L insurers (about half of the failures). The sample size is also reduced by the screening procedure which applies to the study. The final sample will include the 62 insurers which failed between July, 1974 and December, 1981.

Lev [104, p. 151] states that, ideally, financial statement data should be combined with nonaccounting data to form optional failure-prediction models. To a large extent, nonaccounting data is not included in the research. Several general limitations are common to most literature on financial-distress prediction. Foster [59, pp. 476-80] and others point out the following main limitations:

1. Published research is ex-post in nature, while in a decision context it is necessary to make ex-ante prediction about the failure.

2. Limited attempt has been made to develop theories of financial distress, beyond constructing models for failure prediction.

3. Methodological as well as statistical limitations may hamper the validity and reliability of the research. Sampling problems, especially due to the divergence between solvent and insolvent companies and prior populations, are prominent problems. However, validation samples are often used, which permit examination of sample validity and reduction of problems of ex-post prediction.

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8 About half of the insolvent P-L insurers were mutual companies. For most small mutual insurers only incomplete data are available. More data are available on most stock companies. It is hoped that one result of this study will be a more extensive availability of data on mutual and reciprocal P-L insurers.
4. The use of accounting data in insolvent models also warrants caution. Elam [52] and Altman [4] found that there is little difference in predictability when long-term leases are shown on the adjusted balance sheet. Harmelink [67, 68] concludes that the differences between insurance accounting and conventional accounting produces insignificant differences in the ability of the two sets of data to predict a degree of solvency among P-L insurers, as measured by a decline in Best's policyholder ratings.

Plan of Study

Following this introductory chapter, Chapter II is a comprehensive background for the analyses included in this study. The chapter presents models of insolvencies and factors that may lead to insolvency. Problems of identifying and measuring insolvency are discussed and examined.

Chapter III includes a comprehensive literature review on general business failure prediction, and in the insurance business in particular.

Chapter IV presents the NAIC-IRIS and the Best's Ratings system (BR). The insolvency record is also presented and analyzed in this chapter.

Chapter V discusses univariate analysis for predicting insolvencies among P-L insurers. The DM model is described. A new and modified model of DM is developed. The stability of financial ratios over time is introduced, measured, and analyzed. A model for measuring
the profitability/risk is developed. Both the DM and the stability profitability indices are compared with the NAIC-IRIS and the BR.

Multivariate models, including a multivariate discriminant analysis (MDA) which combines the newly developed univariate indices (variables) are presented in Chapter VI. The MDA and multiregression models are developed and discussed. Other probabilistic models (e.g., a logit model) are also examined in this chapter.

Chapter VII addresses accounting issues and emphasizes the theoretical background for employing the different accounting procedures for prediction of insolvency.

Chapter VIII tests the new methods and contains a description and analysis of the sample and methodologies used. A discussion and evaluation of the efficiency of the models is included. Empirical results of both univariate and multivariate models are shown and discussed in this chapter.

Chapter IX is an empirical comparison among the different accounting procedures and their relative merits as related to prediction of insolvency.

Chapter X contains summary, conclusions, and suggestions for future research.

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9 The profitability/risk is measured by: (1) the variability of earnings over time (the temporal risk), and (2) the quasi-systematic risk in the profitability of an insurer as it related to the overall profitability of the whole industry.
CHAPTER II
THE MODELS OF AND REASONS FOR INSOLVENCY

The objectives of this chapter are two: 1) to identify and explore models of insolvency and the causes of insolvencies among P-L insurers; 2) to outline and discuss theoretical models, as well as practical approaches, for classification and measurement of insolvencies.

Criteria and Definitions for Prediction Purposes

Webster's dictionary defines insolvency as the inability to pay debts. However, a company may be technically insolvent and still be able to do business if the payments of its debts or bills can be deferred. This procedure may be a short-lived strategy, because without issuing new capital or obtaining a profitable performance the company will be forced into insolvency.

Stanley and Girth [145] offer the following definitions: 1) Insolvency is the inability to pay debts as they become due. Often it means that the fair value of the debtor's property is less than his obligations. 2) Bankruptcy is a term used generally to describe proceedings undertaken in federal court, when a debtor is unable to reach an agreement with his creditors outside of court. They point out that most bankruptcies are initiated voluntarily by the debtors. 3) In most states, laws authorize a receivership process, where there is a judicial appointment and supervision by a receiver for an expiring corporation. 4) Liquidation refers to insolvency in general.
terms: it may be bankruptcy, insolvency or receivership, but often it refers to liquidation of assets.

Criteria for Insolvency

There are no definite criteria of what constitutes financial insolvency or financial distress. Different authors use different criteria and definitions. Lev [104, p. 133] broadly interprets failure as severe financial or operational difficulties reflected in either insolvency or bankruptcy. Foster [59, p. 462] points out that, given the ambiguity in the terms financial distress, it is not surprising that different authors use different criteria of distress. Beaver [21] considers a failure any event as a result of bankruptcy, bond default, overdrawn of bank account, or nonpayment of preferred stock dividend. Elsewhere, Deakin [43, p. 168] includes firms which became bankrupt, insolvent, or liquidated for the benefits of the creditors; others have used similar criteria for financial distress. Dun and Bradstreet's business-failures include assignment of bankruptcy, cessation of operations with loss to creditors, voluntary withdrawal while having unpaid obligations, involvement in court actions such as receivership, reorganization, or arrangement for a voluntary compromise with the creditors [46].

Insolvencies among insurers are defined almost the same as in other industries. However, Breslin, Troxel, etc. [34, p. 278] emphasize insolvency in a regulatory context. They point out that an insurance company is solvent if its admitted assets exceed liabilities

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1E.g., see Elam [52, p. 26], Blum [32, p. 2], etc.
by a margin at least equal to the minimum capital and/or surplus required by law, but they prefer to define it as "technical solvency." Solvency may also be defined as a mean for the insurer to meet its obligations as they are due. The emphasis should be continued liquidity, adequate loss reserves and appropriate premium rates [34].

Trieschmann and Pinches define financial distress for an insurance firm as a case where the firm has entered into liquidation, receivership, conservatorship, or rehabilitation [156, p. 237]. Hershbarger [73] defines failure as liquidation, receivership, or conservatorship and rehabilitation. A more flexible approach is used by Harmelink, who views the Best's Ratings as surrogates for degrees of solvency of P-L insurers [67, pp. 147-8, and 68].

In this study financial insolvency in the P-L insurance industry is defined as: liquidation, receivership, conservatorship, rehabilitation or restraining order. Voluntary retirement will also be considered as insolvency, although in several steps voluntary retirement will be differentiated from nonvoluntary retirement. The National Association of Insurance Commissioners' early warning system (NAIC-IRIS) defines priority companies as those companies with four or more tests outside the usual (acceptable) ranges. In this study priority and/or weak insurers will be those firms that entered into conditions or circumstances that may lead to insolvency within a few years.

Three Approaches

The lack of an objective criterion for identifying an insolvent insurer might introduce a serious theoretical problem in research
dealing with prediction of insolvency. However, in practice either an abstract definition of insolvency or ex-post empirical actual result might be used. Three major approaches have been used in previous research and/or practical applications.

The first approach emphasized a regulatory viewpoint. This approach considered capital adequacy as a major target of the supervision of P-L insurers. Under this approach insolvency is defined as the occurrence of a negative equity (policyholders' surplus, which includes capital and surplus). This definition is independent of the actual declaration of insolvency. However, a-priori the approach is dependent on an historical event (e.g., occurrence of negative policyholders' surplus).

A second approach employed general terms such as priority companies, unranked companies, or targeted insurers, as indicators for failed companies. This approach allowed the supervisory bodies (e.g., NAIC, or Insurance Departments), or financial service companies (e.g., A.M. Best) to either rank companies or to separate distressed and sound companies, rather than projecting an actual insolvency. (Many of the priority or low-ranked companies do not actually fail and may become sound companies again.) Moreover, in this approach, several insolvent companies were not flagged as priority companies even one year prior to insolvency. Many insurers were not flagged three years prior to insolvency.

The third approach, an ex-post actual declaration of insolvency by courts and/or regulators is the most common method employed in
previous research. Insolvent insurers were identified ex-post, and several characteristics of these insurers were compared with a sample of solvent insurers. Most often these characteristics were financial ratios which were applied as univariate variables and/or as an independent explanatory multivariate set. The companies were grouped into an ex-post insolvent group and a solvent group. Models which related the probability of failure in the current period to those independent variables were developed for one or more years prior to insolvency.

Definitions, Classifications, and Measurement of Insolvency

Definitions of insolvency as related to predicting insolvencies were considered in the previous section. However, the issue of classification and measurement of insolvencies among P-L insurers needs further insight.

The primary questions are: (1) How is insolvency defined?; (2) When does a company become insolvent?; and (3) How do regulators make decisions and handle the issue of insolvency? Since there is not a clear and common accepted definition of insolvency, there is also no explicit yardstick that may point out when a company becomes insolvent. Insolvency is not a clear-cut issue. The status of a company as solvent, distressed, delinquent or insolvent may change across time. Therefore the classification seems to be an arbitrary one.

2The identification of an insurer as solvent or insolvent may not follow rules of dichotomous variables. Ex-ante it may be an arbitrary procedure to put companies on a list of solvent companies (0) and on list of insolvent companies (1).
Ex-post, an insurer becomes insolvent as it is declared so by a court, or when regulators recommend insolvency, receivership, or rehabilitation process. However, there are troubled or distressed companies in the market which are not declared as insolvent, but technically may be in an insolvent state, and ex-ante may even be predicted as insolvent.

This section outlines and discusses the issues of defining, classifying and measuring insolvencies among P-L insurers (the relevant questions are: when? where? and how?). The following section examines causes of insolvencies (the relevant question will be: why?).

Bailey [13] defines solvency as minimum amount and quality of assets needed to assure payment of liabilities. First the liabilities of an insurer should be defined and then a minimum quantity and minimum quality of assets to protect the liabilities should be determined. The problem of defining insolvency is to devise an adequate test to show either insolvency or a predictable trend in the direction of insolvency.

Patterns of Monitoring Solvency

Appraising the solidity, stability and solvency of insurers is a unique and difficult task. Regulators have the authority and the responsibility to conduct such an appraisal. Every insurer has to furnish a financial statement to the insurance department in the state of domicile, and to all other states where it conducts business.

Decision by courts may take a long time. In several decisions it took courts three years or more to reach a decision.
States statutes require the insurance commissioners to conduct periodic field examinations of all insurers authorized to do business in the state. To eliminate duplication of examinations the NAIC divides the country into six zones. Representatives of other zones, excluding the zone where the insurer's headquarters is located, participate in the examination conducted in the state of domicile. As a result of these examinations an insurance department makes a decision as to whether or not a company should be put into a rehabilitation or a liquidation process.

The NAIC has developed a series of tests\(^4\) that have the purpose of providing diagnostic tools for evaluation of insurance company strength. The primary purpose of this system is early identification of companies that may require close surveillance. Most insurers are required to file annual statements to the NAIC. Insurers that may require closer analysis are identified as priority companies [34, pp. 284-9]. In recent years insurance departments have sent representatives to an examination team which reexamines the results and identifies another priority list of companies. This list is divided to immediate-priority companies and targeted-priority companies. Companies which appear on these lists are usually subjected to more comprehensive examination in the state of domicile. The classification of companies on the priority lists is a guarded secret and not

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\(^4\)This system is known as the NAIC-IRIS [12]), and previously was called the early warning system; it will be discussed in Chapters IV and V.
publically announced. The final decision as to whether or not to put a company in an official or unofficial rehabilitation,\footnote{The Wisconsin 1967 code chapter 645, gives the commissioner of insurance many tools or procedures for coping with the whole spectrum of delinquency among insurers. The code permits the insurance department to take certain unofficial and confidential steps against impairments. The NAIC model bill which considers this problem was adopted by four states; eight other states have adopted a form of the Wisconsin law. House bill 830 is now being considered by the Senate Insurance Committee in Ohio. The bill would allow certain actions to be taken by the insurance department without allowing these actions to become part of the public records, including hearings in the chambers of a judge rather than in open court [154].} or in a procedure of liquidation, is the responsibility of the states' regulators. All official rehabilitations or liquidation procedures result from a court decision. The time pattern of these events is depicted in Figure 1.

As presented in Figure 1, the question is whether or not a delinquent company at stages 5 or 6 is considered a solvent or an insolvent company. In the empirical study of this research these companies are still considered solvent, but for other purposes they may be considered as insolvent or technically insolvent.

The issues of identifying and measuring delinquent and impaired insurers seems to be unresolved. Short interviews were conducted with the Insurance Commissioner, and the chief examiner of the Department of Insurance in Ohio in October, 1982. Several general conclusions from these interviews are:

1. There is no formal process for determining which company must be in close supervision and unofficial rehabilitation, and which
Stages:

(1) Financial statement date, Dec. 31.
(2) Financial statement due March 31.
(3) NAIC-IRIS tests are ready.
(4) A three-year current examination by state of domicile.
(5) A company is on the NAIC-IRIS priority list (and/or NAIC Examination team priority list).
(6) Close scrutiny by state of domicile including, steps that are not part of the public record.
(7) Open court procedures.
(8) Final failure date: Liquidation, rehabilitation, etc.

Figure 1. Important Dates for a Failed Insurer.

A Solvent Company

<table>
<thead>
<tr>
<th>Time (Year)</th>
<th>5</th>
<th>4</th>
<th>3</th>
<th>2</th>
<th>1</th>
</tr>
</thead>
</table>

An Insolvent Company

<table>
<thead>
<tr>
<th>Time (Year)</th>
<th>5</th>
<th>4</th>
<th>3</th>
<th>2</th>
<th>1</th>
</tr>
</thead>
</table>

Failure Date

company should be brought to court for an insolvency process. The decision process which must be taken by the insurance department is not defined. A written statement does not exist, nor is a list of decision criteria available.

2. The decision to start a liquidation or rehabilitation process involves several considerations including: company's management reputation, ability and knowledge; diversification among lines of business and diversification across states; and how the overall industry results compare with the company's results.
3. The NAIC-IRIS tests are considered preliminary indications for problems, rather than decision tools. They point out companies which need a close scrutiny.

4. The Best Ratings are taken into consideration, but they are considered of secondary importance.

5. When a company is considered for a closer scrutiny an extensive examination takes place. Financial statements as well as detailed records are examined and analyzed. The regulators concentrate on the following considerations:

(a) Adequacy of capital and surplus. The examiners try to estimate whether or not a minimum equity is maintained, the net written premiums are compared with the surplus and assets.

(b) Adequacy of reserves, especially the loss reserves, is determined.

(c) The market value of bonds and stocks are considered and compared with the future cash-flow streams. However, a depressed bond market and/or stock market are considered important if companies may be required to sell bonds or stocks in order to generate cash inflow. If companies can demonstrate enough future liquid sources (e.g., premiums and interest) to pay for future loss payments and expenses the value of securities may not be considered as important as they otherwise would be.
(d) A close examination considers the speed of claims payments, and whether or not there are significant delays in claims payments.

6. Informal rehabilitation procedures are considered as part of the new liquidation bill (House bill 830). In the last decade about ten domestic insurers were subjected to such a procedure as the result of mutual agreement between the insurance department and the company management. There were no court procedures, but the department held the company in close scrutiny and served in an effective advisory status. In a few cases, they even participated in making business decisions.

7. The procedure in court may be a long one. The last case of insolvency in Ohio, however, was a very fast one, since owners, managers and regulators agreed on the necessity of liquidating the company (Proprietors). In contrast, a previous case (Manchester) took about 3 years in court, because the managers of the company disagreed with the insurance department on the necessity for liquidation.

The regulators apply various forms of regulation to protect the solvency of insurers. Minimum equity requirements are usually imposed. An initial minimum of capital and surplus is required to establish a company, and to obtain licenses in many states a continuing minimum is often required. Minimum capitalization requirements

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6 Hammond, Shapiro and Shilling [66, pp. 21-30] outline statutory capital requirements for entry of insurers, by states and by types of insurance.
are discussed by Bachman [19], Breslin, etc. [34, ch. 5-6], Hammond, etc. [66] and others.

Regulators often constrain the insurer's exposure (ratio of premiums to equity), the insurer's leverage (ratio of liabilities to equity), and other related ratios. Beckman and Trembling [26] recommend an exposure ratio between 2 and 3; Kenny [93] recommends an exposure ratio of less than 2; the NAIC considers an exposure ratio of less than 3 as an acceptable ratio [121]; and the N.Y. insurance department allows an exposure ratio of up to 3.3. Hofflander and Duvall [79] suggest alternative ratios (e.g., assets divided by premiums). 8

A practical implication of these "norms" is to impose an insolvency procedure on a company which violates one or more of the previous requirements. However, as discussed above, there is no one/or a few defined yardsticks, nor is there a common and strict measure to classify an insurer as insolvent. There are many measures and several possible classifications; none of them give an absolute answer.

Identification of Insolvency: Theoretical Approaches

Finance theory indicate several measures for insolvency. For example, the market value of the insurer is compared with the value of

7 Breslin, etc. [34, p. 228] defined "technical insolvency," see explanation in the previous section.

8 For more details and discussion on financial ratios see Chapters III, IV, and V.
its liabilities (measured at their present value). The market value of the insurer might be measured by the dollar value of its outstanding stocks. However, the stocks of most insurance companies have not been traded in the securities market.  

The financial viewpoint may lead to two extreme definitions of insolvent insurer. One extreme definition of insolvency may be when a company is unable to meet its obligations as they are due. This is a relatively flexible requirement. In the extreme case when the insurer is not able to pay the next debt there is a clear case of insolvency. However, from the consumer as well as regulator viewpoint, it is too late, since the current policyholder or claimant has no repayment.  

A second extreme may be to compare the market value of assets (MVA) with the present value of liabilities (PVL). The difference can be considered as the financial equity (FE), or financial surplus of the insurer.  

At any point in time \( t \), this financial equity is:

\[ FE(t) = MVA - PVL \]

9About 2/3 of the P-L insurers are mutual companies, and it is estimated that less than 30 stock insurance companies have significant trading of their stock in the securities market.  

10This financial approach differs from the accounting approach. Under SAP and GAAP liabilities are measured at terminal (current) values, without any discounting factor. Therefore the liabilities under these accounting methods are larger than under the financial method, while the surplus is smaller. Assets, generally, are measured on cost basis (and/or cost or market—the lower) under GAAP. Under SAP bonds are carried at amortized cost, while stocks are carried at market value (stocks have been about 20% of total assets of insurers on the average during the late 1970s). A-priori it is not possible to measure the effect of valuing all assets at market value on the total value of assets. The FE may be larger or smaller than equity under accounting methods.
$F_{Et} = MV_{At} - PVL_t$

This financial equity varies over time, and can be viewed as random walk changes in a continuous time framework. At any point of time an insurer may become insolvent whenever $F_{Et} < 0$. However, if there is a minimum equity requirement, $K$ (e.g., $F_{Et} > K$), then an insurer can become insolvent whenever $F_{Et} \leq K$. The process is described in Figure 2.

Two practical problems with this financial approach are:

1. to determine what is the proper discount rate;
2. to determine the market value of assets.\textsuperscript{11}

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure2}
\caption{Financial Equity (FE) as a Random Walk Process.}
\end{figure}

Note: $S_0$ - Minimum capital required for entry

\textsuperscript{11} Determining the market value of assets may be a very difficult task, many bonds do not have market values. Municipal and local government bonds and other tax-exempt bonds are currently about 40% of total assets (2/3 of the bond portfolio) of P-L insurers; most of these bonds do not have market value.
Even under the continuous time framework there is not an objective standard of when and how to draw the line for insolvency. Two implied reasons are: 1) the continuous time framework demonstrates that an insurer can be technically insolvent at one point of time and become solvent at a later point of time, and 2) part of the liabilities (the unearned premium reserve, UPR) may not be paid if the insurer continues its operation. Once again, the issue becomes a matter of an arbitrary decision by regulators. The decision is not a clear-cut issue (as 0, 1, dichotomous variables), and the status of a company may change over time. A further complication is indicated by the existence of troubled or distressed companies in the market, while regulators cannot make a final decision as to whether or not to liquidate them.

A third financial approach is advocated by Weaver, Lilly and Findaly [160] who model the insurance company operation by an application of the option-pricing theory. They view the common stock of a P-L insurer as a contingent claim on the asset portfolio of the company. The derived model, based on a hedge portfolio, is:

\[ 0 = \text{St} + 1/2 \left( \text{Sa} \text{ca}_2 \text{A}^2 + 2 \text{Sa} \text{ca}_1 \text{pal} + \text{S1a}_1 \text{L}^2 \right) \]  

(2-2)

where \( S \) is the value of the company (equity) at a point of time. \( S(x) \) = the partial derivative of \( S \) with respect to \( x \); and \( x \) presents any variable as time (t), asset value (A), etc.
- \( A \) = the value of P-L insurer's assets.
- \( L \) = the value of P-L insurer's liabilities (can be considered in present value).
- \( \text{ca}_2 \) = variance of rate of return on assets
- \( \text{cl}_2 \) = variance of rate of return on liabilities
- \( \text{pal} \) = correlation coefficient between changes in return of A and L.

12The Wisconsin Code takes almost the same approach. However, the code does not consider present value of liabilities.
The derived equation (1) is based on return \( r \) of a riskless portfolio \( P \) over time \( dt \) [160, pp. 49-54] as follows:

\[
dp = r.P.dt
\]  

(2-3)

and the option values as indicated in [160, equation (16)-(21)]. The Black-Scholes' equation is modified [160, equation (22)] and applied as follows:

\[
S(A, L, t) = A \ N(d'_1) - LN(d'_2)
\]  

(2-4)

where:

\[
d'_1 = \frac{\ln(A/L) + 1/2\sigma^2(H-t)}{\sigma \sqrt{H-t}}
\]

\[
d'_2 = d'_1 - \sigma \sqrt{H-t}
\]

and \( \sigma^2 = \sigma_A^2 - 2\sigma_a\sigma_b \sigma_l + \sigma_l^2 \)

\( N(\cdot) \) is the cumulative normal density function, \( H \) might represent any time horizon, \( t \) periods from the present.

The portfolio variance is of primary importance. The paper demonstrates that managers can increase the value of equity, which is the owners' best interest, by increasing the assets-return variance. However, this increase in asset-return variance increases the risk of insolvency \( P(A < L) \) which is the regulators' worst interest.

While considering the stochastic nature of the insurer's liabilities and entry costs (e.g., the cost of restarting a new insurer company) the equity holder might not default even when liabilities exceed the value of assets (i.e., paying the current claims but not
the unearned premium reserve). A multiperiod pricing model is required. At every end of a period, \( t \), the equity holder faces a choice between exercising his option and receiving \( A_t - L_t \), or having another option for one more period (compound option).

Thus far, the discussion has not addressed the issue of the probability of ruin. A company with an initial equity may operate with profits and losses across time. Regulator may impose a minimum probability of ruin required for an insurer. If this minimum acceptable ruin probability is not met the insurer may be declared insolvent and is removed from the market place.\(^{13}\)

Bachman and Lang [20] found that for a given fixed ruin probability an increasing investment in stocks (coupled with writing more liability lines), will reduce the ratio of premiums written to policyholder surplus (the exposure ratio). This would lead to a reduction in total expected return of an insurer.

Borch [35] assumes that ruin occurs when the equity is completely eliminated (i.e., zero equity). The main task of the government supervisor is to make certain that the company equity remains adequate.

\(^{13}\) The actuarial and insurance literature use the term ruin probability in a few issues. Often the ruin probability is related to the capacity problem. For example, for a given ruin probability (as .01, or .001, etc.) how large can the written premium to surplus be? Another interpretation may be related to Figure 2 and the gambler's ruin problem. An insurer operates with an initial net worth and continuous profits (or losses) from underwriting and investments. The equity fluctuates across time and the question is: What is the probability that the insured is ruined (negative equity, or equity below the minimum requirement) at some point of time? [20,34, pp. 130-3, 277-8].
He may achieve this task by applying a standard of probability that the insurer will meet its obligations. The same definition for ruin as a zero equity is taken by Hofflander and Duvall [79].

Borch identifies insolvency when claim payments $\tilde{X}$, a stochastic variable exceeded premiums ($P$), i.e., $\tilde{X} > P$. The probability ($Pr$) that the insurer will not be able to fulfill its obligations is:

$$Pr (\tilde{X} > S+P) = 1 - F(S+P)$$

(2-5)

Where $S$ is the equity required by regulators, and $F$, $G$, etc., are cumulative distribution functions. If the regulators decide the probability that the insurers must meet their obligations is at least equal to $\alpha$, then:

$$Pr (\tilde{X} \leq S+P) = F(S+P) \geq \alpha$$

(2-6)

Let $Y$ be the stochastic value of the assets when the underwriting losses occur ($\tilde{Y}$ is independent of $\tilde{X}$) with a cumulative distribution function $G(Y) = Pr(Y \leq y)$. The probability that claims ($\tilde{X}$) will not exceed $P+Y$ is $F(P+Y)g(Y)dY$ and the insurer will be able to pay its obligations, (where $g(Y)$ is the density function of $\tilde{Y}$).

Then the regulators' requirement will be satisfied if:

$$\int F(P+Y)g(Y)dY = 1 - \int G(Y)dF(P+Y) \geq \alpha$$

(2-7)

The basic formula is developed further, and the author introduced elements of utility theory and market rate of interest. However, investment earnings and gains are not included in the analysis.

Bachman [19] determines the minimum capitalization requirements of an insurer. His main findings are that the minimum capital required to maintain solvency varies among companies due to the amount
of risk associated with the underwriting profit margin of each company. The results were based on the level of probability at which solvency is maintained (1-probability of ruin), and the efficient frontier of the product-line mix (in the mean-variance dimension).

Hammond, etc. [66] describes the regulation of insurance solidity through equity requirements. The analysis introduced various iso-ruin lines at various exposure ratios in the expected return-risk dimension of underwriting profits for each insurer. Underwriting risk and return coupled with the premium to surplus ratio (exposure ratio) and the underwriting mix are found to be good indicators of insolvency.

Both Hammond, etc. [66] and Bachmann [19] focus on underwriting profits. Kahane [90; 91] includes underwriting and investment returns and risks in the analysis. Examining the influence of the exposure ratio on the efficient frontier (portfolios of underwriting lines and securities), he demonstrates how a ruin constraint can be translated into a practical criterion-constraint such as the premiums to surplus ratio.

The discussion above may lead to developing a simple model that can be applied for regulating the solvency of insurers. The combined profitability of underwriting and investment activities are employed across time. The expected profit on premium (or surplus) and the temporal risk (the standard deviation or variance of the insurer's profitability over time) are considered. The analysis is in ex-ante

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14 The discussion is based on Hammond, etc. [66], and Kahane's [90;91] model. However, in this research profits and/or return on premiums (or surplus) diverse from measurements being used in previous research.
terms, but practical implications (including ex-post analysis) follow. It may be assumed that the expected underwriting and investment profits on premiums for an insurer is denoted by \( E(\bar{R}) \), where \( \bar{R} \) is a random return over time. Let \( Sr \) be the notation for the standard deviation and both \( \bar{R} \) and \( Sr \) are temporal parameters. Return and profit on premiums are used interchangeably.

It may be set

\[ P(\bar{R} < K) \leq \phi \]  \hspace{1cm} (2-8)

where \( \bar{R} \) is a random variable with expected value \( E(\bar{R}) \)

\( \phi = \) the ruin probability

\( K = \) a certain level of return (profits divided by premiums (or surplus))

Defining a ruin as a situation where the rate of return on premium \( (R) \) fall below a certain level, \( K, \phi \) may be set as the upper bound of ruin-probability (equation 8).

Thus, it may be assumed that \( \bar{R} \) is normally distributed across time, then we can write:

\[ P \left\{ \left( \frac{\bar{R} - E(\bar{R})}{Sr} \right) \leq \left( \frac{K - E(\bar{R})}{Sr} \right) \right\} \leq \phi \]  \hspace{1cm} (2-9)

and by using the assumption of normality

\[ \frac{K - E(\bar{R})}{Sr} \leq Z(\phi) \]  \hspace{1cm} (2-10)

\[ \text{Hammond, etc. [66], Bachman [19] found that the combined trade ratio is normally distributed among types of insurers. In future empirical research it might be worthwhile to examine if the profitability ratio (s) is (are) normally distributed over time.} \]
or \( E(\bar{R}) \geq K - Z(\phi) \cdot S_r \)  

where \( E(\bar{R}) = 0 \), then \( S_r \geq K / Z(\phi) \)

Equation (10a) is a ruin constraint that can be plotted on the return and risk dimension. The result may be an iso-ruin line, or a set of iso-ruin lines, which are based on \( K \) and \( \phi \) that might be determined a-priori by regulators. The following Figure 3, demonstrates the situation:

\[ \begin{align*}
\text{Expected return} \\
on premium \\
(or on surplus)
\end{align*} \]

\[ \begin{align*}
E(\bar{R}) \\
Sr \ (\text{standard deviation of return on premium, or on surplus})
\end{align*} \]

Figure 3. The Iso-Line Ruin Constraint

If the insurer falls below the constraint it might be declared as insolvent by regulators.

Assuming an insurer with a combined underwriting and investment profitability ratio as follows:

\[ \text{MPR}_t = 1 - \frac{L}{PE} - \frac{UE}{PW} + \frac{IG}{PW} = 1 + \frac{IG}{PW} - \frac{L}{PE} - \frac{UE}{PW} \]  

(2-11)

---

16 The following notations are used: \( L \)-Loss incurred, \( PE \)-premium earned, \( UE \)-Underwriting Expenses, \( PW \)-Premium Written, \( IG \)-Investment Income and gains (realized and unrealized), \( \frac{L + UE}{PE} \) is known as the combined trade ratio. One less the combined trade ratio is the modified underwriting profitability ratio, while MPR includes also the investment income and gains. This is a modification of statutory profitability ratio which is: \( 1 - \frac{L + UE}{PE} \).
where $\text{MPR}_t$ = the modified profitability ratio for period $t$.

$\text{MEMPR}$ is the average $\text{MPR}$ over time and $\text{SDMPR}$ is the standard deviation of $\text{MPR}$ across time. Ex-post, this research study obtained the profitability ratios in Chapters V, and VIII.

Ex-ante, the regulators may impose the value of $K$ and $\phi$ for an insurer based on its past and future performance (i.e., $\text{MEMPR}$ is an estimation of $E(\overline{R})$ and $\text{SDMRP}$ is an estimation of $S_r$). Unfortunately, this constraint cannot easily be applied to the whole P-L industry, since insurers differ in their profitability, $\overline{R}$, distributions.

The return on premiums may be easily transformed to a return on equity (surplus) by multiplying the return on premium for each year by the exposure ratio (premiums to surplus) for that year.$^{17}$

$$\text{MPR}_{St} = \text{MPR}_t \left( \frac{P_t}{S_t} \right)$$

(2-12)

where $\text{MPR}_{St}$ = modified return on equity for period $t$.

$P_t$ = premiums written (or earned) for period $t$.

$S_t$ = the surplus (equity) for period $t$.

Thus, $\text{MPR}$ can substitute $E(\overline{R})$ in equation (2-10a).

Equations (9) through (12) may also be used for predicting future insolvencies if regulators follow these assumptions of ruin probability and ex-post analysis for each insurer.

$^{17}$Since the MPR is profits/premium and the exposure ratio is premiums/surplus, the modified return on equity is: (premiums/surplus) X (profits/premiums) = profits/surplus. However, the premiums should be modified to express the difference between written and earned premiums. Moreover, if the exposure ratio (P/S) was constant over the time then the modified K, $K'$ would be $K' = K(P/S)$. 
Finally, it may be assumed that each insurer \( (i) \) has its own tolerance probability of insolvency \( (\phi^*) \), so that if \( \phi_i < \phi^* \) the insurer must become insolvent. Defining \( \phi^* \) for a specific insurer may be an arbitrary decision, but a tradeoff between \( \phi^* \) and \( K \) is possible.

The random walks pattern in the stock market indicates that knowledge of past price (or return) behavior of stock-prices cannot be used to predict future prices. Coupled with the inability to impose absolute standards of insolvency, financial distress prediction based on the discussion in this section becomes very difficult. Tools discussed in this section have not been developed to a point where they have widespread practical application.

An ex-post definition of insolvency as an official case (declared by court or regulators), which was presented in the previous section, eliminates many problems which are outlined in this section. This definition might be more appropriate for prediction purposes. It clarifies the difference between solvent and insolvent companies; although it may increase type II errors (solvent insurers are predicted as insolvent) because there are distressed insurers in the market. However, the consequences of type II errors are less important than the consequences of type I errors (insolvent insurers are predicted to be solvent).

**Factors Leading to Insolvency**

The main reasons for failures among insurers are underreserving, overstatement of assets, inadequate surplus relative to volume of business, and management dishonesty and inefficiency.
Some of the broadly defined causes are:

1. Improper underwriting, reserving and claim handling.
2. Inadequate expense controls.
3. Questionable investment practices.
5. Abnormal transactions with agents, brokers, or reinsurers.
6. Excessive commission or management allowances.

Olson [124] found that management dishonesty as reflected by questionable agency balances and falsification of investment were the primary reasons for insolvencies. However, these causes might be considered as reactions of management to financial distress. Moreover, dishonest management is a factor that may be very difficult to predict. Evans [53] pointed out low underwriting standards and questionable investments as primary reasons for failure. Haverland [71, 72] outlined inadequate reserving and overstatement of assets as primary causes. The main two major items in an insurance company's balance sheet which are frequently mistated are the loss reserves and bond values. Haverland argued that the UPR were usually adequate, while loss reserves are frequently understated. He analyzed a sample of 18 companies and found that only 3 were properly reserved at the end of 1974 [70]. Underreserving indicates bad quality or dishonesty of management, moreover, it means overstatement of the surplus, and may lead to underpricing. A study published by The Conning Company indicated that 24 percent of the 240 largest P-L insurers were

\[18^\text{Breslin, etc. [34], p. 305}].\]
underreserved, and at least 13 percent were underreserved by more than 25 percent of their surplus at the end of 1978 [39].

Overstatement of assets has been often caused by overstating the true market value of bonds. Bonds are usually valued at amortized cost, which is required by the statutory accounting. It may disregard the true market value of bonds, since an increase in interest rates decreases the true market value of old bonds. The result is an overstatement of assets and therefore an understatement of surplus. As bonds are liquidated and their true market value is realized the insurer must realize a loss. The problem is even worse since bonds are often liquidated when business declines and/or cash flow decreases. Bachman and Long [20] studied 18 major insurers and found that they overstated their surplus by an average of over 35 percent as a result of overstatement of bond values. At least one company would have been theoretically insolvent if bonds had been placed at their true market value.

Inadequate surplus relative to volume of business may cause distress especially if an insurer has a sudden need to meet catastrophe claims. The surplus ratio was found to be a good predicator of several studies. Moreover, this ratio traditionally has been

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19 Bonds are about 60 percent of the total assets held by P-L insurers.

20 The surplus ratio is the net written premium divided by the surplus (equity). This ratio was shown to be a good indicator of distress by Evans [53] and Nelson [122], and was found to be an important variable in a multidiscriminant analysis (MDA) by Trieschmann and Pinches [156]. It is also denoted as the exposure ratio.
considered as a measure of underwriting risk exposure. Management inefficiencies, such as too large expenses, uncareful underwriting policy, underpricing, and inappropriate reinsurance policy, may also be important causes of insolvencies.

Eck [47] found that dishonesty was involved in 81 percent of twenty-six insolvent insurers domiciles in Illinois. Shortage in the premium trust fund of an agency was found in 14 insurers; over-ride commissions paid to agencies in 16 firms; wrongful conversion of assets in 13 insurers, and an affiliate agency or management contract in existence in 21 insurers. Based on the assumption that most failures result from dishonesty, Eck [48] selected 17 financial ratios that might represent dishonesty better than other financial ratios. Most of these financial ratios had also been used in previous research during the 1970s. By selecting financial data it was plausibly determined that financial statements might point out and/or identify dishonesty and fraud.

The McKinsey & Company study concludes that the predominant cause for insolvencies was underwriting losses. It indicates the importance of the underwriting results and may encourage the use of these results for prediction purposes. However, investment gains (or losses) were not considered as important. Balance sheet misrepresentations and dishonest management were also considered prominent causes. The main causes of insolvencies among P-L insurers compared with the overall causes of failures among all business are listed in Table 1. Balance Sheet misrepresentations are summarized in Table 2.
### TABLE 1

Causes of Insolvencies

<table>
<thead>
<tr>
<th>Property Liability Insurers&lt;sup&gt;1&lt;/sup&gt;</th>
<th>Overall Business Failures&lt;sup&gt;2&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>1974</td>
<td>1973</td>
</tr>
<tr>
<td>Underwriting losses 59%</td>
<td>Neglect 1.6%</td>
</tr>
<tr>
<td>Dishonest management 34%</td>
<td>Fraud 1.3%</td>
</tr>
<tr>
<td>Dishonest or bankrupt agent or reinsurer 6%</td>
<td>Lack of experience 30.5%</td>
</tr>
<tr>
<td>Investment losses 1%</td>
<td>Unbalanced experience 21.6%</td>
</tr>
<tr>
<td>Total 100%</td>
<td>Incompetence 41.0%</td>
</tr>
<tr>
<td></td>
<td>Disaster .6%</td>
</tr>
<tr>
<td></td>
<td>Reasons unknown 3.4%</td>
</tr>
<tr>
<td>Total 100.0%</td>
<td></td>
</tr>
</tbody>
</table>

Sources:  
<sup>2</sup>Dun and Bradstreet, "The Business Failure Record, 1973," and "1979" [46].
TABLE 2.

Distribution of Balance Sheet Misrepresentations among Insolvent P-L Insurers

<table>
<thead>
<tr>
<th>Overstated Assets</th>
<th>% of Insurers</th>
<th>Understated Liabilities</th>
<th>% of Insurers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agent Balance</td>
<td>18</td>
<td>Loss reserves</td>
<td>43</td>
</tr>
<tr>
<td>Securities</td>
<td>13</td>
<td>Other</td>
<td>3</td>
</tr>
<tr>
<td>Reinsurance</td>
<td>12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Totals</td>
<td>54</td>
<td></td>
<td>46 100%</td>
</tr>
</tbody>
</table>


It is possible that overstatement of assets or understatement of reserves are important reasons for an inability to predict failure based on financial statements. However, it is expected that the DM and other models that will be presented in this research will be able to predict failure despite dishonesty and other problems.
CHAPTER III
LITERATURE REVIEW

This chapter is an overview of literature in regard to prediction of financial distress of business organization in general, and insolvencies of P-L insurers in particular. Some related research is also included in Chapters II, and IV through VII.

Overview of Related Research on Insolvency

There is growing concern among researchers in different fields about bankruptcy among firms. More than forty-five years have passed since Winakor and Smith [164] addressed the potential issue of business failure. Since then a growing body of literature has evaluated the problem from the perspective of accounting, finance, banking, and insurance.

Research on insolvency and/or bankruptcy has taken several directions. The first direction is descriptive as well as analytical. Researchers explain the process, performance, and problems related to bankruptcy. The bankruptcy act and legal cases are extensively discussed. Stanely and Girth [145] describe the meaning of bankruptcy with emphasis on the economics of bankruptcy. The issue is discussed from the legal and business economics point of view. A detailed analysis of the bankruptcy process, administration and financing is presented. Altman [2] examines how aggregate economic factors affect
business failure. His main finding is that failure rate was negatively correlated with changes in the GNP; slowdown in economic activity increases the failure rate. In a recent book, Altman and Sametz [9] edit research on financial crises, describing institutions and markets in a fragile environment. The second part of the book includes research by 18 scholars on the problems of the fragile financial environment and endangered financial markets.

A second body of literature consider the construction of a theory of corporate failure. However, Lev [104, p. 124] points out that this research is unsatisfactory, primarily because of the complexity and diversity of business operation, and the lack of well defined economic theory of firm under uncertainty. Nevertheless, literature on theoretical issues related to financial insolvency developed during the 1970s. Most of the research is an attempt to construct and relate corporate bankruptcy to modern finance theories. Gordon [63] points out that academicians with first-hand knowledge leave the subject of bankruptcy, and develop models to evaluate the common equity and debt as companies fall into financial distress. Stiglitz [146] investigated the relationship of insolvency to the Modigliani-Miller capital structure theory. He developed a model and shows that under restrictive conditions, when there is a real possibility of bankruptcy, and if firms issue too much debt, the firm valuation is dependent upon its debt-equity ratio. Therefore, under these conditions, financial policy may have an effect on the value of the firm.

Wilcox [161; 162; 163] adapts the gambler-ruin probability approach, and based upon net liquidation value and other variables,
constructs a theory for prediction of failures. The net liquidation value (NLV) is determined by inflow less outflow of liquidation measures over time (a few alternative definitions for net liquidity measures are employed). Cash inflows and outflows are matched over time. Applying a Markov chain approach the probability of failure (ruin) is defined as:

$$\Pr(\text{failure}) = \begin{cases} 1 & \text{if } p < q, \text{ inevitable failure} \\ \left(\frac{q}{p}\right)^N & \text{otherwise} \end{cases}$$

(3-1)

Where:
- $N$ - number of states over time away from failure
- $p$ - probability of winning one's bet
- $q$ - probability of losing one's bet
- $p + q = 1$, and the bet is the amount of cash flow at risk each period.

The firm starts with a given NLV at period $t$, and at time $t+1$ the firm wealth is either $NLV + \text{the bet}$, or $NLV - \text{the bet}$.

The statistic $\left(\frac{1-X}{1+X}\right)^N$ is the estimate of $Pr(\text{failure})$; while $X$ is the firm average winning (e.g., average adjusted net cash flow) per period divided by the size of the bet (the size of adjusted cash flow at risk each year). When the firm's (player's) wealth is reduced to zero, the firm is ruined and must quit. Otherwise, it might continue indefinitely.

Prediction of Corporate Failure

A third direction is an attempt to predict corporate failures. The literature is developed along two main routes: univariate models of distress prediction, and prediction of distressed firms by using multivariate models. In both routes financial ratios have been used...
extensively. Horrigan [80], Altman [1] Beaver [21,22] are among the first persons who found financial ratios useful for predicting insolvencies. Most univariate models concentrate on comparing financial ratios of failed firms to those of nonfailed firms. These prediction models include the use of a single variable (ratio), assume that the distribution of the variable among nonfailed companies differs from the distribution of the variable among failed companies, and consider the capitalization of this systematic difference by the prediction model. Winaker and Smith [164] use a sample of 183 solvent firms and reported deterioration in the mean ratios of distress firm even ten years before failure. However, no control sample of solvent firms is examined. Beaver [21,22] compares means of 30 financial ratios for each year in the five years prior to failure and finds remarkable differences for most ratios between failed and nonfailed firms. Since means examine only one point in the distribution, Foster [59] recommends the use of median, significant tests for the equality of means, and confidence intervals in order to increase reliability of the research.

The univariate research focuses upon dichotomous classification, analysis of likelihood ratios, and comparison of means. Deakin [43] replicates Beaver's analysis on another sample discovers quite similar results. Theil [151,152] and Lev [102,104] construct the Decomposition Measures (DM). Lev [103] relates the DM to predict distress firms. The DM is based on implication of expected value of information and is constructed as a special part of information theory, while
defining the informational content of a message.¹ Lev [103] uses Beaver's sample to test the predictive power of the Decomposition Measures (DM). Failed firms have larger DM than nonfailed firms; the results of a dichotomous classification indicated lower misclassification percentage than the univariate ratios (except cash flow to total debts).

Pendlebury [126] and Walker, Stow and Moriarity [158] comment recently on the usefulness of the DM to measure stability of financial statements over time. Walker, etc. [158] find that the DM has about the same prediction power as the best financial ratio. It is noted that the asset decomposition measures have very little discriminating ability. Booth [33] finds in recent research that some DM discriminate between failed and nonfailed firms. However, discriminant analysis model employing a few derived decomposition measures are not successful in predicting financial failures.

Wilcox [162] conducted an empirical test for his model. Ninety-four percent of pairs observed were predicted correctly one year before failure, but only 76 percent five years prior to failure. Based on this research, it seems that univariate models have limited power to discriminate between solvent and nonsolvent firms.

The first multivariate model of failure prediction was developed during the 1930s. Wall [159] establishes a weighted index based on seven ratios. Altman [1] was the first to use a multivariate

¹For further discussion, see Chapter V.
discriminate analysis (MDA), including 22 variables. His sample includes 33 bankrupt firms paired with 33 nonbankrupt ones. Pairing of firms is based on the basis of industry and asset size. The discriminate functions that did the best overall discriminatory prediction is:

\[ Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.0006X_4 + 0.010X_5 \]  \hspace{1cm} (3-2)

Where: \( X_1, \ldots, X_5 \) presented five financial ratios (out of the 22 original variables).

The predictive ability and percent of misclassification are impressive. Since the first research, MDA has been used by many studies. Models using MDA were published by Blum [32], Elam [52], Edmister [49], Altman and Loris [7], Pettway [127], and Pettway and Sinkey [128].

Meyer and Pifer [115] use a linear regression model with dummy dependent variables \([0,1]\) and find similar results. Altman and McGough [8] demonstrate that auditors' decisions on the evaluation of companies as going concerns can be aided by MDA models for distress prediction. Altman, Haldeman and Maryaman [6] develop the Zeta model for bankruptcy prediction; seven ratios (variables) were expressed in a logarithmic form. The model outperforms alternative bankruptcy classification models. Moyer [118] reexamines Altman's model on a new data set, and compares the results with a MDA where the cash flow/debt ratio (the best univariate ratio in Beaver study) as well as the total balance sheet DM are employed. The results are comparable with Altman's results. Moreover, it appears that the two-variables model has fewer type I errors.
Most of the models use primarily financial ratios as variables. At least 34 ratios and several more variables are used. In a recent study Chen and Shimerda [37] compare and reconcile procedures in an attempt to reduce and confine the number of variables (ratios) for failure prediction as well as for other purposes. Using factor analysis they find several ratios that capture most of the characteristics which were contained in the factors. In summary, MDA in general is found to have a greater discriminatory power between solvent and insolvent firms, than the use of univariate models.

A fourth direction considers multidiscriminant analysis (MDA) or other approaches to predict insolvencies in specific industries. Studies on predicting failures in specific industries were published by Altman [3] on railroad bankruptcies; Meyer and Pifer [115], Sinkey [142], Korobow and Stuhr [94], Korobow, Stuhr and Martin [95] on bank failures; Altman [5] on saving and loan associations; and Altman and Lorris [7] for brokers and dealers. Collins [38] compares an Altman's MDA model with Meyer and Pifer's (0,1, regression) Type Model for predicting failures for credit unions, and finds about the same predictive ability for both models. Pettway [127] and Pettway and Sinkey [128] apply the asset pricing model to predict failures in banks.

Probabilistic Models

A fifth direction has emphasized a probabilistic approach to the prediction of bankruptcy. Wilcox's [161, 162, 163] theory was previously described. Santomero and Vinso [136] define failure as the probability of a negative capital and apply a safety index to identify
the group membership of problem banks. Martin [111] and Ohlson [123] employ a logit model to predict insolvencies among commercial banks and industrial firms, respectively. The cumulative logistic distribution was applied to every failed firm, \( j \), with the probability that the firm fails, \( \Pr(Y_j = 1) \), is summarized:

\[
\Pr(Y_j = 1) = G(W_j) = \frac{1}{1 + e^{-W_j}}; \quad j = 1, \ldots, N \text{ firms}
\]

(3-3)

where: \( G \) - is the cumulative logistic distribution

\( W \) - a linear combination of independent variables (financial ratios)

Scott [138] reviews theoretical models and empirical predictions of insolvencies and presents a new model or theory of bankruptcy with perfect access as well as imperfect access to external capital.²

**Related Research in the Insurance Discipline**

Moving from the general to the particular, the following section considers research on the problem of insolvencies of P-L insurers. Articles and news on the issue of insurers' insolvencies are discussed by Breslin, etc. [34, pp. 305-6]. Jenkin [85] recommends assessment of the grey areas in order to avoid the insurance insolvency catastrophe. In a recent descriptive article, he recommends the use of the following yardsticks: 1) the capital and solvency margin; 2) premiums volume; 3) maximum line and maximum retention; 4) reinsurance transactions; 5) investment policy, and 6) profitability.

²Further theoretical and practical analyses of these studies are employed in Chapter VI.
Munch and Smallwood [119] report empirical evidence concerning the effect of solvency regulation on the number of insolvent companies and the frequency of insolvencies. Minimum capital requirements appear to reduce the number of insolvencies; other forms of regulation have ambiguous or no effects. Olson [124] found several factors among high-risk automobile insurers, including intentional management ineptness and fraudulent behavior.

Low underwriting standards and questionable investment are cited by Evans [53], as important factors leading to failures among substandard automobile insurers. Nelson [122] reports a significant portion of retirement among P-L insurers. He finds significant differences between solvent and insolvent insurers in regard to the underwriting expense incurred; the net premium written to surplus, the loss adjustment expenses to premium earned, and the net investment income to total assets.

NAIC-IRIS, Best's Ratings and Related Methods

Several researchers examine the A.M. Best rating (BR) and the NAIC-IRIS. Denenberg [44] reviews several methods of an insurer selection. He concentrates on Best's rating for life as well as for non-life insurers. He finds that Best's rating for P-L includes about 70 percent of the companies rated as A+ or A. Based on a sample of companies he concludes that BR is an effective tool for avoiding delinquency in insurance companies, based on historical performance.

\[3^3\text{For additional discussion see Chapter II.}\]
Harmelink [67] uses Best's policyholder's rating as surrogates for degrees of solvencies of P-L insurers and supported Denenberg's conclusion that companies should be interested in maintaining excellent ratings. The main purpose of the research is to examine the use of GAAP vs. the Statutory accounting to value insurer's investments. The results indicated that the two accounting methods produced insignificant differences in the ability by the two sets of data to predict the degree of impairment among insurers as measured by decreasing BR during the late 1960s. In a second article, Harmelink [68] presents models to predict a decline or maintenance in BR. The primary conclusion for insurance companies is that accounting data can predict maintenance or decline in Best's rating with significant accuracy.

Breslin, etc. [34, p. 264] point out that more than two thirds of the companies are classified as excellent in 1977. This fact alone indicates that the BR system is not meant to disclose differences among insurers.

Hershbarger [74] surveys the Best's policyholders rating and Best's financial rating for all companies which were examined by Best during the years 1973-1979. Hershbarger uses simple correlation analysis, with the main conclusion that Best's ratings are not sufficiently discriminatory.

However, companies that were not rated (about 20 percent of the companies) were not included, and almost one half of the P-L insurers (especially the small ones) are excluded from Best's files.
The effectiveness of the MAIC-IRIS in predicting financial insolvencies among P-L insurers is examined by a few researchers. Thornton and Meador [155] examine 11 P-L insurers licensed in Texas which failed during 1973-1976. They investigate the tests one year, three years and five years prior to failure. Their primary conclusion is that the NAIC-IRIS tests do not adequately discriminate between troubled and sound companies. Another important conclusion is that the system is not truly early in nature. While 82 percent of the failed firms are expected to be predicted as failure three years and five years prior to failure, only about 50 percent are classified as priority companies three years prior to failure and only 20 percent five years prior to failure. Herbarger [73] uses random sampling to compare forty sound companies with forty priority companies (flagged by the NAIC-IRIS), and 34 failed companies. His main conclusions are: (1) some of the IRIS tests have little or no value in predicting failures. (2) The early warning system puts a burden on regulators, because of large numbers of sound companies misclassified into the priority category. (3) The NAIC-IRIS does a poor job in predicting failures even two years prior to the actual failure. In the second study Hershbarger [74] finds some relationship between the Best's rating and the NAIC-IRIS, but this relationship is not proven to be statistically significant. The literature reveals that both the NAIC-IRIS and the Best's Rating do not seem to be an efficient and early prediction of insurance companies failures.
Ruth Salzmann [135] recommends a new method, the "RLS yardsticks" to identify financially troubled insurers. The RLS places primary emphasis on evaluation of reserves, liquidity, and surplus level. Two indexes are developed based on analytical analysis of financial data. However, no empirical study are conducted to examine the yardsticks, and the investment results are not considered.

Univariate and Multivariate Models

Multivariate models are examined by few researchers in the insurance industry. All of these studies use multivariate discriminant analysis (MDA). Trischmann and Pinches [156] use MDA to classify insurers into two groups (a solvent group and insolvent group) Six final ratios (variables) are used to classify the companies into the two groups. The six ratios are: (1) agent balance/total assets, $X_1$; (2) stock cost/stock market price, $X_2$; (3) bond cost/bond market price, $X_3$; (4) loss adjustment expenses and underwriting expenses/net premiums written $X_4$; (5) combined trade ratio, $X_5$; and (6) premiums written direct/surplus, $X_6$. These ratios are relatively independent of each other ($r < .485$). The final Z score (unadjusted) was:

$$Z = 11.086X_1 - 1.507X_2 + 3.536X_3 - 2.498X_4 - 2.453X_5 - .245X_6 \quad (3-4)$$

Many other ratios that were highly correlated to at least one of these six ratios are excluded. The authors use the ratios for the year next

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5 These ratios were a final result of a screening process which started with about 70 ratios.
to the last year before distress. The model classifies a sample of 52 insurers, 26 solvent and 26 insolvent during the late 1960s and early 1970s. The model classifies correctly 49 companies (about 94% of the sample).

Cooley [40] presents a framework which considers both prior probabilities that the firm will become insolvent, and the relative cost of errors in prediction among P-L insurers. Employing Trischmann and Pinches data he demonstrates that the cutoff midpoint between the centroids of the discriminant scores of the distressed and solvent firms (as it is employed by Trischmann and Pinches [156]) may not be an optimal cutoff point.

Pinches and Trischmann [130] examine the efficiency of univariate models compared with multivariate models for the same sample of 52 companies. Through the use of statistical tests it is shown that MDA was found to be a more accurate predictor than univariate ratios. However, the authors use data only for two years before insolvency; the issue of earlier prediction was not examined.

The authors use the ratios for the year next to the last year because: (1) They want the model to be more useful for an effective regulation (prediction based on data from last year before failure, may be too late); (2) the variability of data for the last year becomes too large; and (3) the authors observe some "window dressing" phenomena—managers trying to manipulate data and hide their difficulties by shifting financial data to place themselves in a better position. The DM may capture such a tendency.

Nine ratios out of 70 original ratios were chosen after eliminating those who did not correctly classify at least 70% of the companies, and variables with $r = .50$ or more with each other. Out of these 9 variables 6 were used by the multivariate analysis.
Eck [48] selects 17 financial ratios that may represent dishonesty, and employs a 0,1 multiregression analysis to predict financial insolvencies among P-L insurers. The procedure is applied to 50 insurers: 25 solvent companies, and 25 insolvent firms, which failed during 1965-1977 (data for 1975 the worst year in the insolvency record was not included), 17 financial ratios are included, but investment earning and gain are not included. Employing stepwise regression the model is found to have the best results with 7 financial ratios as independent variables. The model correctly classified 76 percent of the insurers one and three years prior to insolvency. While employing a new holdout sample the model is successful in correctly classifying 88 percent of the firms three years prior to insolvency. However, only 12 failed firms are examined (the error percentage is: 17%, type I error). The holdout sample includes insolvent insurers during the 1960s; a prediction "from the present to the past." These facts may explain the improvement in the classification ability of the holdout sample. (Usually when holdout samples were applied in past research the misclassification percent increased.)

The AIA/Aetna study [12] recommends the use of an insolvency index which is a Z score of a MDA. Fifty solvent companies are compared with 50 troubled and insolvent insurers. The system employs financial ratios as independent variables. They suggest that the best model with 6 independent variables correctly predicts about 90 percent of the insurers one year prior to deliquency, and 81 percent three years prior to deliquency (32 percent of the troubled companies were misclassified, type I error).
Hershbarger [73] develops a MDA based on the NAIC-IRIS tests. The model results are mixed. The MDA does a better job than the NAIC-IRIS for predicting failures one year prior insolvency; 96 percent of all cases are correctly classified, and 91 percent of the failed firms are correctly predicted compared with 89 percent by the NAIC-IRIS. However, predictions of failures among insolvent insurers two years to failure (61 percent) are below the NAIC-IRIS 81 percent. Inclusion of variables related to asset size improve the results slightly for one year (97% of all cases and 97 percent of failed firms were correctly classified), but not for two or more years prior to failure. His main conclusion is that both the NAIC systems and the MDA did a relatively poor job in predicting failures two years prior to the actual failure. Thus, the NAIC-IRIS did not appear to be an early indicator of insurance company failure.

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These variables (policyholder surplus, earned premiums, and total assets) are not ratios, and indicate insurer's size.
CHAPTER IV
INSOLVENCIES AMONG P-L INSURERS

The objective of this chapter is to provide an overview of the insolvency phenomenon among P-L insurers. The insolvency record is presented and analyzed, and the present guaranty mechanism is described. The primary existing tools to identify troubled insurers are the NAIC-IRIS, and the A.M. Best ratings. Both methods are described, and an outline of these methods is presented. However, the ability of the method to predict failures among P-L insurers is examined in Chapter V and in the empirical Chapter VIII.

The Retirement Record

Data sources for insolvency records are limited, and the primary source is the A.M. Best Company. Table 3 is a summary table of company retirements during the last ten years. The table includes voluntary and nonvoluntary retirements as well as mergers.¹

Almost 850 companies retired during the last twenty-year period, about 1/3 of those companies during the most recent ten years. One hundred and fifty companies became insolvent during the last decade.

¹The "Corporate Change" is published annually in Best's Review (P/C), usually in March [40]. For total premiums and insurers in the various fields of insurance, see Bickelhaupt [31, pp. 76-88, 770-771].
### TABLE 3

Analysis of Property-Liability Company Retirement

<table>
<thead>
<tr>
<th></th>
<th>Liquidation, Receivership, Rehabilitation, Conservatorship, Restraining Order, etc.</th>
<th>Voluntary Retirement</th>
<th>Total Insolvencies</th>
<th>Mergers</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1961-1970</td>
<td>148</td>
<td>142</td>
<td>240</td>
<td>305</td>
<td>545</td>
</tr>
<tr>
<td>1971-1975</td>
<td>58</td>
<td>33</td>
<td>91</td>
<td>99</td>
<td>140</td>
</tr>
<tr>
<td>1976-1980</td>
<td>32</td>
<td>27</td>
<td>59</td>
<td>50</td>
<td>104</td>
</tr>
<tr>
<td>Total 1971-1980</td>
<td>90</td>
<td>60</td>
<td>150</td>
<td>149</td>
<td>299</td>
</tr>
<tr>
<td>Total 1961-1980</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>


Unfortunately, these data have the following deficiencies:

1. Data are aggregated together especially for nonvoluntary insolvencies.

2. Mergers probably include insurers that would not be able to sustain operations.

3. Several companies are counted twice (e.g., at least 10 companies were put on rehabilitation, and were liquidated in a consecutive year). This double counting is not excluded in Best's list.

A better determination of insolvent companies is obtained from Best's Key Rating Guide [30], and Best's Insurance Report (P/C) [29]. These sources outline insolvent companies including those which are
not reported by Best's Review [41]. Data are presented in Table 4. The table presents the failure trend of P-L insurers. An average failure record of 18 companies per annum is demonstrated. The failure rate among P-L insurers was larger than the failure rate of all business during 1971-1980. The failure rate among P-L peaked in 1975 and generally decreased afterward.

Breslin, etc. [34, p. 304], argue that failures are concentrated among small insurers and inflect relatively small economic cost on the State Guaranty Funds and the total industry. However, the McKinsey & Company report [114] reveals that unlike life insurance companies, P-L insolvencies are much less concentrated among smaller companies. Data in Table 5 reveals that most of the failures were among medium P-L insurers, but failures among larger insurers tend to increase over time.

Large amounts of surplus are required by law for new insurers in many states. Therefore, fewer new small insurers operate in the industry compared with other industries. Nevertheless, Table 6 demonstrates a significant difference by size between P-L insurers failure and the failure distribution of other businesses.\footnote{Data are not available for about 20\% of the insolvent insurers; probably most of them are small or medium insurers.}

\footnote{Data for all businesses are measured by liability size while data for insurers is by asset size. However, data are comparable since liabilities (reserves) have been about 70\% of the total assets of insurers during the 70s.}
### TABLE 4

Number of P-L Insurer Insolvencies—1971-1980

<table>
<thead>
<tr>
<th>Year</th>
<th>Nonvoluntary Insolvency</th>
<th>Voluntary Retirement</th>
<th>Total Insolvencies</th>
<th>Failure Rate per 1,000 P-L Insurers</th>
<th>All Businesses</th>
</tr>
</thead>
<tbody>
<tr>
<td>1971</td>
<td>13</td>
<td>4</td>
<td>17</td>
<td>6.2</td>
<td>4.2</td>
</tr>
<tr>
<td>1972</td>
<td>7</td>
<td>8</td>
<td>15</td>
<td>5.5</td>
<td>3.8</td>
</tr>
<tr>
<td>1973</td>
<td>8</td>
<td>6</td>
<td>14</td>
<td>4.4</td>
<td>3.6</td>
</tr>
<tr>
<td>1974</td>
<td>7</td>
<td>10</td>
<td>17</td>
<td>5.9</td>
<td>3.9</td>
</tr>
<tr>
<td>1975</td>
<td>30</td>
<td>7</td>
<td>37</td>
<td>12.8</td>
<td>4.3</td>
</tr>
<tr>
<td>1971-85</td>
<td>65</td>
<td>35</td>
<td>100</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1976</td>
<td>7</td>
<td>11</td>
<td>18</td>
<td>6.2</td>
<td>3.5</td>
</tr>
<tr>
<td>1977</td>
<td>7</td>
<td>9</td>
<td>16</td>
<td>5.5</td>
<td>2.8</td>
</tr>
<tr>
<td>1978</td>
<td>11</td>
<td>11</td>
<td>22</td>
<td>7.5</td>
<td>2.4</td>
</tr>
<tr>
<td>1979</td>
<td>9</td>
<td>8</td>
<td>17</td>
<td>5.8</td>
<td>2.8</td>
</tr>
<tr>
<td>1980</td>
<td>8</td>
<td>4</td>
<td>12</td>
<td>4.2</td>
<td>-</td>
</tr>
<tr>
<td>1976-80</td>
<td>42</td>
<td>43</td>
<td>85</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Total 1971-1980: 107, 78, 185

1. Total number of companies is based on Insurance Fact, 1971-1981 [83].

2. Based on "The Business Failure Trend," Dun and Bradstreet, 1979, p. 2 [46].

### TABLE 5

Failure Distribution By Size ($ of Assets)

<table>
<thead>
<tr>
<th>Period</th>
<th>Under 100,000</th>
<th>100,000 to 500,000</th>
<th>500,000 to 1 mil.</th>
<th>1 mil. to 5 mil.</th>
<th>5 mil. to 12.5 mil.</th>
<th>12.5 mil. to 50 mil.</th>
<th>50 mil. to 100 mil.</th>
<th>Over 100 mil.</th>
<th>NA</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>71-75</td>
<td>9</td>
<td>15</td>
<td>8</td>
<td>25</td>
<td>11</td>
<td>8</td>
<td>1</td>
<td>0</td>
<td>23</td>
<td>100</td>
</tr>
<tr>
<td># Cos</td>
<td>(9)</td>
<td>(15)</td>
<td>(8)</td>
<td>(25)</td>
<td>(11)</td>
<td>(8)</td>
<td>(1)</td>
<td>(0)</td>
<td>(23)</td>
<td>(100)</td>
</tr>
<tr>
<td>(Percent)</td>
<td>(9)</td>
<td>(15)</td>
<td>(8)</td>
<td>(25)</td>
<td>(11)</td>
<td>(8)</td>
<td>(1)</td>
<td>(0)</td>
<td>(23)</td>
<td>(100)</td>
</tr>
<tr>
<td>76-80</td>
<td>11</td>
<td>13</td>
<td>12</td>
<td>19</td>
<td>7</td>
<td>7</td>
<td>5</td>
<td>1</td>
<td>10</td>
<td>85</td>
</tr>
<tr>
<td># Cos. (percent)</td>
<td>(12.9)</td>
<td>(15.4)</td>
<td>(14.1)</td>
<td>(22.3)</td>
<td>(8.2)</td>
<td>(8.2)</td>
<td>(5.9)</td>
<td>(1.2)</td>
<td>(11.8)</td>
<td>(100)</td>
</tr>
<tr>
<td>Total</td>
<td>20</td>
<td>28</td>
<td>20</td>
<td>44</td>
<td>18</td>
<td>12</td>
<td>9</td>
<td>1</td>
<td>33</td>
<td>185</td>
</tr>
<tr>
<td># Cos. (Percent)</td>
<td>(10.8)</td>
<td>(15.1)</td>
<td>(10.8)</td>
<td>(23.8)</td>
<td>(9.7)</td>
<td>(6.5)</td>
<td>(4.9)</td>
<td>(.6)</td>
<td>(17.8)</td>
<td>(100)</td>
</tr>
</tbody>
</table>

### TABLE 6

Distributions of Failed Companies by Size, Selected Years

<table>
<thead>
<tr>
<th></th>
<th>P-L Insurers by $ Assets</th>
<th>All Business by $ Liabilities</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Under 100,000 (%)</td>
<td>To 1 mil (%)</td>
</tr>
<tr>
<td></td>
<td>To 1 mil (%)</td>
<td>To 5 mil (%)</td>
</tr>
<tr>
<td>1971</td>
<td>7.7</td>
<td>7.7</td>
</tr>
<tr>
<td>1975</td>
<td>12.9</td>
<td>35.5</td>
</tr>
<tr>
<td>1979</td>
<td>7.1</td>
<td>42.9</td>
</tr>
<tr>
<td>1980</td>
<td>18.1</td>
<td>27.3</td>
</tr>
</tbody>
</table>

Notes: 1 Total 100 percent per annum. About 30 insurers without data are excluded, probably most of them small firms.

NA - Not available.

Compiled and computed from Best's Key Rating Guide [30], and Dun and Bradstreet [46], 1979.
While new firms dominate failures in the overall business, age does not seem to be a dominate factor in failures of P-L insurers. Most of the failed P-L insurers were in business for more than 10 years. Table 7 presents data on the age of failed insurers. Table 8 presents the failure age trend among P-L insurers compared with other businesses. Hershbarger [74] observes that there is not a strong statistical relationship between age of the firm and Best's figures or the NAIC-IRIS classifications.

A $\chi^2$ Karl Pearson goodness of fit statistic is applied to the data presented in Table 9. The null hypothesis is that the distribution of insurers by size for the insolvent companies is the same as the distribution of insurers by size for the whole population of insurers. The statistic $\chi^2$ is:

$$\chi^2 = \sum_{i=1}^{K} \frac{(X_i - E(X_i))^2}{E(X_i)}$$

(4-1)

Where: $E(X_i)$ - expected number of insolvent insurers in category i, if the distribution of insolvent insurers is the same as in the whole population.

$X_i$ - the observed number of insolvent insurers in category i.

$i = 1...K$ categories of insurers by size. In Table 9, $K = 11$, or $K = 10$ (if the NA category is excluded).

This $\chi^2$ is compared with the critical $\chi^2$ with $K-1$ degrees of freedom. For further information see Marascilo and McSweeney [109, Ch. 10].

The computed score is 177.2 for the whole insurers (including the not available), there are 11 size categories and the results are
### TABLE 7
Numbers of Failed Insurers, by Age, 1971-1980

<table>
<thead>
<tr>
<th></th>
<th>In Business 5 Years or Less</th>
<th>In Business 5-10 Years</th>
<th>In Business 10-20 Years</th>
<th>In Business Over 20 Years</th>
<th>Data NA</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1971</td>
<td>2</td>
<td>-</td>
<td>7</td>
<td>5</td>
<td>3</td>
<td>17</td>
</tr>
<tr>
<td>1972</td>
<td>2</td>
<td>3</td>
<td>-</td>
<td>4</td>
<td>6</td>
<td>15</td>
</tr>
<tr>
<td>1973</td>
<td>-</td>
<td>2</td>
<td>3</td>
<td>6</td>
<td>3</td>
<td>14</td>
</tr>
<tr>
<td>1974</td>
<td>2</td>
<td>1</td>
<td>4</td>
<td>7</td>
<td>3</td>
<td>17</td>
</tr>
<tr>
<td>1975</td>
<td>4</td>
<td>4</td>
<td>7</td>
<td>17</td>
<td>5</td>
<td>37</td>
</tr>
<tr>
<td>1971-1975</td>
<td>10</td>
<td>10</td>
<td>21</td>
<td>39</td>
<td>20</td>
<td>100</td>
</tr>
<tr>
<td>(Percent)</td>
<td>(10)</td>
<td>(10)</td>
<td>(21)</td>
<td>(39)</td>
<td>(20)</td>
<td>(100)</td>
</tr>
<tr>
<td>1976</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>8</td>
<td>2</td>
<td>18</td>
</tr>
<tr>
<td>1977</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>9</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>1978</td>
<td>5</td>
<td>4</td>
<td>1</td>
<td>11</td>
<td>1</td>
<td>22</td>
</tr>
<tr>
<td>1979</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>10</td>
<td>3</td>
<td>17</td>
</tr>
<tr>
<td>1980</td>
<td>-</td>
<td>-</td>
<td>3</td>
<td>8</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
<td>1976-1980</td>
<td>11</td>
<td>9</td>
<td>11</td>
<td>46</td>
<td>8</td>
<td>85</td>
</tr>
<tr>
<td>(Percent)</td>
<td>(12.9)</td>
<td>(10.5)</td>
<td>(12.9)</td>
<td>(54.1)</td>
<td>(9.4)</td>
<td>(100)</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1971-1980</td>
<td>21</td>
<td>19</td>
<td>32</td>
<td>85</td>
<td>28</td>
<td>185</td>
</tr>
<tr>
<td>(Percent)</td>
<td>(11.4)</td>
<td>(10.3)</td>
<td>(17.3)</td>
<td>(45.9)</td>
<td>(15.1)</td>
<td>(100)</td>
</tr>
</tbody>
</table>

Computed and compiled from Best's Key Rating Guide [30].
### TABLE 8
Number of Failures by Age, among P-L Insurers (PLI), Compared with Other Businesses (OB)

<table>
<thead>
<tr>
<th>Year</th>
<th>In Business 5 Years of Less (%) PLI</th>
<th>In Business 6 to 10 Years (%) PLI</th>
<th>In Business over 10 Years (%) PLI</th>
<th>Total PLI</th>
<th>In Business 5 Years of Less (%) OB</th>
<th>In Business 6 to 10 Years (%) OB</th>
<th>In Business over 10 Years (%) OB</th>
<th>Total OB</th>
</tr>
</thead>
<tbody>
<tr>
<td>1971</td>
<td>14.3</td>
<td>-</td>
<td>22.2</td>
<td>85.7</td>
<td>23.6</td>
<td>100</td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>1972</td>
<td>27.2</td>
<td>33.3</td>
<td>27.4</td>
<td>44.5</td>
<td>21.4</td>
<td>100</td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>1973</td>
<td>-</td>
<td>18.2</td>
<td>22.4</td>
<td>81.8</td>
<td>20.6</td>
<td>100</td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>1974</td>
<td>14.2</td>
<td>7.2</td>
<td>20.8</td>
<td>72.6</td>
<td>19.3</td>
<td>100</td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>1975</td>
<td>12.5</td>
<td>12.5</td>
<td>22.7</td>
<td>75.0</td>
<td>19.9</td>
<td>100</td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>1976</td>
<td>25.0</td>
<td>12.5</td>
<td>26.0</td>
<td>62.5</td>
<td>19.9</td>
<td>100</td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>1977</td>
<td>6.7</td>
<td>13.3</td>
<td>27.5</td>
<td>80.0</td>
<td>19.2</td>
<td>100</td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>1978</td>
<td>23.8</td>
<td>19.0</td>
<td>23.4</td>
<td>57.2</td>
<td>19.4</td>
<td>100</td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>1979</td>
<td>7.1</td>
<td>27.0</td>
<td>85.8</td>
<td>19.4</td>
<td>100</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Sources: (1) Compiled from Table 7 (excluding 28 firms with no data).
(2) "The Business Failure Trend," Dun and Bradstreet [46], 1979, p. 11.


### TABLE 9

Profile of P-L Insurance Companies by Size of Assets
Total Industry Vs. Insolvent Companies

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>NA</td>
<td>7</td>
<td>76</td>
<td>0</td>
<td>83</td>
</tr>
<tr>
<td>1. 1 - 100</td>
<td>- 369</td>
<td>0</td>
<td>369</td>
<td>12.46</td>
</tr>
<tr>
<td>2. 100 - 500</td>
<td>16</td>
<td>782</td>
<td>10</td>
<td>808</td>
</tr>
<tr>
<td>3. 500 - 1,000</td>
<td>49</td>
<td>236</td>
<td>11</td>
<td>296</td>
</tr>
<tr>
<td>4. 1,000 - 2,500</td>
<td>129</td>
<td>155</td>
<td>11</td>
<td>295</td>
</tr>
<tr>
<td>5. 2,500 - 5,000</td>
<td>126</td>
<td>103</td>
<td>8</td>
<td>237</td>
</tr>
<tr>
<td>6. 5,000 - 12,500</td>
<td>188</td>
<td>74</td>
<td>11</td>
<td>273</td>
</tr>
<tr>
<td>7. 12,500 - 25,000</td>
<td>144</td>
<td>44</td>
<td>6</td>
<td>194</td>
</tr>
<tr>
<td>8. 25,000 - 50,000</td>
<td>95</td>
<td>40</td>
<td>6</td>
<td>141</td>
</tr>
<tr>
<td>9. 50,000 - 100,000</td>
<td>66</td>
<td>32</td>
<td>2</td>
<td>100</td>
</tr>
<tr>
<td>10. Over</td>
<td>113</td>
<td>40</td>
<td>12</td>
<td>165</td>
</tr>
<tr>
<td>Total</td>
<td>933</td>
<td>1951</td>
<td>77</td>
<td>2961</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>% Excluding NA</th>
</tr>
</thead>
<tbody>
<tr>
<td>31.5%</td>
</tr>
</tbody>
</table>

Notes:
1) Data for the whole population are based on 1975/76 results (the approximate median year of the period).
2) NA - Not Available
3) Groups are not considered in this analysis.
4) 000 are omitted in the category size
5) Possible breakdown: small cos.: (cat. 1-3); medium: (cat. 4-6); larger: (cat. 7-9); very large: (cat. 10).
6) Observations (excluding NA): (a) About 1/2 of the cos. are small (cat. 1-3) 51%. (b) Most of the insolvent are medium and large (cat. 4-9) 54%. (c) The proportion of medium (cat. 4-6) insolvent insurers is larger among Insolvent (41%) than in population (28%).
compared with critical $\chi^2$ with 10 degrees of freedom. The computed score for the adjusted data (without the not available insurers) is 27.96 and the results are compared with $\chi^2$ with 9 degrees of freedom. The results are highly significant at 10 and 9 degrees of freedom, respectively. An analysis of Table 9 (with the adjusted data) demonstrates that there are about 51 percent small companies in the population (categories 1-3) compared with about 44 percent small insurers among the insolvent companies. However, there are about 28 percent medium companies in the population (categories 4-6) compared with 41 percent medium companies among the insolvent insurers.

In summary, the primary conclusion is that in general failed firms tend to be younger and smaller, while failed P-L insurers tend to be of medium size and older firms.

The Present Guaranty Mechanism and Unresolved Problems

Recognizing the dangerous losses from insolvent insurers most states \(^4\) enacted legislation for insolvent funds in the early 1970s. States (excluding New York) have preferred post-solvency assessment approaches rather than funded programs. Generally, the overall record of the funds appears favorable. Some observers might argue that since the guaranty funds were imposed the problem of insolvency among P-L insurers is not important. This statement is misleading because: first, the mechanism was unable to reduce the number of insolvencies; second, it is doubtful whether the plans would be able to respond to a

\(^4\) Alabama, Arkansas and Oklahoma did not have Guaranty funds by the late 1970s.
major company failure; and third, the plans use a single-state guarantee plan for multiple-state insurance operations.⁵

Problems that remain unsolved by the funds are:

1. There is a maximum coverage limit per claim, often $300,000, but a smaller amount applies in several states.
2. A deductible of at least $100 is applied in the majority of states.
3. Coverages and deductible vary significantly among various states.
4. At least nine states have no provisions for the return of unearned premiums to the insureds.
5. Even if all losses are paid by the funds, they are not paid promptly.
6. The failure of an insurer means extra expenses and extra work for regulators, agents, risk managers and insureds. The insured must find a new insurer and more efforts for replacing coverage are required from both agents and insureds.
7. States may lose premium tax dollars because assessments paid by the funds are tax deductible to the other insurers in most states.
8. Not all insurers licensed in a particular state have their obligation guaranteed.
9. Several lines of direct insurance are not included. Most states exclude the following lines: life and annuities, title,

⁵For further discussion, see Breslin, etc. [34, Chapter 6].
surety bonds, credit insurance, and ocean marine insurance.\(^6\)

It is clear that although the consequences of insolvencies among insurers have been alleviated by the present guaranty mechanism, the main problems and consequences of insolvencies among P-L insurers have not yet been solved.

**The NAIC-IRIS Tests**

The insurance Regulatory Information System (IRIS) was defined by the NAIC in 1977. This system was formerly known as the Early Warning System. The main purpose of the system is to assist the state insurance departments for surveilling the financial conditions of insurers. The system was developed in 1971 and became operational in 1973. During the first years the tests were called "Solidity" or "Solvency-Tests." However, because their primary purpose was to flag troubled insurers, the name was changed to the "Early Warning System" in the mid 1970s, and since 1978 to "IRIS" tests [121]. These tests should not be considered as substitutes for field examination and auditing of the financial statements. The tests should be used

---

\(^6\)Sections 3955.01 to 3955.20 of the Ohio Revised Code exclude the following kinds of insurance: 1) title, 2) surety bonds, 3) credit, 4) guaranty insurance, 5) mortgage guaranty insurance, 6) ocean marine insurance, 7) life insurance, 8) fraternal benefit insurance, 9) mutual protective insurance, 10) several kinds of sickness and accident insurance, 11) reciprocal or interinsurance contracts, 12) health services subscribers by any nonprofit organization, and 13) insurance underwritten by agency of the state or Federal government.
as supplements to other forms of financial surveillance.\(^7\)

The NAIC-IRIS model is a combination of 11 tests, most of the tests are financial ratios. The IRIS include four groups of ratios: overall ratio, profitability ratios, liquidity ratios, and reserve ratios. Eleven ratios are used in the model; each ratio has an acceptable range and an outside-usual range. If a company is outside the acceptable ranges on four or more tests it is placed in a priority classification, and needs to be examined by the insurance department. In 1978 more than 10 percent of 1900 P-L insurers participating in the model were outside the norms on 4 or more tests.

The following summary results are available for companies that failed 4 or more tests during 1976-1981.\(^8\) These results are presented as percentages of total companies participating in the model:

- 1976 - 17 percent
- 1977 - 15 percent
- 1978 - 11 percent
- 1979 - 9 percent
- 1981 - 7 percent

About 1750 companies reported data to the NAIC-IRIS in 1976 compared with 2002 insurers in 1982 [133, p. 217; 72]. Brostroff [36] pointed out that if a company has four or more exceptional ratios, its

\(^7\)A survey indicates that 50 percent of the commissioners felt that the tests lead to problem companies, while 70 percent of the respondents said that tests had been used to determine whether a company should be authorized to write insurance in a state [153, p. 32].

\(^8\)The data are based on the Proceedings of the NAIC, 1981 [133, p. 218] and Haverland, R.A., How Agent Can Protect Against Insurance Company Insolvency [72].
financial statements are analyzed closely by the insurance department in the state of its domicile as well as by the examiner team at the NAIC office each year. Companies with three or less exceptional values may also be examined by the team if the coordinator of the project believes it is necessary. Seven percent of the companies were identified by the examiner team as requiring priority examinations for 1978, and about 7.4 percent in 1979 [133, p. 213].

All 11 tests are limited to a minimum of 99 percent and maximum of 999 percent. The ratios along with the values outside the usual range are outlined in Table 10.

Bailey [16] examines insurers that fail since March 1972 through 1975. Of the 20 insurers that reported data to the NAIC, 85 percent have exceptional results on 4 or more tests. However, of the 17 insurers for which there was data, three years prior to failure, only 47 percent had exceptional results on 4 or more tests. After adjustment to the scoring system (in 1976) for 24 insurers, 88 percent were flagged (four or more exception tests) one year prior to insolvency, but only 54 percent three years prior to insolvency.

The effectiveness of the NAIC-IRIS is determined in the following manner. A variety of scores spanning the range of possible scores is selected for each test. For each score, the percentage of all companies and flagged (failed) companies are determined. The results are plotted, forming a curve like that of test A or test B in Figure 4. Point G presents a score where test A flags about 65 percent of the failed companies, but only 15 percent of all companies. Point H
TABLE 10
The NAIC-IRIS Tests

<table>
<thead>
<tr>
<th>Ratio</th>
<th>Equal to or Over</th>
<th>Under (in percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Premium to Surplus</td>
<td>300</td>
<td>--</td>
</tr>
<tr>
<td>2. Change in Writings</td>
<td>33</td>
<td>-33</td>
</tr>
<tr>
<td>3. Surplus Aid to Surplus</td>
<td>25</td>
<td>--</td>
</tr>
<tr>
<td>4. Two Year Adjusted Underwriting Ratio</td>
<td>110</td>
<td>--</td>
</tr>
<tr>
<td>5. Investment Yield</td>
<td>9.9</td>
<td>5.0</td>
</tr>
<tr>
<td>6. Change in Surplus</td>
<td>50</td>
<td>-10</td>
</tr>
<tr>
<td>7. Liabilities to Liquid Assets</td>
<td>105</td>
<td>--</td>
</tr>
<tr>
<td>8. Agents' Balance to Surplus</td>
<td>40</td>
<td>--</td>
</tr>
<tr>
<td>9. One Year Reserve Development to Surplus</td>
<td>25</td>
<td>--</td>
</tr>
<tr>
<td>10. Two Year Reserve Development to Surplus</td>
<td>25</td>
<td>--</td>
</tr>
<tr>
<td>11. Estimated Current Reserve Deficiency to Surplus</td>
<td>25</td>
<td>--</td>
</tr>
</tbody>
</table>

Note: Ratios with scores outside the usual ranges are considered "exceptional."

Source: NAIC-IRIS P-L Insurers. The NAIC, Wisconsin, 1978 [121, p. 28].
presents a score where test B also flags 65 percent of the failed companies, but 45 percent of all companies. The closer the curve to the horizontal axis, the more discriminating is the test. Thus, test A is more effective than test B. The closer the curve to the horizontal axis and to the point representing 100 percent of failed companies, the more discriminating the test. Finally, curves A and B may also represent the same test, but with failed companies the results are taken at different years before insolvency. A judgment can be made whether the test increases or decreases in effectiveness as the company approaches insolvency [157, p. 69, 155].

Source: Modified from [157, p. 68]
The advantages of the system are: (1) the tests include a few dynamic ratios that may enable analysis of stability and changes of an insurer over time; (2) the IRIS enables uniformity in surveillance throughout the country; (3) the IRIS provides understandable standards for insurance departments in various states; (4) a summary report by percentile ranking for each test is available.

The main limitations of the IRIS are:

1. The system is dependent on the accuracy of the financial statements. A misstatement or a data-processing error cannot be identified by the system.

2. The test interpretation must rely upon judgment, knowledge and experience of the analyst.

3. A considerable effort and analysis of data is required.

4. The tests are mainly financial ratios. They are only indicators; they cannot provide decisions for action by the states. More often, they point out areas where further investigations are required.

5. The acceptable ranges are arbitrary, although they are based on long periods of experience, and generally may be correct.

6. The results are considered confidential and are not generally available to the public. Several states allow the results to be inspected in their offices.

7. The participation is voluntary, and only about two thirds of the P-L insurers participate in the model. Most small mutual companies are not participating.
8. A large number of misclassifications of sound companies as priority ones is found by Hershbarger [73], thus the system puts a burden on regulators.

The NAIC expects about 15 percent of the companies to be flagged, and 96 percent of the failed insurers to be correctly predicted as priority companies one year before failure, and 82 percent three years prior to insolvency. A literature review on the effectiveness of the system for predicting insolvency was presented in Chapter III.

It is expected that the larger the number of tests outside the norms, the more the probability that an insurer will become insolvent. The number of tests outside the acceptable ranges is considered a univariate variable in this study. The empirical results will be examined in Chapter VIII, these results are compared with the DM and other univariate variables. The purpose is to examine the effectiveness and the efficiency of alternative models in predicting failures among insurers.

**A.M. Best's Company Ratings**

The financial strength of an insurer may be judged by the Best's rating of P-L insurers. Two ratings are published by Best: The policyholders' rating (BPR), and the financial rating. The policyholders' rating uses six classifications: from A+ (excellent) to C (fair). Five factors that affect the financial strength are measured: (1) the adequacy of the reserves; (2) the adequacy of the surplus to absorb unusual shocks; (3) the underwriting results; (4) the expense ratio which measures the efficiency of management; and (5) soundness,
diversification and liquidity of the insurers' investments.

The effect of insurer size is measured by the financial rating. The financial rating is estimated by a net safety factor which is the size of a company's surplus plus all equities less shortages in the reserves. Fifteen groups of net safety factors according to the size have been developed. However, since most insolvent insurers did not have financial ratings, this rating is not included in the analysis.

The two primary advantages of the Best's ratings are: (1) Best modified the financial statement while other models usually take the financial statements for granted, and (2) the ratings are simple to understand and supply a quick reference to companies. The major disadvantages are: (1) the ratings provide only relative measures of strength; (2) about 3,000 P-L insurers operate in the U.S., but only about 1500 insurers are graded by Best (many small companies especially small mutual companies are thus not included); (3) rating is omitted or deferred for companies with difficulties, weak companies, new companies, etc. Between 15 percent and 20 percent of the listed companies are not rated each year. 4) About two-thirds of the companies are rated as excellent A+ or A. (5) Ratings are published almost seven months after the balance sheet date.

A literature review and discussion are presented in Chapter III, and only important issues are outlined here.

Bailey's [14] research, on 19 insolvent companies that failed from January 1969 to late 1971, tests the Best's policyholders' ratings (BPR) as predictor of insolvency. While about 850 companies
(70 percent) of all insurers reported to Best's in 1969 were rated A+ or A, none of the failed insurers rated as A+ one or two years prior to insolvency, and only 3 failed insurers were rated as A companies. To be safe, a policyholder would be advised to do business with those insurers rated A+ (over 50 percent of the insurers). It appears that BPR are closely correlated with the relative likelihood of insolvency, beginning with a zero likelihood for insurers rated A+, and increasing for each successively lower rating. In a recent report, [15] Bailey examined 61 P-L insolvent insurers that failed during the years 1969-1979. For these companies, assessments were made by guaranty funds to cover insolvencies. Of these companies, 43 reported data to Best's. Only one insurer was rated A+ three years prior to insolvency, and no company was rated A+ one year before insolvency. The relatively high frequency of insolvent insurers was concentrated among C and C+ insurers, and to some smaller extent, among B and not-rated companies. These results support the conclusion of Denenberg [44] that A+ is really a passing grade, and the Best's rating is an effective tool for avoiding deliquent insurers. Harmelink [68] finds that accounting data can predict a decline in BPR with a significant accuracy. However, based on an empirical study Hershbarger [74] concludes that BPR are not sufficiently discriminating.
CHAPTER V
RESEARCH METHODOLOGY AND FRAMEWORK: UNIVARIATE MODELS,
FINANCIAL STABILITY MEASURES FOR PREDICTING
FINANCIAL DISTRESS

Introduction: A Brief Presentation of the Models

Two main stages are considered in the methodology. The first stage is to develop new stability models and to use them as univariate variables for failure prediction in the P-L insurance industry. Each model produces or generate a stability index of insolvency. Multivariate analysis is used in the second stage.

The attempt is not made to examine every possible variable or model. The research determines how a given set of variables may be useful for predicting insolvency. Even the stability of other possible variables over time (e.g., the stability of the exposure ratio = premium/surplus) is not examined. No attempt is made to find the best stability variable, and only a limited number of variables are examined. Also the research does not find the optimal multivariate model. Instead, the objective is to find the most effective and/or the most efficient model with a limited number of stability measures as variables in the models.

In the first stage the study concentrates on stability measures as univariate models. These stability measures are compared to two existing variables that were presented in the preceding chapter. The first variable represents the NAIC-IRIS, this univariate variable will be the number of tests outside the acceptable ranges, and the variable
will be denoted as NAIT. The Best's policyholders rating (BPR) will be the second univariate variable.

This chapter presents several models which measure the financial stability of the financial statements over time. Three groups of variables are examined, first the decomposition measures (DM) and the square-proportions models examine the stability (or relative change) in components of the balance sheet. To some extent the DM are advocated by Lev [102,104] and Thiel [152] as measures of financial stability. Stability is defined as relative changes in components of an insurer's financial statement over time. The extent of structural changes as measured on the balance sheet are regarded as measures of stability. In the second group of variables the variability vs. the average return of the insurers examined as measurements of the stability of insurers' profitability (including investment income and gain) over time. The third group the quasi-"systematic risk" which examines the amount of risk of the insurer's profitability that may be associated with the industry-overall profitability.

The first part of this chapter concentrates on the DM. The DM are developed for the liability side, for the asset side and for the whole balance sheet of each insurer. After the DM score is determined for each insurer the company is classified as belonging to the solvent group or to the insolvent group. A cutoff point is selected as the dividing line between solvent and insolvent firms. The purpose is to minimize the number of misclassifications. Insolvent insurers are expected to have high DM, while solvent insurers are expected to have
low DM. The exact placement of the cutoff point will be described in the chapter. The same procedure is described for the NAIT and the BPR. However, the DM is considered as a model which formulates the relative changes of the financial statements over time. Then, the model generates a DM score, and this index (or variable) can be used to predict financial insolvency.

All these variables produce over ten indices (variables). The objectives of this stage are twofold: First to examine if each index (variable) generated by each model is efficient as predictive indicator of insolvencies among P-L insurer. Second, to compare and evaluate which model generates the best univariate index in terms of predictive ability.

The second stage will be to apply a multivariate analyses. The former univariate variables will be applied in several relevant combinations and an aggregate failure indices will be examined. The necessity to apply more variables (e.g., financial ratios) to the aggregate failure indices is in a large extent an empirical question.

In summary, in the first step the models generate indices of insolvency, each index is considered a variable. The variables (indices) are compared in the second step and the most efficient variables are distinguished. Multivariate models which are based on the previous variables, are examined in Chapter VI.
Classification Procedures

The NAIC-IRIS defines two stages of classification of insurers as solid insurers or as priority companies. First acceptable vs. exceptional ranges of scores are identified for the 11 financial tests. Second, if a company has 4 or more exceptional tests it is flagged as a priority company. The following procedure of classification differs significantly from the above classification.

Several classification techniques are used in previous research. The first approach involves a cutoff point which minimizes the number (or probability of) misclassification (sum of errors). A scale of scores is determined for each variable, then the optimal cutoff point is obtained by visually inspecting the data. Every insurer in the sample is classified ex-post into a group of solvent companies or a group of insolvent companies, based on the cutoff point score. A type I error occurs when insolvent insurer is classified as solvent, while a type II error occurs when a solvent insurer is predicted to be an insolvent company but does not become one. The cutoff point which minimizes the total number of incorrect predictions was first applied by Beaver [21,22] and later in many other studies.¹

A second approach employed for each variable, either the grand mean or the midpoint between the groups means is determined as a cutoff

¹Although it might seem unrealistic to apply this method to the whole population of P-L insurers (e.g., see footnote 10 in Pinches and Trieschmann [130]) the procedure is easily employed by applying computer programs (e.g., "Proc Univariate" and "Proc Sort" by SAS [137] might be helpful).
point. Then the dichotomous classification reclassifies ex-post every insurer either to the solvent group or to the insolvent group based on the value of the variable for the specific insurer compared with the cutoff point. Treischmann and Pinches [156;130] apply these methods for both the univariate ratio analysis as well as to the MDA ratio analysis.

A third approach emphasizes Bayesian considerations in classification procedures. Prior probabilities of group membership are taken into consideration. Cooley [40] applies consideration of prior probabilities of group membership to Trieschmann and Pinches' data and presented determination of several optimal cutoff points with Bayesian considerations.

Finally, a fourth approach is to minimize misclassification costs. When a midpoint between group means is employed, an assumption of equal cost of misclassification is made. The cost to regulators of classifying a solvent insurer as insolvent one (type II error) is small (the cost of further investigation and examination) compared with the cost of classifying an insolvent insurer as a solvent one. A cutoff point

---

2 A midpoint between the mean value of the solvent group and the mean value of the insolvent group.

3 Generally the insolvent group is small compared with the solvent. This affects the prior probability of group membership. For a comprehensive discussion see, e.g., Tatsuoka [148], Overall and Kelt [125], and Green [65].

4 Although the state guaranty funds provide a partial alleviation to the policyholders there are many unresolved problems as described in Chapter IV. Moreover, since assessments on the other insurers receive tax credit, states lose insurance premium taxes.
that minimize type I error may therefore be preferred to the first classification procedure.

Different cutoff points yield a tradeoff between the two types of errors as well as prior probabilities and cost considerations. The scope of this research is limited to the first two classifications. A-priori probabilities of group membership, as well as cost considerations, are not included. An empirical comparison between the two first different classification methods is demonstrated in Chapter VIII and Appendix C.

A zone of ignorance (an overlap area) between the two groups may be considered. Companies inside the zone are subject to further investigation. By employing such a zone of ignorance the number of the two type errors is reduced, while the cost of further examination is increased.

The following examples demonstrate the application of the first classification procedure to the NAIC-IRIS (variable NAIT), and to the Best Policyholders’ rating (BPR).

Example 1: The NAIT

The number of tests outside the acceptable ranges are determined for each company in a sample. Since there are eleven tests, the range of this univariate index (number of tests outside the acceptable ranges) for an insurer can vary from zero up to eleven. Based on this score each firm is classified as belonging to the solvent group of insurers or to the insolvent group of insurers. It is expected that insolvent insurers will have larger number of tests outside the norms.
Then for each company $j$

$$0 \leq \text{NAIT}_j \leq 11$$  \hspace{1cm} (5-1)

where $\text{NAIT}_j =$ the number of tests outside the acceptable norms, for company $j$.

A second step is to relate the score $\text{NAIT}_j$ of each company to a cutoff point which discriminates between solvent and insolvent insurers. This cutoff point ($c$) on Figure 5 is the dividing line between solvent and insolvent insurers in the sample. The purpose is to minimize the number (or probability) of misclassification. The cutoff point may be determined by visually inspecting the data, with the help of computer programs.

<table>
<thead>
<tr>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>solvent insurers</td>
<td>insolvent insurers</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(1) $c$ - is a possible cutoff point.
(2) * - denoted on insurer in the sample
(3) For an insurer $j$, if $\text{NAIT}_j > c$ the insurer is classified as insolvent, and if $\text{NAIT}_j < c$ the insurer is classified as solvent.

Figure 5. The Optimal Cutoff Point and Classification Procedure.

The objective is to minimize the misclassifications. A type I error occurs when an insolvent insurer is predicted to be solvent (e.g., it has less than 5 tests). A type II error occurs when a solvent insurer is predicted to be insolvent, as explained above. Type I
errors are considered more important. A zone (range) of ignorance (e.g., score of 4 up to 6) rather than a cutoff point can also be considered; insurers within the range may require further analysis to determine their status, or these insurers may be considered a third group. This procedure of classification is repeated for one and three years before insolvency. This process of classification is repeated for all other variables (indices).

Example II: BPR

The same is divided into two groups of solvent and insolvent insurers by determining the cutoff point that minimize the number of misclassification. The score scale is determined as follows:

\[ 1 \leq BPR_j \leq 9 \] (5-2)

where \( BPR_j \) = the score of Best's Policy Rating for company j.

A numerical score is related to the BPR as follows:

\[
\begin{align*}
A+ & = 1 & C & = 6 \\
A & = 2 & \text{Inapplicable, will rate} & = 7 \\
B+ & = 3 & \text{Deferred} & = 8 \\
B & = 4 & \text{Omitted} & = 9 \\
C+ & = 5 & \\
\end{align*}
\]

A company with a rate A+ is scored one, and another company with a rate "omitted" is scored as nine. The cut-off point is C on Figure 6 minimized the number of misclassifications.

Based on the previous cutoff points each new company that is not included in the sample can be classified. It is important to examine the predictive ability of each univariate variable. Therefore, a new

\[5\] The scores are measured on interval scale (not on a ratio scale).
sample (termed a validation or hold out sample) can be used. For practical application, the cutoff point can be used for examining the scores for all companies in the industry. Those companies with scores above the cutoff point are predicted to become insolvent. If a cutoff range is used, those companies that are within this range require further analysis and scrutiny. This cutoff range may be viewed as a filter (or a screen), those insurers which are above the range are predicted to be insolvent, those insurers which remain within the range require the further scrutiny.

The Decompositions Measures (DM)

Decomposition analysis has been applied to various sciences. Theil [151] advocates applying them to financial statement analysis.

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Theil [151] and Lev [104] list those sciences as accounting, economics, geography, sociology and psychology. Two examples of implications are: (1) Hirsh and Lev [77] applies the DM to the distribution of export sales and find them to be associated with the riskness of these sales. Theil [152] finds that small firms have larger DM than large firms.
Lev [104] argues that decomposition analysis is generally designed for the study of allocation problems. Their primary objective is to study the change over time of the firm inputs and outputs as measured by the financial statements. The DM indicate occurrence of important environmental and/or internal events worthy for further investigations.

The DM are used by Lev [103] to predict financial failures. The DM of bankrupt firms are larger than those of solvent firms, and were comparable to the best performed ratios in Beaver's [21,22] study. Booth [38] finds that the stability and size of some balance sheet DM discriminates between failed and nonfailed firms. Walker, etc. [158] finds that the DM are generally larger for failing firms, have the same bankruptcy prediction as a good financial ratio, and DM on the asset size [Da] have very little ability to discriminate between solvent and insolvent firms.

It seems that the DM are efficient and convenient device for determining whether significant change in financial statement occurs, and where these changes are allocated. Since DM are indicators for stability in the financial statements over time and it is assumed that insolvent insurers may face significant changes in their financial statements several years before the insolvency. Therefore, it is expected that an insolvent insurer has a larger DM than a solvent one.
The liabilities DM, D1 is defined as:

\[ D1 = \sum_{i=1}^{n} Qi \log \frac{Qi}{Pi} \]  

where

- \( Qi \) = component or type of liability (including surplus).
- \( Pi \) = the relative share (fraction) of component \( i \) to total liabilities (including surplus) for a previous year.
- \( 0 < Qi, Pi < 1 \).

The following illustration (Table 11) demonstrates the relative share of each liability of Buckeye Union Ins. Co. for the years 1978 and 1977.

The fraction of loss reserves \( Pi \) was .5194, in 1977, and in 1978, \( Qi = .5063 \). The same computation can be done for the other components.

Using formula 5-3 the DM is generated for the liabilities for the years 1978/1977:

\[ D1 = .5063 \log_{e} .5194 + .2219 \log_{e} .2239 + .0292 \log_{e} .0289 + .2426 \]

\[ \log_{e} .2426 = .00066 \text{ nits.} \]

The choice of the logarithm's base is based on the user preference. Lev [104, p. 50] prefers to use natural logarithms, and denotes one unit of measurement as a nits. For the convenience of the user integers are used, and denoted as "units." Then one unit is equal to

\[ 7 \text{This presentation is based on Lev [103, pp. 48-56]; several modifications have been made.} \]
TABLE 11

Buckeye Union Ins. Co., Liabilities and Relative Shares for the Years 1977, 1978 (000 Omitted)

<table>
<thead>
<tr>
<th>The Component</th>
<th>1977</th>
<th>1978</th>
<th>i</th>
<th>Component Relative Share (fraction)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss Reserves</td>
<td>375,344</td>
<td>386,396</td>
<td>1</td>
<td>Pi = .5194</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Q1 = .5063</td>
</tr>
<tr>
<td>Unearned Premium</td>
<td>161,822</td>
<td>169,403</td>
<td>2</td>
<td>P2 = .2239</td>
</tr>
<tr>
<td>Reserve (UPR)</td>
<td></td>
<td></td>
<td></td>
<td>Q2 = .2219</td>
</tr>
<tr>
<td>Other liabilities</td>
<td>20,899</td>
<td>22,319</td>
<td>3</td>
<td>P3 = .0289</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Q3 = .0292</td>
</tr>
<tr>
<td>Policyholders'</td>
<td>164,640</td>
<td>185,146</td>
<td>4</td>
<td>P4 = .2278</td>
</tr>
<tr>
<td>Surplus (Equity)</td>
<td></td>
<td></td>
<td></td>
<td>Q4 = .2426</td>
</tr>
<tr>
<td>Total</td>
<td>$722,705</td>
<td>$763,264</td>
<td>Σ Pi = 1.000</td>
<td>Σ Qi = 1.000</td>
</tr>
</tbody>
</table>

10^{-5} nits (1 nits = 10,000 units). The results for Buckeye Union are: .00066 nits (or 66 units) for 1978/77; .00201 nits (or 201 units for 1979/78; and .00035 nits (or 35 units) for 1980/79.

The asset decomposition measures (Da) are computed in the same way and the same formula is used. The Qi's and Pi's are fractions of assets components at two points of time. 8

The balance sheet decomposition measures Dbs are defined as:

\[ Dbs = \sum_{g=1}^{2} \sum_{i=1}^{n} Q_{gi} \log \frac{P_{gi}}{P_{g1}} \]  

(5-4)

Where i = 1, ..., n.

g = 1, 2 (1 for assets, and 2 for liabilities).

8 Da for Buckeye was .01001 nits in 1977/78.
The assets and liabilities are divided into several categories (e.g., total of eight categories, 4 for the assets and 4 for liabilities). Dividing each of the categories by twice the balance sheet total yields a set of nonnegative fractions which sum to 1. Each component is denoted (or category) as Qgi for the last year. The index i takes values from 1 to n, while g takes the values 1 or 2, for assets or liabilities, respectively. The following Figure 7, presents the arrangement:

<table>
<thead>
<tr>
<th>Assets</th>
<th>Liabilities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bonds</td>
<td>Loss Reserves</td>
</tr>
<tr>
<td>Q11</td>
<td>Q21</td>
</tr>
<tr>
<td>Stocks</td>
<td>U.P.R.</td>
</tr>
<tr>
<td>Q12</td>
<td>Q22</td>
</tr>
<tr>
<td>Agent Balances</td>
<td>Other Liabilities</td>
</tr>
<tr>
<td>Q13</td>
<td>Q23</td>
</tr>
<tr>
<td>Other Assets</td>
<td>Surplus</td>
</tr>
<tr>
<td>Q14</td>
<td>Q24</td>
</tr>
<tr>
<td>Total</td>
<td>Total</td>
</tr>
<tr>
<td>Q1. = 1/2</td>
<td>Q2. = 1/2</td>
</tr>
</tbody>
</table>

Figure 7. Balance Sheet Compositions

The Pgi's stand for the relative fractions of the previous year. The larger the changes in the relative fractions (Qgi compared with Pgi), are the larger the measure (Dbs). Lev [102] proves that the balance sheet decomposition measures (DBs) are equal to the arithmetic average of the asset decomposition measures (Da) and the liabilities decomposition measures (Dl), for the same components (proportions). The Dbs for Buckeyes Union was .00534 nits in 1978/77. Lev [104] also proves that the DM is always nonnegative.
A New-Modified Decomposition Measures Model (NDM)

Why a Modified Model is Necessary

Lev [103] shows that the DM are useful in prediction models, and can distinguish between failed and nonfailed firms. This section considers modifying the formula primarily for the purpose of predicting failures. Theil [152] and Lev [104] both consider the DM as measures of distance rather than direction. The DM are unable to distinguish whether a change is toward an optimal position.

These considerations may not be accurate due to the negative sign an element i takes whenever Qi < Pi. This characteristic is inherent by the mathematical property of a logarithmic function, log Yi < 0 when 0 < Yi < 1. Whenever $\frac{Q_i}{P_i} < 1$ then $\log \frac{Q_i}{P_i} < 0$ (and when $Q_i > P_i$, $\log \frac{Q_i}{P_i} > 0$). For example in Buckeye Union the reduction in the proportion of the UPR between 1978 and 1977 ($Q_i = .2219$, $P_i = .2239$) takes a negative sign which reduces the overall value of the DM.

This property of the DM has the following two disadvantages. First, it reduces the value of the DM, while for the purpose of prediction of failures the goal is to capture all changes in the proportion of components over time. Any change or departure from stability should increase the value of the DM. In general, the greater the change the greater the instability, therefore, the value of the DM should be larger. Lev [102, p. 27] points out that the DM design to indicate the degree which actual behavior of an item deviates from the proportional development, a reduction in the overall value of the DM does not contribute to this indication. For the purpose of prediction of insolvency there is no practical reason why a reduction in a proportion
of an item (e.g., $Q_i = 0.2219$, $P_i = 0.2239$) must reduce the value of the DM.

Second, a larger DM should indicate more instability and more chance for a failure. Any reduction in the proportion of an item ($Q_i < P_i$) reduces the value of the DM. However, a-priori, a reduction in a proportion of an item may not indicate a change toward improvement, or an increase in a proportion of an item ($Q_i > P_i$) may not indicate a disturbance and an undesired change. For example, a reduction in the proportion of surplus may be considered as an undesired development, yet this reduction takes a negative sign and reduces the overall value of the DM. In practice, if a reduction in a proportion of a surplus is undesired such a change should take a positive sign and increase the value of the DM. However, while employing the NDM the relationship to expected value of information may be lost.\footnote{For a further discussion see Appendix B. An excellent brief discussion on the expected value of information, and DM in econometric context is presented in Judge, Griffith, etc. [89, pp. 601-606].}

Presenting the New Decomposition Measures (NDM)

A few shortcomings of the use of DM for predicting of insolvency were mentioned above in order to eliminate these practical shortcomings using absolute value is recommended in this study. Formula 5-3 is modified and new decomposition measures are created, and denoted by NDM ($ND_l$ - for liabilities, $ND_a$ = for assets, etc.).

\[
ND_l = \sum_{i=1}^{n} Q_i \left| \log_e \left( \frac{Q_i}{P_i} \right) \right| \tag{5-5}
\]
All the notations in the formula are the same as in formula (5-3), \[ | | \] is the absolute value.

Formula (5-5) has the following characteristics:

1. None of the \( n \) components in the formula can take a negative value.

2. \( ND_1 \geq D_1 \) (or in general, \( NDM \geq DM \)) for all \( i \).

3. \( ND_1 = D_1 = 0 \) only if \( P_i = Q_i, \left( \frac{Q_i}{P_i} = 1 \right) \) for all \( i \). The NDM will be at the minimum and will take the value zero. By definition it is nonnegative (the same as for the DM).

4. The larger the change in the relative fraction of a component the larger the NDM.

5. NDM also obey the mathematical property of additivity.

Figure 8 is a graphical presentation of any component of the NDM vs. any component of the DM. As it is demonstrated in the figure any single component \( i \) cannot have a negative value under the NDM, while it may have a negative value under the old DM.

Under formula (5-5) every change in a proportion of a component is captured and increases the value of the DM.

Since the NDM is more sensitive to any change in the fractions of items, ex-ante the NDM is expected to discriminate more accurately between failed and nonfailed firms. Both the DM and the NDM are examined and compared in the empirical study. All types of DM and NDM will be examined as univariate variables, as well as variables in the MDA.

For a further discussion of the DM, their relationship to information theory and the properties of the DM, see Appendix B. An empirical
a. Under the existing formula for DM, \( Y_i = \log_e \frac{Q_i}{P_i} \)

b. Under the NDM, \( Y_i = |\log_e \frac{Q_i}{P_i}| \)

Figure 8. Decomposition Measures: Underlying Values of a Component i.
examination of the DM and the NDM for prediction of insolvent insurers is presented in Chapter VIII. The same procedures of classification which were applied to NAIC-IRIS (NAIT) and BPR are applicable to all types of DM. For each kind of DM insurers can be classified to solvent and insolvent firms with a dividing line or cutoff point, C.

**The Square-Proportions (SP) Method**

The changes of the proportional fractions (shares) of components on the balance sheet are measured by squaring the differences of the relative fractions. A weighted sum of differences is applied in this section in order to reflect the importance of each fraction (share) in the total assets or liabilities. \(^{10}\)

The square-proportions for liabilities (SP1) can be defined as follows:

\[
SP1 = \sum_{i=1}^{n} Qi (Q_i - P_i)^2
\]  

(5-6)

where 
- \(i = a\) component or type of liability (including surplus).
- \(i = 1 \ldots n; n\) is the number of components on the liabilities side.
- \(Q_i = the\ relative\ share\ of\ component\ i\ (liability\ i)\ to\ total\ liabilities\ (including\ surplus)\ for\ the\ last\ current\ year.\)
- \(P_i = the\ relative\ share\ of\ component\ i\ (liability\ i)\ to\ total\ liabilities\ (including\ surplus)\ for\ a\ previous\ year.\)

\(0 \leq Q_i, P_i \leq 1\)

The primary property of the square-proportions is \(0 \leq SP \leq 1\.

It is zero when there are no changes in the fractions across time,

---

\(^{10}\) For a similar discussion about the weighted sum on DM see Appendix B. Without these weighted elements formula (5-6) would be \(SP = \sum (Q_i - P_i)^2\). See Appendix B for further discussion.
and the SP is 1 when the maximum possible change occurs.\textsuperscript{11}

The square-proportions of Buckeye Union, using Formula (5-6) and Table 11, is:

\[
SP_1(1977/8) = 0.5063(0.5063-0.5194)^2 + 0.2219(0.2219-0.2239)^2
+ 0.0292(0.0292-0.0289)^2 + 0.2426(0.2426-0.2278)^2 = 0.000141
\]

The assets square-proportions (SPa) are computed in the same way so the same formula is used.

Since it can be assumed that insolvent insurers may face significant changes in their financial statement several years before insolvency, it can be expected that insolvent insurers may have larger SPs than the solvent insurers. Like the DM, the SP measures stability and therefore can be used as a univariate variable for prediction of insolvency. The model generates scores for each company (either for assets or for liabilities, or for both). The classification procedure described for NAIC-IRIS is applied for the SP, which will be considered a univariate variable\textsuperscript{12} for prediction of insolvency among P-L insurers.

\textsuperscript{11}For a short proof see at the end of Appendix B.

\textsuperscript{12}Two univariate variables will be examined one SP1 (for liabilities) and the second SPa (for assets).
Financial Ratios Analysis and the Insurer Financial Solvency

Since financial ratios are used extensively in the insurance industry, this study will attempt to exclude using financial ratios as variables for predicting financial failures among insurers. However, financial ratios may be applied in the future in order to examine whether they can significantly improve the predictive ability of the models.

The financial solvency and strength of the insurers are analyzed by using financial ratio analysis. The policyholders surplus ratio, the surplus ratio (the exposure ratio), the loss ratio, the expense ratio, and the combined trade ratio are often used.\(^\text{13}\)

The policyholders' surplus ratio (equity divided by all other liabilities) is widely used in the industry. Kenny [93] recommends that the ratio of the policyholders surplus to the unearned premiun reserve (UPR) should be at least one in order to maintain a safe margin for solvency. Several other analyses recomend that the policyholders' surplus ratio should be at least 1:1 in order to protect the policyholders. Other analyses consider that this limit may be too conservative. It may eliminate the growth of the insurer and increase

\(^\text{13}\) The policyholders' surplus ratio, is the ratio of the policyholders' surplus (equity) to all other liabilities (reserves). The surplus ratio is the net written premiums divided by the policyholders' surplus (equity), which is also referred as the exposure ratio. The reader should distinguish between the "policyholders' surplus" ratio and the "surplus" ratio. The loss ratio is the loss and loss adjustment expenses/earned premium; the expense ratio is expenses incurred/premiums written; the combined trade ratio is the sum of these two ratios.
the capacity problem. The policyholders' surplus ratio for the P-L insurance industry was only .359 in 1980 (.311 in 1978).

The surplus ratio (exposure ratio) is another measure of financial solvency. Kenny [93] recommends an acceptable ratio of no more than 2:1. The New York insurance department allows a surplus ratio of up to 3.3. The NAIC-IRIS model sets an acceptable range of maximum 3:1.\(^\text{14}\) In this ratio, the premiums substitute debt as a measurement of risk. The premiums are considered the amount of an insurer's exposure, and there should be enough surplus as an aid or a shield against the risk exposures. In 1980 the surplus ratio for the insurance industry was 1.834 (2.009 in 1978).

The NAIC-IRIS, Kenny's rules, and state's regulation considerations apply arbitrary and deterministic rules for capitalization requirements. These rules accelerate the capacity problem and may reduce the return to the invested capital and surplus. The rules are criticized by several scholars. Hofflander [78, p. 438] criticized as arbitrary rules of thumb without justification, and Greene [64] emphasized the importance of profitability ratios. Bachman [19] found that a company can increase its surplus ratio without treating solvency by changing the product-line mix. The results support the idea that the industry's wide acceptable range and traditional benchmarks for the surplus ratio are not valid. Instead, each company must be examined by itself. Some companies can operate at a very high surplus ratio

\[^{14}\text{The NAIC-IRIS model is a combination of 11 tests. Most of the tests are financial ratios including the surplus ratio.}\]
without deliquescing their solvency while others may need a lower surplus ratio.

The modern financial statement analysis determines that no ratio has a correct value. However, while analyzing the insurer the analyst should find the trends in a ratio across time, and then compare it with the same ratio-trend of others insurers. The industry average ratio is widely used in such a comparison. The ratio of an insurer is compared to the industry average ratio a year by year across time. Figure 9 illustrates such a comparison.

Financial ratios are only indicators of circumstances underlying the insurer operation. They usually can point out areas where further investigation is necessary by regulators, they rarely provide a final answer.
**Stability of Financial Ratios Over Time: Profitability Measures As Indices for Predicting Insolvencies**

The stability of components (fractions) on the balance sheet are measured and used for predicting insolvencies in the previous sections. The focus of this section is on the stability of the financial ratios of the insurer over time. The discussion considers only the stability of the profitability ratios. Data are measured based on SAP, but modification of profitability ratios is made, and data will be modified to GAAP in Chapter VII. Unlike previous research [64,130] this study does not focus on the profitability ratios themselves, but concentrates on the average return vs. the variability of the return. The choice between return and risk is faced by every insurer. As it is advocated by the finance theory [110,139], the expected return (the average return) is used as measure of profitability and the standard deviation of the return (across time) as measure of risk.  

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**Average Profitability, the Temporal Risk and the Stability of Return**

The purpose of this subsection is to develop another measure for prediction of insolvency. The average return vs. the temporal risk

---

15The term return is used in general sense to identify either the rate of profitability on equity (policyholders' surplus), or profitability rate on premiums. In this section the return is measured as percentage of premiums, and it can be converted to return on equity by multiplying the return on premiums by the exposure ratio (premiums divided by surplus). The words return and profitability on premiums (or equity) are used interchangeably. In this study the expected return and the variability of return are estimated empirically; therefore the measures are the average return and the temporal variance or standard deviation (i.e., the average return and variability of the insurer's profitability over time).
are compared for each company over time. It is expected that an insolvent insurer will have a small (or negative) average return and large standard deviation of return across time. A solvent insurer is expected to have a larger average return, as well as a smaller standard deviation, compared with an insolvent insurer.

Underwriting profits and investments yields are two profitability tests measured by the NAIC-IRIS. Traditionally, the underwriting profitability of an insurer is measured by the combined trade ratio which shows the relationship between losses plus expenses to premiums. Investment gains are not considered by this ratio, although Greene [64] pointed out that investment profits constituted the largest portion of total profits.

The combined trade ratio (CTR) for an insurer can be written for one period as follows:

\[
CTR = \frac{L}{PE} + \frac{UE}{PW}
\]

where
- \(CTR\) = combined trade ratio for the current year.
- \(PE\) = premiums earned during the current year (under SAP).
- \(PW\) = premiums written during the current year.
- \(L\) = losses incurred in the current year.
- \(UE\) = underwriting expenses incurred in the current year.

\[16\] The combined trade ratio is the sum of the loss ratio and the expense ratio. The loss ratio is the losses and claim adjusted expenses divided by premiums earned. The expense ratio is the expenses incurred divided by the written premiums.

\[17\] For modification to GAAP further adjustment is necessary across time, see Chapter VII and Appendix A-2. The present modification will be referred to as the modified SAP.
This ratio (CTR) is a modification of the SAP (the modified SAP), since under SAP the combined trade ratio (CTRS) would be:

$$CTRS = \frac{L + UE}{PE} = \frac{L}{PE} + \frac{UE}{PE}$$

(5-7B)

The profitability (the modified ratio of underwriting profits, (MRUP) as ratio of premiums is unity minus the combined trade ratio, as follows:

$$MRUP = 1 - \left(\frac{L}{PE} + \frac{UE}{PW}\right) = 1 - CTR$$

(5-8)

The underwriting combined trade ratio is an important factor in Best's policyholders' rating (BPR). A two-year adjusted underwriting combined trade ratio is one test used by the NAIC-IRIS. Investment yield is another test used by the NAIC-IRIS; the ratio is net investment income divided by the average invested assets. This ratio reflects the profitability of the company's investment portfolio. However, the arbitrary acceptable ranges as well as the measurement of invested assets may reduce the effectiveness of this ratio as a tool for predicting insolvency.

For the purpose of measuring insolvency investment gains should also be considered. While investment gains and underwriting profits (or losses) are measured separately by conventional analyses, it is worthwhile to combine them together. For profitability to be an indicator for future insolvency underwriting, results are combined with investment gains.\(^{18}\) Therefore in addition to the underwriting combined

---

\(^{18}\) The general term investment gain includes interest, dividends, etc., as well as realized gains on stocks and bonds, and unrealized gains on stocks. The term refers to the net investment income and capital gain as it reflected by gains or losses in policyholders' surplus.
trade ratio (CTR), a ratio of net investment income to written premiums is subtracted from the CTR; a new ratio denoted as the combined profitability ratio (CPR) is established. If this ratio (CPR) is larger than 100 percent the insurer has an overall underwriting and investment loss during the accounting period.

The combined profitability ratio (including investment gains) can be written as follows:

\[
CPR = \frac{L}{PE} + \frac{UE}{PW} - \frac{IG}{PW} = CTR - \frac{IG}{PW}
\]  

(5-9)

where \( IG = \) investment gains (earnings and capital gains) during the current year.

The modified profitability ratio can be written as:19

\[
MPR = 1 - CPR = 1 - \left( \frac{L}{PE} + \frac{UE}{PW} - \frac{IG}{PW} \right) = 1 - \frac{L}{PE} - \frac{UE}{PW} + \frac{IG}{PW}
\]

\[
= 1 + \frac{IG}{PW} - \frac{L}{PE} - \frac{UE}{PW}
\]

(5-10)

Equation (5-10) is the modified profitability of the insurer as percent of premiums.

For the prediction of insolvency, the focus is placed on the average modified profitability ratio for an insurer across time. For \( n \) years the mean ratio is written as follows:

\[
MEMPR = \frac{1}{n} \sum_{t=1}^{n} \frac{MPR_t}{n}
\]

(5-11)

19The modified profitability as a ratio of the policyholders' surplus (surplus), MPRS, can substitute the modified profitability ratio (MPR). Then \( MPRS = 1 - \left( \frac{L}{PE} \cdot \frac{PW}{surplus} \right) - \frac{UE}{surplus} + \frac{IG}{surplus} \); for a modification under SAP or under GAAP see Chapter VII.
where \( \text{MEMPR} \) = is the average MRP across time and 
\( t \) = index of periods (years); \( t = 1, 2, \ldots, n \).
\( \text{MPR}_t \) = the ratio for one year \( t \).

In the empirical research \( n = 9 \) for the year prior to insolvency (i.e., average ratio for the last nine years before insolvency; denoted by \( \text{MEMPR}_1 \)), and \( n = 7 \) for three years prior to insolvency (\( \text{MEMPR}_3 \)).

Business risk is often expressed in terms of fluctuations. The variability or volatility in the modified ratio of underwriting profits (MRUP), as well as the modified profitability ratio (MPR), are measured for each company. The temporal standard deviations of these ratios show the magnitude by which the profitability ratios varied over time. As a result of the limitation of data, only variabilities from seven and nine years means \( (n = 7 \) for three years before insolvency, or \( n = 9 \) for one year before solvency) are measured.\(^{20}\) The standard deviation is a proxy measure of the underwriting and profitability risk of a company over time. Since a sample is taken the standard error of estimate around the seven or nine years means can also be measured for each company. The sample standard deviation for the MRP across time \( (n \) years) is written as:

\[
\text{SDMPR} = \sqrt{\frac{\sum_{t=1}^{n} (\text{MPR}_t - \text{MEMPR})^2}{n-1}} \quad (5-12)
\]

where \( \text{SDMPR} \) = is the standard deviation of the MPR across time \( (n \) years).

---

\(^{20}\) More than nine year period might be too long. An insolvent insurer might be very solid ten years ago, and taking a long period might present a wrong signal.
Finally, the coefficient of stability (CoS) an index for predicting insolvency is the ratio of the average return (MRP) divided by the standard deviation of the return (SDMPR), (equation (5-11) divided by equation (5-12)) as follows:

\[
\text{COS} = \frac{\text{Eq. (11)}}{\text{Eq. (12)}} = \frac{\text{MEMPR}}{\text{SDMPR}} = \text{CosMPR}
\]  

(5-13)

It is expected that solvent insurers will have larger CoS, while insolvent insurers will have small or negative CoS.\(^{21}\) A cutoff point (C) is determined for minimizing the number of misclassifications.

**Integrating External Factors: Industry Averages the Accounting Beta, and the Quasi-Systematic Risk**

The profitability performance of an insurer is compared to the overall industry profitability over time. However, other research focuses on the underwriting results with only minor attention given to investment gains.\(^{12}\) The underwriting losses of the P-L insurance industry were $1.7 billion in 1980, and were estimated to be at least $4 billion in 1981 [84], while updated to $4.5 billion [28]. However, the net investment gains were $15.9 billion (including $4.3 billion

\(^{21}\) A transformation may be required for negative values of CoS.

\(^{22}\) 1975 is considered the worst year in the P-L insurance business. However, 1975 was a good year in terms of investment gains; the overall profitability to premium was about 10 percent. 1974 was the worst year, coupled with large investment loss the overall profitability loss was over 10 percent. It is not surprising that the largest number of insolvencies occurred in 1975, as a result of the dual impact of underwriting and investment losses in 1974.
appreciation) in 1980, and $10.9 billion (after $2.7 depreciation in stocks' value) in 1981 [28].

Data on the whole industry combined trade ratio are published by A.M. Best [28]. The investment gains are computed and added in order to find the overall profitability of the industry. The results are summarized in Table 12.

The profitability of an insurer $j$ is associated with the whole P-L industry's profit. One possible measurement of this relationship is employed by measuring the temporal variability of an insurer's profitability over time.

The variability of the profitability of an insurer is viewed as affected by two factors: the variability of the industry profitability as a whole, and the variability of profitability specific to an insurer. This partition is known from the portfolio theory and the security market as the "Market Model." The first component is known as the systematic risk, the latter as the unsystematic risk [100,139].

The market model assumes a linear relationship between the return on each single security $\tilde{R}_j$, and the overall market return $\tilde{R}_M$:

$$\tilde{R}_{jt} = \alpha_j + \beta_j \tilde{R}_{Mt} + \varepsilon_{jt}$$  \hspace{1cm} (5-14)

where $\tilde{R}_{jt}$ = the rate of return on asset $j$ (security $j$) for period $t$.  
$\tilde{R}_{Mt}$ = the market aggregate return 
$\varepsilon_{jt}$ = the residual error term for asset $j$ in period $t$.

This model is based on the pioneering work of Markowitz [110], and Sharp [139].
<table>
<thead>
<tr>
<th>Year</th>
<th>Less Ratio</th>
<th>Expense Ratio</th>
<th>ICTR</th>
<th>IMRUP</th>
<th>ICPR</th>
<th>IMPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1961</td>
<td>64.2%</td>
<td>32.3%</td>
<td>96.5%</td>
<td>3.5%</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>1966</td>
<td>67.5</td>
<td>29.6</td>
<td>97.1</td>
<td>2.9</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>1971</td>
<td>67.5</td>
<td>27.2</td>
<td>94.7</td>
<td>5.3</td>
<td>82.4%</td>
<td>17.6%</td>
</tr>
<tr>
<td>1972</td>
<td>66.6</td>
<td>27.7</td>
<td>94.3</td>
<td>5.7</td>
<td>79.2</td>
<td>20.8</td>
</tr>
<tr>
<td>1973</td>
<td>69.3</td>
<td>28.0</td>
<td>97.3</td>
<td>2.3</td>
<td>100.1</td>
<td>- .1</td>
</tr>
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<td>1974</td>
<td>75.5</td>
<td>28.2</td>
<td>103.7</td>
<td>-3.7</td>
<td>110.6</td>
<td>-10.6</td>
</tr>
<tr>
<td>1975</td>
<td>79.3</td>
<td>27.3</td>
<td>106.6</td>
<td>-6.6</td>
<td>89.9</td>
<td>10.1</td>
</tr>
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<td>1976</td>
<td>75.4</td>
<td>25.9</td>
<td>101.3</td>
<td>-1.3</td>
<td>86.0</td>
<td>14.0</td>
</tr>
<tr>
<td>1977</td>
<td>70.7</td>
<td>25.3</td>
<td>96.0</td>
<td>4.0</td>
<td>89.0</td>
<td>11.0</td>
</tr>
<tr>
<td>1978</td>
<td>70.1</td>
<td>25.8</td>
<td>95.9</td>
<td>4.1</td>
<td>86.4</td>
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<tr>
<td>1979</td>
<td>73.1</td>
<td>26.0</td>
<td>99.1</td>
<td>.9</td>
<td>86.3</td>
<td>13.7</td>
</tr>
<tr>
<td>1980</td>
<td>74.9</td>
<td>26.5</td>
<td>101.4</td>
<td>-1.4</td>
<td>84.8</td>
<td>15.2</td>
</tr>
</tbody>
</table>

Average 1971-79 | 98.8% | 1.2% | 89.9% | 10.1% |
St. Deviation 71-79 | 4.2 | 4.2 | 9.6 | 9.6 |

ICTR = Industry Combined Trade Ratio
IMRUP = Industry Modified Ratio of Underwriting Profits
ICPR = Industry Combined Profitability Ratio (including investment gains)
IMPR = Industry Modified Profitability Ratio

Sharp [140], Linter [100], and Mossin [117] extend the market model to the capital asset pricing model. Based on restrictive assumptions, it can be shown that:

\[
E(R_j) = R_f + \beta_j [E(R_M) - R_f]
\]  

(5-15)

Where \( E(R_j) \) = the expected rate of return on asset \( j \), for one period. 
\( R_f \) = rate of return on a riskless asset 
\( \beta_j \) = the systematic risk of asset \( j \). 
\( E(R_M) \) = the expected return on the market portfolio.

Many studies have focused on the question of the association between market risk measures (e.g., betas) and accounting risk measures. Ball and Brown [17;18] measure the relationship between the accounting income of a firm to the aggregate income of all firms. Their model can be expressed as:

\[
AI_{jt} = \alpha_{jt} + \beta^*_{j} AI_{Mt} + e_{jt}
\]  

(5-16)

where \( AI_{jt} \) = the accounting income of firm \( j \) in year \( t \). 
\( \beta^*_{j} \) = the accounting systematic risk for firm \( j \) (the accounting beta). 
\( AI_{Mt} \) = the accounting income for the market (industry, firms in the sample, etc.).

Beaver, Kettler and Scholes [23] examine the correlation between the market based risk measure (e.g., \( \beta \)) and seven accounting based risk measures. The accounting earning variability and the accounting covariability (e.g., \( \beta^* \)) are found to have significant correlation with the market risk measures. They find indications that accounting risk measures (including the accounting beta) can be viewed as surrogates for the systematic risk. Research since then has focused on issues of methodology and variables' specification; e.g., Goodness [61], Beaver and Manegold [24], and Beaver, Clark and Wright [25].
A linear regression model is used in my study to segregate the systematic and unsystematic profitability risk. The industry modified profitability ratio (IMPR) is taken for every year. Then the MPR for a company is regressed on the annual IMPR. This linear regression model measures the relationship between the MPR in a company and the industry IMPR across time (over seven or nine year period). The model is presented in formula (5-17).

\[ \text{MPR}_{jt} = \alpha_j + \beta_j \text{IMPR}_{jt} + \epsilon_j \]  

where  
- \( t = 1 \) through 9, denotes for years (or 7 years for three years prior to insolvency) 
- \( j \) = index of an insurer, \( j = 1, \ldots, N \); number of companies in the sample. 
- \( \text{MPR}_{jt} \) = the combined profitability ratio for company \( j \) at the end of year \( t \). 
- \( \alpha_j \) = the regression constant for company \( j \). 
- \( \beta_j \) = the regression coefficient which measures the systematic risk of company \( i \). 
- \( \text{IMPR}_{jt} \) = the industry modified profitability ratio for year \( t \). 
- \( \epsilon_j \) = the error which is the main component of the unsystematic risk.

This regression equation is developed separately for each company in the sample. For each company specific values \( \alpha_j, \beta_j, \) and \( \epsilon_j \) are observed. As many equations as companies in the sample (\( N \)) are obtained. Each equation includes \( t \) observation (\( t = 9 \) in this examination).

The same model is used for the MRUP and it is specified in formula (5-17a).

\[ \text{MRUP} = \alpha'_j + \beta'_j \text{IMRP}_{jt} + \epsilon'_j \]  

Traditionally, \( \beta_j \) indicates the extent to which company \( j \) is subject to the systematic variability of the market (insurance industry.
profitability, in this study). Thus, for an investor (insured), $\beta_j$ measures the riskness of a security (an insurer). $\alpha_j + \varepsilon_j$ is the unsystematic risk, which can be eliminated by combining investments and/or securities into a portfolio (dividing a specific risk by buying a portfolio of policies from many insurers).

The modified profitability ratio has already been divided into two components. The first one is dependent on the IMPR; this component $\beta_j$ (IMPR) is referred to as the "quasi-systematic" risk. The second component, $\alpha_j + \varepsilon_j$, is the unsystematic risk which can be washed out by an insured who buys many small policies with large number of insurers, or by investors (including policyholders in mutual P-L insurers) who invest in P-L insurer and many other investments.

Unfortunately, an insured would not spread his risks by purchasing a portfolio of small contracts from large number of insureds. An additional reason for purchasing many contracts would be to reduce possible losses as a result of insolvency of a single insurer. Some large corporate risks are transformed on this basis to many insurers. However, in most cases, transaction costs and other considerations may indicate writing contracts with a single insurer.\textsuperscript{24} Since the type of systematic risk considered in this paper is often not used as a mean of diversification by insureds, this risk is called "quasi-systematic" risk.

\textsuperscript{24}Dorethy and Tinic [45] argue that under conditions of demand induced reinsurance the insurer can reduce and diversify the ruin risk by reinsurance. Reinsurance may also be more efficient and less expensive mechanism, from the insured's viewpoint, than to buy many policies by a single insured from many insurers.
The quasi-systematic risk: reflects the relationship between the profitability (or the variability of the profitability) of an insurer and the overall industry profitability (or variability of profitability) across time. Ex-ante, it is expected that insolvent insurers will have larger quasi-systematic risk, and therefore it will be a possible tool to classify and discriminate between solvent and insolvent companies.

The quasi-systematic risk associated with the MPR of a company is equal to \( \beta \) SDIMPR, where SDIMPR is the standard deviation of the industry IMPR. This quasi-systematic risk cannot be eliminated through diversification across insurers. The (quasi) unsystematic risk in the regression is the component \( \alpha_j + \beta_j \) which is not explained by the variability in the industry combined profitability ratio (SDIMPR). \( \beta_j \) is the relative quasi-systematic risk for a company \( j \). Since SDIMPR is equal and constant for all \( N \) companies, \( \beta_j \) is separate as the quasi-systematic risk of insurer \( j \).

It is expected that \( \beta_j \), the quasi-systematic risk, may be used to discriminate between failed and nonfailed insurers. The larger the \( \beta_j \), the more probability there is that the company will fail. The \( \beta \) is examined as a univariate variable and is compared with the other univariate variables for the purpose of predicting financial failures of insurers.

Unfortunately, coupled with the spread of risk problem, there are a few more problems that may hamper the validity of the "\( \beta \)" analysis:
1) β must be estimated based on 9 or 7 observations for each company. Therefore β is very unstable.\textsuperscript{25}

2) The average MPR (or MEMPR) is influenced by less than one hundred giant insurers who write over 80 percent of the P-L premiums.\textsuperscript{16} Since small and medium companies are of most interest, but not very large insurers, the IMPR for the whole industry may not be representative. A more appropriate average excludes these larger insurers. The mean ratios of a large sample of small and medium companies are more appropriate. This problem is denoted by the first measurement problem. A-priori, the sample means of profitability ratios might surrogate the industry means.

3) Another measurement problem is related to the accounting data. The MRUP and the MPR both are modifications of SAP, not fully adjusted to GAAP. These adjustments are examined in Chapter VII.

4) The measurement of the accounting beta (quasi-systematic risks) may be a subject to significant measurement error.

\textsuperscript{25} β for securities are estimated based on hundreds of observations for each security in the finance literature. However, for predicting purposes the effectiveness of our analysis is reduced if more than 9 observations (years) are considered.

\textsuperscript{26} These large insurers also expected ex-ante to have smaller standard deviations in their profitability ratios.
Summary

Four groups of univariate variables have been presented in this chapter. Each group includes models or methods that generate variables that may be useful as indices for prediction of insolvency among P-L insurers. The indices are developed and analyzed in this chapter, and their ability to discriminate between solvent and insolvent insurers are examined in Chapter VIII. It is expected that insolvent insurers will have different scores than those of the solvent insurers. Classification procedures have also been presented in this chapter. Each univariate variable is examined one and three years prior to insolvency.

The first group of variables represents the existing methods. Two univariate variables are discussed:

1. NAIT - The number of tests (ratios) outside the norms.
2. BPR - The Best's policyholders' rating is measured on 1 to-9 scale.

Each variable is examined one year prior to insolvency (e.g., NAIT1), as well as three years prior to insolvency (e.g., NAIT3)\textsuperscript{27}

\textsuperscript{27}The following abbreviations are also used: a) 1 or 3 = one or three years prior to insolvency (e.g., DL1 = Decomposition measures on the liability size, one year prior to insolvency); b) ME = Mean or average score across time; c) SD = standard deviation over time; d) Var= variance over time; e) CoS = Coefficient of stability (mean divided by the standard deviation, ME/SD); f) AV = average value of a variable over the scores on this variable for a given period (e.g., AVDL35 = the average value of the decomposition measures on the liabilities size, for years three through five prior to insolvency).
The second group of variables measures the stability of components (their relative fractions) of the balance sheet over time. Three couples of variables, or six univariate variables are developed:

1. **DM** - The decomposition measures are denoted as D1 for the liability size of the balance sheet and Da - for the assets size of the balance sheet.

2. **NDM** - The new decomposition measures are denoted as ND1 - for the liability size, and NDa - for the assets size.

3. **SP** - The square proportions are denoted as SP1 and SPA for the liabilities and for the assets, respectively.

A third group of variables represents the stability of financial ratios over time. However, only the stability of the profitability ratios over time is examined. Four major variables are examined:

- **MRUP** - The modified ratio of underwriting profits on premiums (1 - the combined trade ratio; 1-CTR)

- **MPR** - The modified ratio of total profits (including investment gains) on premiums.

- **MRUPS** - The modified ratio of underwriting profits on policyholders' surplus.

- **MRPS** - The modified ratio of total profits on policyholders' surplus.

The emphasis of the research is not on the ratios themselves, however, but rather than their stability over time. Three major measures are used: 1) the average ratio over time for each company; 2) the standard deviation or the variance of each ratio over time for each company (the temporal standard deviation/or variance); 3) the
coefficient of stability (CoS) of each ratio over time for each company. For the MPR ratio the following abbreviations are denoted:

1. MEMPR - The mean of the MPR ratio over the years prior to insolvency for every insurer.\(^{28}\)

2. SDMPR - The standard deviation of MPR over time for every insurer.

3. CoSMPR - The coefficient of stability of the MPR ratio over time for each insurer (MEMPR/SDMPR). The emphasis in this group will be on this variable.

The same three measures are employed for the others three ratios above. In the multivariate analyses the mean/variance of each ratio are also examined and denoted as CSVMPR, CSVMPRS, etc.

The fourth group of variables measure the association between the insurers' profitability and the overall industry profitability measured by the same ratios. The "quasi-systematic" risk (beta) is measured for the ratios of each insurer in the sample. The following notation is employed:

BETAMPR - The quasi-systematic risk of the modified profitability ratio on premiums (BETAMPR1 - for one year prior to insolvency). The same type of notations are used for the other three profitability ratios. However, due to empirical, statistical and measurement problems, the discussion and the analysis of the results are considered as preliminary;

\(^{28}\) It is denoted as MEMPR1 for one year prior to insolvency, and it is the average of the MPR for the last nine years. The variable is denoted as MEMPR3 for three years prior to insolvency, average over seven years.
recommendations for future research, employing this group of variables, are outlined in Chapter X.

All these variables are examined in the empirical Chapter VIII. The effectiveness and the efficiency of each variable to predict financial insolvency are determined. Each univariate variable is compared with other variables for one and three years prior to insolvency, and those variables with the best predictive ability are pointed out.
INTRODUCTION

Each of the three sections of this chapter presents a different type of multivariate classification model. The first section explores the multidiscriminant analysis (MDA) which is considered a similar procedure as the analysis of variance (ANOVA). Given information on the independent variables, the population can be separated into two (or more) different groups. A sample of insurers may be drawn from the two groups. Each insurer is then reclassified into a group (solvent or insolvent), or a new observation will be classified into a group, based on a set of variables, a discriminant function, and a discriminant score. The focus is to find which group is the source of the observation through the reclassification process given information only on the independent variables.

The second section explores the multivariate regression models. The dependent variable takes on only two dichotomous values, 0 or 1 (e.g., 0 for the solvent group and 1 for the insolvent group). The models relate this dichotomous dependent variable to sets of independent variables that measure and/or cause the event of insolvency (e.g., those univariate independent variables may be the ones developed in the previous chapter). Each insurer in the sample is reclassified
into a group (solvent or insolvent) based on its observed score, $Y_j$, the causal flow, and the optimal or the median cutoff points.

The third section explores the previous two models, and other models, in terms of a probabilistic approach for prediction of insolvency. In addition to the MDA models, and the linear 0-1 regression models; probit models as well as logic models are explored. All these models are considered through probabilistic presentations.

Finally, directions for the empirical study are outlined, but the empirical data are analyzed in Chapter VIII.

**Multidiscriminant Analysis**

MDA provides a procedure for assigning insurers (observations) to predetermined populations (e.g., solvent and insolvent insurers). Several variables may be applied, and may consider simultaneously the entire characteristics of the insurers. A discriminant function $Z_j$ is determined for each insurer, $j$, the discriminant function is of the form:

$$Z_j = V_1X_1 + V_2X_2 + \ldots + V_kX_k$$  \hspace{1cm} (6-1)

where $X_1, \ldots, X_k$ = independent univariate variables (indices). (e.g., the CosMFR or NDM, etc.)

$V_1, \ldots, V_k$ = discriminant coefficients, parameters of the function.

$Z_j$ = the discriminate score for firm $j$.

This function is determined based on assigning sample cases from the given populations.
Assumptions and Steps

The sample observations (insurers) are assigned to two (or more) predetermined populations. The main assumptions are:

1) There are two known groups of insurers solvent and insolvent (total N companies).

2) Each insurer has a set of identified characteristics (variables) which are common to all observations (insurers).

3) The variables are approximately arisen from multivariate normal distribution. The variance/covariance matrix of variables are approximately the same for each group. However, the means of the variables in each group are different. The MDA is considered a fairly robust, and violations of these assumptions might not eliminate the applications of the models.

The following steps may apply:

1) Constructing a discriminant function that maximize the differences between the groups means and/or the ratio of the between groups sum of squares to the within groups sum of squares. This function takes the form $Z_j = V_1X_1 + V_2X_2 + \ldots + V_kX_k$. Where $k$ is the number of variables, $X_1, \ldots, X_k$ are the variables (indices), $V_1, \ldots, V_k$ are the discriminant coefficients. For each company $j$, the independent

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1 Additional groups might be: weak and priority companies, merged companies, etc.

2 If data are multivariate normal and the variance/covariance matrix are unequal then a quadratic discriminated function may apply. For a detailed discussion see Pinches and Trieschmann [131].

3 For a brief primary discussion of the discriminant analysis see S. Fox [60]. For more detailed and analytical discussion see M. Tatsouka [148], Overall and Klet [125], Greene [65], and Pinches and Trieschmann [131].
variables are multiplied by the discriminant coefficients $V_i$'s, to obtain an estimated score $Z_j$, this $Z_j$ is the failure index for each company.

2) Selecting a cutoff point for deciding whether company $j$ will be assigned to the predicted solvent group or to the insolvent group. The objective is to minimize the number of misclassifications.

3) Adjusting the discriminant coefficients for differences in units of measures, standardized coefficients are obtained. The adjustment shows the relative importance of each variable in the discriminant model; this may not be a necessary step.

4) Finally, examining the predictive ability of the MDA model by a validation sample or by other techniques.

The $Z_j$ score for each insurer is determined by multiplying the discriminant coefficient by the values of the independent variables (indices) for each insurer. Based on the $Z$ score each insurer is classified as belonging to the solvent group or the insolvent group of insurers. A cutoff point $C$ is then selected as the dividing line between solvent and insolvent insurers, as demonstrated in Figure 10. A cutoff range (e.g., between a and b) is also possible. Then a

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4 Assuming only two variables and $V_1 = .20$ while $V_2 = 5.$, based on the discriminant function analysis. Then an insurer $j$, with NAIC-IRIS = 2 tests ($X_1 = 2.0$) and NDM = .0200 nits ($X_2 = .0200$) has a $Z$ score of $Z_j = (.20) (2.) + (5.) x .0200 = .40 + .10 = 0.500$. The $Z$ score can take any score.

5 If the cutoff point is $C = 0.800$ then insurer $j$ is classified as a solvent insurer. In general terms, if $Z_j < C$ insurer $j$ is in the solvent group.
Figure 10. Classification Procedure With MDA.

classification procedure can be employed. Every new insurer P is
classified into a solvent or insolvent group based on the cutoff point
C; while in the reclassification procedure, any insurer, p, from the
original group or a new observation are reclassified to the insolvent
group if $Z_p > C$.

The Discriminant Function and Significances of Variables

The discriminant function is presented in a matrix notation
denoted as $X'V$, and the scalar discriminatory score $Z_j$ can be
expressed as:

$$Z_j = X'(V)k$$

where $X'k$ = the transformed row vector of the independent variables,
for insurer $j$ the vector is in the form $X'jk$,
$V_k$ = the coefficients column vector
$Z^k_j$ = the reduced space one dimension discriminatory scalar
(score).

The discriminant coefficients $V_1, ... V_k$ are estimated by using
the between group sum of square, matrix B, and the within group sum
of square, matrix W; maximizing the ratio of the between group sum of
squares to the within groups sum of squares as well as the difference
between the two groups centroids and solving the equation:
\[(W^{-1} B - \lambda I) V = 0 \]  

(6-3)

where \( V \) = the coefficient column vector; \( (V_1, \ldots, V_k) = V \)

\( k \) = the number of independent variables

\( I \) = the identity matrix

\( \lambda \) = the eigenvalue of the equation

The validity of each model and each variable in a MDA model is often measured by the Wilks lambda \( \Lambda \) statistics as well as other statistics. The Wilks lambda can be defined as:

\[ \Lambda = \frac{|W|}{|T|} \]  

(6-4)

where \( W \) = the determinant of the within groups sum of squares matrix

\( T \) = the determinant of the total pool groups sum of squares matrix and \( T = W + B \)

The MDA models are estimated by using the discriminant program available through the Statistical Package for the Social Sciences (SPSS) [144]. Direct as well as Wilks methods are employed in this study. The direct method includes all the independent variables

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6 The vector \( V \) maximizes the ratio of the between group sum of squares matrix to the within group sum of squares matrix as well as the ratio of the between group sum of squares matrix to the total pool-groups sum of squares.

7 The eigenvalue \( \lambda \) is defined as:

\[ \lambda = \frac{V'BV}{V'WV} \]

The solutions to the eigenvalue \( \lambda \) is obtained in general by solving the matrix \( W^{-1} B \), where \( \lambda_1, \ldots, \lambda_s \) are the \( s \) nonzero roots of the matrix. However, since in this study there are only two groups \( s = 1 \), and there is only one root, \( \lambda \). The eigenvalue indicates the significance of the discriminant function. The larger the \( \lambda \) is the greater the marked and robustness of the discriminant function. For further discussion see Pinches and Trieschman [131], Tatsuoka [148], etc.
applied in each model. Each variable is assigned with the parameter $V_k$. The Wilks method in SPSS is a stepwise technique, it enables to reduce the number of variables in a model, in order to gain more insight about the effectiveness of different subsets of variables for the purpose of predicting insolvency. The Wilks stepwise procedure also increases the efficiency of the models by enabling to employ a smaller number of variables. The Wilks lambda also indicates the discriminate power of the univariate variables in the model. The smaller the Wilks lambda the greater is the discriminatory power of each variable and/or each subset of variables. $F$ and/or $\chi^2$ statistics are employed, based on the Wilks lambda or related statistics. The major criteria for evaluating the relative contribution of each univariate variable is the univariate $F$ statistic. When the stepwise technique is used, variables are entered into the model based on the additional contribution of each variable to the multivariate $F$ statistic.  

**Violations of the Assumptions and Application Problems**

Several possible problems while employing MDA may be encountered. The first one is related to the assumptions of the MDA previously outlined. Two major violations of these assumptions may be: 1) the distributions of the variables in the two groups are not multivariate

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8For further information see SPSS [144], Tatsouka [148], Overall and Klet [125], and Greene [65]. The Wilks lambda is converted to $F$ and $\chi^2$ statistics which indicate how significantly different the two groups are for each other as well as the significance of each parameter, $V$, in the models.
normal, and 2) the variance/covariance matrices of the two groups are unequal. If the multinormality assumption is largely violated transforming the data (e.g., log-transformation or square values) may improve normality. If the variance/covariance matrices of the two groups are in large extent unequal, a quadratic classification rule might be applied. In those cases where both assumptions are violated the Lachenburch Jackknife procedure might be applied [98,99]. The normality assumption is not needed when the procedure is employed. This technique is recommended as well as demonstrated by Eisenbeis [51], Pinches and Trieschmann [131], and others.

Several studies (e.g., Trieschmann and Pinches [156], Edmister [49] and others, are concerned with the multicolinearity problem; therefore they excluded highly-correlated variables. However, others such as Eisenbeis [51] argue that multicolinearity is irrelevant to MDA as long as it is possible to invert the dispersion matrices.

Since oftentimes prediction is made based on ex-post prediction, validation techniques such as the holdout sample method are often employed. Usually, the original sample is split to running-on sample and an holdout sample. Then the parameters (vector V), which are based on the first sample, are employed to classify observations (insurers) in the holdout sample. Usually a large sample is required,

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9The Lachenburch procedure classified each observation based on a discriminant function which rests on all other observations, excluding the particular one. With N observations each function is rested on N-1 observations, and the procedure must be repeated N times until all observations are classified.
and only the running-on sample data can be used to estimate the parameters, \( V_s \). Trieschmann and Pinches [156] employ a stimulated sample approach because of their small sample sizes. The original firms are scrambled and reassigned to new groups. Hershberger [73] did not use a validation sample, and many other past studies in other industries also did not employ any validation technique.

Joy and Tollefson [87] point out that several studies confuse ex-post discrimination with ex-ante prediction. They emphasize the differences between cross validation tests (with a holdout sample), and intertemporal validation tests. They suggest to employ validation samples based on past data as a running-on sample, in order to predict the results on companies for future predictions (inter-temporal validation).

The present study includes 124 observations and therefore a split-out validation technique may be employed. Since it is important to examine the validity of the parameters to predict ex-ante new failures, as well as to measure the sensitivity of the parameters to time span in addition to correct classification, the two types of validation techniques (a cross validation and intertemporal validation) are examined in Chapter VIII.

The MDA is considered as a fairly robust procedure. Because departure from the basic assumptions outlined above reduces efficiency very little in the analysis. Most research seems to be unconcerned about departures from the assumptions. Because the purpose of the MDA is to develop a discriminatory device, the departures may be considered irrelevant as long as significant classification power is
demonstrated. Nevertheless, the research may be very conservative, at the most by employing the Lachenburch Jacknife technique which does not assume normality. Linear MDA, quadratic MDA and Lachenburch techniques are employed in the empirical research part of this study.

Discussion and Applications

Univariate models (e.g., the Best's rating) are not found to have satisfactory discriminatory power between failed and nonfailed firms in the insurance industry. This study reexamines this conclusion by adding several new univariate variables that have been mentioned above. Multivariate financial ratios are found to have a limited discriminatory power in other industries (see Literature Review). Most if not all MDA use financial ratios as the primary input variables. In this research, the variables are not the financial ratios themselves, although ratios might be applied in the future.

The research focus is on employing MDA to the the univariate variables developed in the previous chapter, and examining whether MDA can improve the predictive ability of these variables. The MDA will examine the effectiveness as well as the efficiency of the different models, in addition to the search for the best predictive models. The variable sets and subsets are examined once for the last year before insolvency, and secondly for three years prior to insolvency.

The following primary models will be examined:

1) MDA with all variables in the model; the Wilks stepwise procedure as well as the Direct procedure are applied in the following equation.
\[ Z_j = V_1D1 + V_2Da + V_3ND1 + V_4NDa + V_5NAIT + V_6BPR + V_7COSMPR \]
\[ + V_8COSMPRS + V_9BETAMPR + V_{10BETAMPR} + V_{11SP1} + V_{12SPa} \]  

Where \( D1 \) - Decomposition measures for liabilities
\( Da \) - Decomposition measures for assets, etc.; all variables are denoted in Chapter V.

The model might be enlarged by introducing the mean (ME) and standard deviations (SD) of the profitability ratios, and the mean, SD, and CoS of the underwriting profit ratios. Average decomposition measures over time (e.g., AVDL 35 for the years three through five prior to insolvency) might be employed. The Wilks method eliminates the nonsignificant variables from the analysis.

2) Models that examine a smaller number of variables and compared them with the Wilks procedure on all variables, e.g.: \( Z_j = V_1DL + V_2NDL + V_3COSMPR \). These kind of models examine the efficiency of MDA with the most important univariate variables employed.

3) A model which uses the two existing methods, the NAIT and BPR, is applied and compared with other MDA models.

4) Any combination with the given set of variables might be examined. However, a complete trial and error procedure is not employed for all possible combinations of two or more independent variables in order to find the most efficient set (the model with the highest predictive ability while employing the minimum number of variables).

While employing both the Direct and the Wilks stepwise procedure some efficiency is obtained and a tradeoff between effectiveness (high percent of correct classification) and efficiency (correct classification as well as small number of variables) might be obtained.
Linear Regression Models (LRM)

Standard linear regression models are employed in several studies of failure-prediction. Meyer and Pifer [115], Edmister [49], Collins [38], and others applied LRM in their studies. In a recent study Eck [48] applies LRM for predicting troubled P-L insurers. These studies employ a 0-1 LRM with the dependent variable equal to zero for the nonfailed companies, and one for the failed companies. The independent variables are usually financial ratios, forward stepwise regression procedure and/or backward stepwise regression procedure are applied.¹⁰

The Zero-One Linear Regression Model

The general zero-one linear regression model can be presented as:

\[ Y_j = a + b_1 X_{j1} + \ldots + b_k X_{jk} + e_j \]  \hspace{1cm} (6-6)

where \( X_1, \ldots, X_k \) = the independent variables (e.g., DL, NDL, etc.)
\( b_1, \ldots, b_k \) = the regression coefficients derived by the ordinary least square method.
\( e_j \) = the error term for observation (insurer) \( j \).
\( Y_j \) = the dependent variable with 0 notation for an insolvent insurer and 1 notation for insolvent insurer.

In general matrix form the predicted model can also be presented as:

\[ \hat{Y}_j = X'_j b_k = \sum_{k=1}^{k} X_{jk} b_k \] \hspace{1cm} (6-6A)

¹⁰The forward stepwise regression procedure applies the F value and the residual sum of square as a selection criterion. Variables are entering the model in accordance with their partial contribution to the overall F and/or \( R^2 \) statistics; variables that do not satisfy minimum required F value are excluded. In the backward stepwise regression variables are excluded whenever their partial contribution falls below the required-specified F critical-value.
where \( X'_{jk} \) and \( b_k \) are row and column vectors respectively

and

\[ Y_j = \begin{cases} 0 & \text{if the insurer is solvent} \\ 1 & \text{if the insurer is insolvent} \end{cases} \]

and \( \hat{Y}_j \) is the predicted value of the dependent variable for insurer \( j \). The relationship between \( Y_j \) and \( \hat{Y}_j \) is:

\[ Y_j = \hat{Y}_j + e_j \] (6-7)

The theoretical framework of the LRM follows three major assumptions concerning the error term:

1) The expected value of the error term is zero; \( E(e_j) = 0 \)
2) The variances of all error-terms are identical; \( E(e_j^2) = \sigma^2 \)
3) The covariance of an error-term \( j \), and an error-term of another observation, 1, is zero; \( \text{COV}(e_j, e_1) = 0, \ j \neq 1 \).

Adjustments are often applied when the first and/or second assumptions are violated.

Only the dichotomous 0-1 LRM are employed in this study. Although other LRM models are warranted for a special discussion, the general LRM models are commonly used and discussed in the literature.\(^\text{11}\) Only a brief discussion follows, while concentrating on the 0-1 LRM.

The computation of the 0-1 LRM coefficients (\( b' \)s) are similar to the two groups MDA coefficients. Furthermore, the regression coefficients can be used in order to calculate the MDA coefficients (\( V' \)s). Thus, it is demonstrated that the relationship between the 0-1 LRM coefficients and the MDA coefficients is a proportional relation, but

\(^\text{11}\) For a general discussion on LRM see Overall and Kelt [125], Green [65], and Judge Griffith, etc. [89].
it is only true for the two group models. As long as both methods employ the same classification rules, the methods produce the same classification results. However, because different classification rules and different assumptions are used, interpretations and applications of the two methods may be different.

Problems and Difficulties

The 0-1 LRM may have the following problems and difficulties: 12

1) Autocorrelation and multicolinearity may limit the validity of any LRM.

2) The predicted values, \( \hat{Y}_j \) can be greater than one or less than zero, therefore the general assumption of \( E(e_j^2) = \sigma^2 \) is violated.

3) The results of the 0-1 LRM are very sensitive to the values of the independent variables, and the parameters may not be stationary over samples.

4) Tests of significant as well as the \( R^2 \) may not be meaningful if the assumptions are violated.

5) If the \( \hat{Y}_j \)'s are not normally distributed linear estimation functions might not be efficient.

6) If the independent variables are also transformed to 0-1 variables, information may be lost, and the partition may be an arbitrary one.

Although these difficulties should be considered, at the worst the parameters might be biased. However, several correction

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12 Further details are discussed in Judge Griffith, etc. [89, pp. 586-587].
techniques may be used, and adjustments for autocorrelations and/or
transformation techniques (to adjust for normality) may be applied.
As long as the 0-1 LRM possess significant classification power,
departure from the basic assumptions, and other problems mentioned
above, might be irrelevant.

The 0-1 LRM is applied in this study and the parameter and the
efficiency of the models are estimated using the Statistical Analysis
System (SAS) [137]. Comparisons with MDA are employed\textsuperscript{13} in an attempt
to determine which system is more efficient for correct classifica-
tion and prediction of insolvencies among P-L insurers.

\textbf{Probability Models}

This section explores probablistic approaches for prediction of
insolvency. Both the MDA and the 0-1 LRM as well as other models are
investigated. The most common probablistic models are: 1) the linear
probability model (LPM); 2) probit models, and 3) logit models.\textsuperscript{14}

\textbf{Specification of the Models}

The dependent variable $Y$ can take only two values

$$Y_j = \begin{cases} 
0 & \text{if insurer } j \text{ is solvent} \\
1 & \text{if insurer } j \text{ becomes insolvent}
\end{cases} \quad (6-8)$$

\textsuperscript{13} In this study different classification procedures are compared. The optimal cutoff point is also examined, and the MDA and the 0-1 LRM may produce different results.

\textsuperscript{14} The discussion in this section is based on analyses by Amemiya [10], Judge, Griffith, etc. [89], MacFadden [113], and applications by Martin [111], Ohlson [123], and others.
j = 1...n, we consider n insurers for both groups.

The dichotomous random variable Y can take value 1 if the event (insolvency) occurs, and 0 otherwise (insolvency does not occur). The probability of the event depends on a vector of independent variables X (e.g., the univariate variables presented in the previous section), and a vector of unknown parameters, V's. The probability that an insurer j will become insolvent may be written as:

$$P_j = P(Y_j=1) = F(X_j'b) = F(X_j^k\mathbf{b})$$

(6-9)

j = 1,...n.

Thus, the linear regression model (LRM) is identical to the LPM, as is also demonstrated below. The LRM is defined in probability terms while adjusting (6-8) to the following form:

$$Y_j = \begin{cases} 
0 & \text{with probability } 1-P_j \\
1 & \text{with probability } P_j 
\end{cases} \quad (6-10)$$

Therefore the conditional expected value of $Y_j$ is:

$$E(Y_j/X_j) = 0(1-P_j) + 1(P_j) = P_j \quad (6-10A)$$

and since $E(e_j)= 0$

We can write $E(Y_j/X_j)$ as

$$E(Y_j/X_j) = a + b_1x_{j1} + \ldots + b_kx_{jk} = X_j^k\mathbf{b}^* \quad (6-10B)$$

where $\mathbf{b}^* = \text{the vector of unknown } b^*_1, b^*_2, \ldots, b^*_k$

$X^*_jk = \text{vector of k independent variables and constant } X^*_{jk} = (1, x_{j1}, \ldots, x_{jk})$

k is the number of independent variables
which means that since $E(Y_j/X_j) = P_j$, therefore

$$P_j = X_{jk}^* b^*$$

Equations (6-8) through (6-10C) demonstrate that the LRM is also a linear probability model (LPM).

One major disadvantage of the LPM is that the predicted values of $Y_j$ (or $F X_{jk}^* b^*$), $\hat{Y}_j$, are not constrained by the range 0-1 as probability should. Therefore, often the LPM (equation 6-10C) is modified as follows:

$$P_j = \begin{cases} 
0 & \text{if } X_{jk}^* b^* \leq 0 \\
X_{jk}^* b^* & \text{if } 0 < X_{jk}^* b^* < 1 \\
1 & \text{if } X_{jk}^* b^* \geq 1 
\end{cases}$$

Probit and Logit Models

Amemyia [10], Judge, Griffith, etc. [89] and others recommend the use of cumulative distribution models, or transformation function approaches that are bounded between 0 and 1. A probit model which assumes probability of insolvency $P_j = X_{jk}^* b$, but $P_j$ is a standard normal distribution may apply as follows:

$$G(W) = F(X_{jk}^* b) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{W} e^{-t^2/2} \, dt$$

where $W = a + b_1 X_1 + \ldots + b_k X_k$

t = standard normal random variable

However, computational as well as application difficulties are among the reasons that recent research has focused on the logit model
which was advocated by Berkson [27] over 30 years ago. The logit model (or transformation) is expressed by a cumulative distribution function $G(W)$:

$$G(W) = \frac{1}{1+e^{-W}} \quad (6-13)$$

where $W$ is a linear combination of the independent variable. As a density function (6-13) is expressed as:

$$g(W) = \frac{-W}{(1+e^{-W})^2} \quad (6-13A)$$

Formula (6-13) is applied to prediction of insolvency

$$P(Y_j=1) = \frac{1}{1+e^{-W}} \quad (6-13B)$$

The logit function coefficients are determined by several approaches. Martin [111] derives the logic coefficients and show that the linear MDA function is a special case of the logit model. Martin [111], and Ohlson [123] apply logic models to predict insolvencies. Both use the maximum likelihood estimation function, where $B_1, \ldots, B_k$ are obtained by maximizing the likelihood function $\text{Max } L(B)$, $\sum_{B}$

$W = \sum_{jk} X'_{jk} B_k = \sum_{k=1}^{k} X'_{jk} B_k$, and $P(Y_j = 1)$ defined as in equation (6-13B).

Martin [111] presents the maximum likelihood function for $n$ observations as:

15 For a comprehensive discussion see Judge, Griffith [89, pp. 592-93], and Martin [111, pp. 256-60]

16 For a mathematical analysis of the logit model and the maximum likelihood function, see McFadden [113].
For computation purposes Martin suggests minimizing the following likelihood function:

\[ -2 \ln L(Y_j, B) = \sum_{j=1}^{n} Y_j \ln p_j + (1-Y_j) \ln(1-p_j) \]  \hspace{1cm} (6-14A)

Ohlson prefers presenting the likelihood function as:

\[ L(B) = \sum_{j=1}^{n_1} \log P(x_j, B) + \sum_{j=1}^{n_2} \log [1-P(y_j, B)] \]  \hspace{1cm} (6-15)

where \( n_1 \) firms are bankrupt and \( n_2 \) firms are solvent.

The solutions may require nonlinear optimization process in order to derive the \( B \) coefficients for the maximum likelihood function. The general least square solution for the estimators of \( B \)'s is presented by Judge, Griffith [89, p. 543].

Amemiya [10, pp. 1509-1510] also compares the logit and the MDA models. He expects the logit model estimator to be more robust. However, he cites samples where the MDA estimations where the MDA estimation were almost as robust as the logit coefficients.

In this research the focus is on applying new stability measures for predicting of insolvencies, and the emphasis is on practical applications. The MDA and the LRM are common methods, with intuitive interpretation understood by scholars, industry managers and regulators. The logit and/or probit model may be more difficult to understand as well as to interpret. The LRM and the MDA are
employed in order to compare the results with previous research, because the emphasis is not on techniques but on new measures. Logit and probit are not examined empirically. However, applying MDA and LRM enables comparison of the results with previous studies which employed these methods on other variables (mostly financial ratios). Moreover, comparing accounting procedures for prediction purposes is also a primary purpose of the research; too many models that may apply to at least four different accounting techniques may be confusing. Because prediction devices are the objective, the empirical results of the MDA and LRM as well as univariate analyses (all with the new stability variables) may be satisfactory. Nevertheless, logit and probit models should be examined in future research and should be compared to the results with MDA and LRM.

Summary

Only the major points of the many issues in this chapter are briefly reviewed.

Two basic multivariate approaches are discussed, the MDA and the LRM. Theoretical foundations for both procedures are explored. Both procedures are employed in the empirical study. However, in this chapter these procedures are explored, problems and difficulties are examined, and possible solutions are outlined. The primary issue remains correct classification. The question of whether or not a

---

17 Past studies did not employ multivariate analysis, rather than the MDA or the LRM for predicting insolvencies in the insurance industry.
model fits its assumption is of secondary importance as compared with whether or not a model is a good discriminatory device.

The MDA seems to be a fairly robust procedure; derivations from its basic assumptions reduce efficiency very little in the analysis. As long as the procedure demonstrates significant predictive power, those departures are considered irrelevant. Nevertheless, the Jack-kniffr technique (correction) is also employed; this technique does not rely on restrictive assumptions. The LRM has also restrictive assumptions, but corrections and transformations are applied, and again the primary concern is whether or not the model demonstrates a significant classification ability for prediction of insolvency.

Alternative probabilistic models are also presented. The probit model has application and computational problems. Logit models are more general and seem to have less restrictive assumptions or theoretical problems. However, they may be less convincing for practical usefulness and have more computational difficulties, and are more difficult for potential users to understand than the MDA or the LRM. Nevertheless, for future research, their use may be warranted.

Because the choice of the best model (or models) to a large extent should be based on empirical results, Chapter VIII is devoted to: (1) describing the selection of the sample of insurers; (2) examining the methodology; (3) deriving the empirical results; (4) evaluating the findings; (5) examining the models' efficiency, and (6) discussing the results and further applications.
CHAPTER VII

DIFFERENT ACCOUNTING PRACTICES: THEIR IMPACT ON PREDICTING INSOLVENCY

The objectives of this chapter and Appendix A are three:

1) To present an overview of the Statutory Accounting Principles (SAP), and to compare the SAP with Generally Accepted Accounting Principles (GAAP) and other accounting practices.

2) To construct the theoretical foundation for valuation of assets, and for measuring of profits under the different accounting procedures.

3) To explore how different accounting practices may affect the input data that are employed for prediction of insolvency. The new stability measures (indices) are explored and computed from SAP financial statements as well as financial statements adjusted by other practices. The alternative accounting practices are evaluated in terms of their ability to predict insolvency among P-L insurers.

Overview of Financial Accounting and Statutory Accounting

Statutory accounting in P-L insurance industry differs significantly from conventional accounting. The main departures from conventional accounting (GAAP) are: (1) matching revenue and expenses, (2) treatment of nonadmitted assets, (3) determining the liquidation
value of assets, and (4) evaluating the reserves.¹

The main reasons for using statutory accounting in P-L insurance are: 1) statutory accounting is concerned with maintenance of solvency, its primary objective is to examine the solvency of the insurers on a liquidation basis, while GAAP is more concerned with the going concern concept; 2) the evaluation of the financial statement under SAP is primarily from the policyholders' point of view and differs from an evaluation from a stockholder's viewpoint which is emphasized by GAAP; 3) statutory accounting emphasizes a strict protection of policyholders' claims against a company's assets, based on liquidation and a conservative viewpoint; 4) statutory accounting includes many details and schedules that are considered appropriate by regulators.

The liabilities of P-L insurers are called reserves. They should not be confused with funds; their main meaning is estimated liabilities of indefinite or uncertain amount. The reserves are required by law. They must be held because not all premiums are immediately earned, and losses immediately paid. The three main types of reserves are: 1) the unearned premium reserve (UPR), 2) the loss reserve, and (3) voluntary reserves. These reserves do not include the policyholders' surplus (equity). The three primary subjects to be considered while analyzing liabilities are (1) solvency and strength, (2) adequate reserves,

¹Fieringer [129, pp. 926-38], Henss [75, pp. 53-61], Koogh [96, p. 413] and Masterson [112, pp. 151-181] argue that P-L statutory accounting violates many accounting principles, but there are reasons for each violation.
and (3) the contingency nature of the reserve.$^2$

Reserves of the P-L insurers are not adjusted in this research because of the following reasons: 1) The UPR would be the same under all four accounting procedures employed. The UPR is recorded by SAP in the same way it would be recorded by GAAP or other procedures.$^3$

2) The loss reserves might be modified under GAAP to reflect the individual case method, but many kinds of loss reserves have already been recorded on individual case basis since the introduction of computers. Moreover, data for modifying loss reserves to an individual case-basis are not available.

The primary change due to different practices is in the policyholders' surplus, resulting from differences in recording assets and profits, rather than in recording liabilities.

**Four Accounting Procedures, Purposes and Presentation**

The insurance industry is deemed to be a business vested with the public interest. A principal objective of regulators statutes is to develop measures that are designed to promote the following: 1) solvency, 2) propriety of premiums rates, 3) fair dealing with the policyholders, and 4) uniform financial reporting [AICPA-Industry Audit Guide, 11, p. 10].

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$^2$For further discussion see Appendix A.

$^3$Employing the market value of assets procedures would not change the value of the UPR, unless nonaccounting evaluations such as present value considerations are introduced.
Monitoring insolvency is considered a primary objective of regulators, and they have promoted measures that designed to detect insolvency. Furthermore, regulators argue that SAP provides better data to investigate and monitor solvency among P-L insurers than do other accounting procedures. This study does not support or counter this position, but provides empirical evidence on the validity of this argument. The study also attempts to compare SAP with other accounting practices in order to examine which one produces better data for prediction of insolvency.

Assets' valuations, measures of profits and the stability indices are examined under four different accounting procedures: 1) The Statutory Accounting Principles (SAP), 2) the modified SAP, 3) GAAP, and 4) valuation of assets at market values (MVA). Furthermore, based on the four accounting practices four different sets of stability measures are employed through univariate and multivariate analyses for prediction of insolvencies.

SAP is generally employed in the P-L insurance industry because it is the required practice by all states' statutes. The major deviation from SAP by GAAP and the other procedures are related to valuation of assets, modifications of profits, and adjustments in surplus. Table 13 summarizes the major adjustments by the different

---

4 The modified SAP and the MVA are not common accounting practices. The modified SAP is a modification of the underwriting profits, while the MVA records assets at market values. Therefore, these two methods will be referred to as procedures, but the terms procedures and practices will be used interchangeably.
**TABLE 13**

Modifications and Adjustments for Different Accounting Procedures

<table>
<thead>
<tr>
<th>List of Adjustments (SAP Vs. GAAP and Other Methods)</th>
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<tbody>
<tr>
<td><strong>Assets</strong></td>
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<td>Bonds</td>
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<tr>
<td>Stocks</td>
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<tr>
<td>Non-Admitted</td>
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<tr>
<td>PUE**</td>
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</tbody>
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<table>
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<tr>
<th><strong>Reserves and Surplus</strong></th>
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<tbody>
<tr>
<td>UPR</td>
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<tr>
<td>Less Res.</td>
</tr>
<tr>
<td>Surplus (equity)</td>
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<tr>
<th><strong>Profits and Gains</strong></th>
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<tr>
<td>Underwriting-profits</td>
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<td></td>
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<tr>
<td>Investment Earnings</td>
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<th><strong>Investment-Capital Gains</strong></th>
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</thead>
<tbody>
<tr>
<td>Realized (stocks)</td>
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<tr>
<td>Unrealized (stocks)</td>
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<tr>
<td>Unrealized (bonds)</td>
</tr>
</tbody>
</table>

**Notes:**

* Bonds and stocks that are purchased for short periods may be evaluated on "cost or market the lower."

** PUE - prepaid underwriting expenses, a new asset (smaller under GAAP than under the modified SAP).

*** may be evaluated at present-value for research purpose only.

+ under GAAP loss reserves may be modified for "individual-basis."

NI = Not Included.
accounting procedures. With this introduction the discussion turns to valuation of assets and modifications of profits, both discussed in the following sections.

**Valuation of Assets**

The issue of valuation of assets (primarily investments) at market versus at costs, has gained a considerable interest. Public hearings on accounting for asset valuations, and for equity securities were held by the American Institute of Certified Public Accountants (AICPA) during the 70s. Several scholars advocated the employment of market value for all assets, or at least for securities (e.g., see Edwards and Bell [50], Sprouse and Moonitz [143], and Llyod and Weygardt [106] for an empirical study. The issue was also debated in the insurance industry (e.g., Mack and Shapiro [108]).

Bonds and stocks are about 80 percent of the total P-L insurers' assets. About 60 percent of the total assets of P-L insurers were invested in bonds, and over 20 percent of the assets were in stocks during the period 1979-1981. All other assets were less than 20 percent of the total assets.

**Valuation of Stocks**

Investments in stocks are recorded at market value. However, those investments in subsidiaries (or when there are no market or bid price) are valued at the appropriate share of the equity of the
subsidiary. Most stock prices are reflected in manuals published annually by the NAIC. Preferred stocks are also reported at market value. However, redeemable preferred stocks are generally reported at amortized cost [Financial Accounting Standard Board (FASB). #60:54, p. 46].

The adjusted sets of data consist of the following. Stocks are recorded at cost when GAAP practice is employed; accumulated appreciation (or depreciation) is excluded from assets and policyholders' surplus. When MVA procedure is employed, the value of stocks will be the same as it is recorded under SAP.

### Valuation of Bonds

Bonds are valued on an amortized cost by SAP. If bonds are in default, values published by the NAIC must be used. In addition to amortized basis, a few states also require the use of scientific methods (e.g., the yield method). Some "companies which record

---

5 Stocks of subsidiaries are "valued at the pro rata portion of their capital stocks and surplus at the statement date," AICPA, Industry Audit Guide [11, p. 42].

6 Redeemable preferred stocks are very small portion of total assets, less than 1 percent of total assets in most cases.

7 Harmelink [67] adjusted only the value of stocks while comparing SAP and GAAP sets of data. He finds that both accounting practices predict maintenance or decline in Best Policyholders' Rating (BPR). However, the differences between the predictive ability of the two methods are not significant. Harmelink does not include nonadmitted assets in the adjusted data. He does not adjust the value of bonds, and he does not match revenues with expenses as it would be required by GAAP.
amortization on their records reflect amortization of the premiums and
accrual of the discounts as an adjustment of interest income of the
period[ AICPA, 11, p. 41]. Small but material differences appear
between cost value and amortized value of bonds in almost all P-L
insurers. As required by GAAP, bonds would be recorded at cost value,
thus excluding the amortization from the records. 8

Market value of bonds is disclosed in schedule D of the financial
statements. The MVA procedure employs these figures in the empirical
research. However, the NAIC allows insurers to show the amortized
value for municipal issues for any issue of bonds not listed in the
NAIC manual in the market-value column of schedule D. Because there
are over 1,000,000 issues of municipal bonds, it would be impractical
to estimate market value for most of them. In this research the
market value of municipal and special issues bonds are in accordance
with the records in schedule D. Data on market value of most municipal
bonds are not available.

Mack [108] argued that most of the arguments supporting market
value reporting appear to be vehicles for accounting theorists to
modernize statutory accounting. Because market values are not avail­
able for significant portion of the bonds portfolio, they could be
estimated. However, market values of securities that are determined

8 Since bonds and stocks are generally purchased for long periods
both are recorded at cost value when the GAAP practice is employed.
Although several stocks that were bought for short periods should be
recorded at the lower cost or market, data are not available to make
such an adjustment.
other than by actual transactions are subject to significant error. Furthermore, market value of bonds has significance only if a company must liquidate bonds to pay bills, but past records do not support this phenomenon.

Shapiro [108] argues for disclosure of the market value of bonds. There are many sources from which insurers can obtain reasonably accurate market value of many municipal bonds.

In summary, bonds will be recorded at: 1) cost value for GAAP, 2) amortized value for SAP, and 3) obtainable market value for the MVA procedure. Since modified SAP varies from SAP only for matching revenues and expenses, bonds and stocks will be recorded by modified SAP as they are recorded by SAP.

Valuation of Other Assets

Nonadmitted assets (NAA) are not included among the assets in SAP annual statements.\(^9\) In this study NAA are recorded for GAAP and for MVA procedures. Because only partial data are available, NAA will be recorded as they appear on exhibits 1-2 in the financial statements. It is expected that those NAA (oftentimes mostly premiums balances over 90 days due) will benefit future periods.

When revenues are matched with expenses while GAAP is employed, a new asset, prepaid underwriting expenses (PUE), is recorded. This

---

\(^9\) For a list of nonadmitted assets see Appendix A, as well as AICPA [11, Ch. 8]. Harmelink [67] estimates that the size of the NAA is relative small, approximately 1-3 percent of admitted assets. This is true for the solvent P-L insurers. However, several insolvent insurers had material NAA (in a few cases over 10 percent of total admitted assets).
asset is also recorded when modified SAP is employed. The PUE are recorded in this study for both GAAP and modified SAP.

Measures of Profits

At least five earning measures can be useful in the P-L insurance industry:

1) Underwriting profits.

2) Underwriting profits and investment earnings.

3) Underwriting profits, investment earnings, and realized capital gains. This measure is in accordance with GAAP, where underwriting profits are modified to GAAP.

4) Underwriting profits, investment earnings, and capital gain earnings (including all realized capital gains and unrealized capital gains from investment in stocks). This measure is in accordance with SAP.

5) Underwriting profits, investment earnings, and total capital gains earnings (including realized and unrealized capital gains from investments in bonds and stocks). This measure is in accordance with MVA procedure.

---

10 Foster [56, 57, 58] distinguishes between three series of earnings of P-L and life insurance companies in examining the capital market reaction to annual earnings of 72 stock life and P-L insurance companies. In a recent study he employs three different earning measures. He finds that earning measures that include underwriting earnings, investment earnings, and capital gain earnings (#4 above) are more highly associated with stock prices of 22 P-L insurers, than two other earning measures (#1 and #2, above). Other important findings concerning capital market efficiency, and reporting of capital gains in the P-L insurance industry are not discussed here.
Measuring the Underwriting Profits

Under SAP underwriting expenses are charged as current expenses while premiums earned are reported prorata over the policies' terms; thus the UPR is established. Otherwise, if GAAP costs are matched with revenues, costs that would not be identified with the period would be accrued as prepaid underwriting expenses (PUE). The AICPA Industry Audit Guide [11, pp. 59-60] recommends to "increase or decrease the acquisition costs applicable to unearned premiums" where a statement of adjusted net income (to GAAP) is employed.

A linear adjustment of the SAP underwriting profits is employed by financial analysts, and this formula is sometimes called the Moodys' formula. It is also employed by Standard and Poors when they adjust the statutory underwriting earnings. A.M. Best and the NAIC and insurance professionals also adjust the SAP underwriting profits whenever the combined trade ratio is applied.11 This modification of the underwriting profits is termed as the modified SAP, or the modified underwriting profits (MUP). The underwriting profits under SAP, (MUP), and underwriting GAAP profits are presented in the following formulas.

11 Kross [97] argues that this linear version of the SAP provides figures which are close to actual GAAP figures. Kross uses this adjustment as an approximation to GAAP, and compares the ability of SAP Vs. these numbers (which he termed as "GAAP") to predict market risks for 24 P-L insurers with an active trading of their stocks in the securities markets. He concludes that investors using these GAAP figures are able to make better prediction of market risk level than those using SAP earning numbers.
The underwriting profit under SAP can be determined as follows:

\[ \text{SUP} = \text{PE} - \text{L} - \text{UE} \] (7-1)

where
- \( \text{SUP} \) = statutory underwriting profit for the current calendar year \( t \).
- \( \text{PE} \) = Premium earned in the current calendar year \( t \).
- \( \text{L} \) = Losses incurred in the current calendar year \( t \).
- \( \text{UE} \) = Underwriting expenses incurred in the current calendar year \( t \), measured on a statutory basis.

Equation (7-1) can be modified by adding underwriting expenses which can be distributed over the life of the policies, therefore the underwriting profits can be modified as follows:

\[ \text{MUP} = \text{PE} - \text{L} - \text{UE} + \text{PUE} \] (7-2)

where
- \( \text{MUP} \) = Modified underwriting profits for the current calendar year \( t \).
- \( \text{PUE} \) = Prepaid underwriting expenses for the current calendar year \( t \) which can be distributed over the life of the policies, these expenses can be recorded as prepaid expenses.

This formula is the modified SAP, and it applies as the numerator in the combined trade ratio. Studies \([19,97]\) claim that this formula presents modification to GAAP.\(^{12}\) Although the statutory underwriting profit

\(^{12}\) This formulation is based on Bachman [19]. However, his analysis was for one policy or line of business. Bachman even claimed that the modification follows GAAP for any individual policy or group of policies. His statement is right only for one year. However, generally the modification will not follow GAAP after the first year of modification. He ignores the influence of this adjustment across time. For reflecting the underwriting profits across time further adjustment is necessary in accordance with GAAP. Bachman uses his result to measure the mean and standard deviation of the profitability margin across time, but his results do not follow GAAP, except in specific cases.
profits are modified, a further modification is necessary across time to reflect a real transformation from SAP to GAAP.

If it is assumed that all policies are written only for one year and the policies are written pro rata over the year, then the equation (7-2) is modified to GAAP as follows:

\[
GUP_t = PE_t - L_t - UE_t + PUE_t - PUE_{t-1}
\]  

(7-3)

Profit Margin on Premiums: The Underwriting Profit Ratio

The statutory underwriting profit ratio (SRUP) for an P-L insurer is obtained by dividing through equation (7-1) by the premiums earned (PE), which yields the following result:

\[
SRUP = \frac{PE - L - UE}{PE} = 1 - \frac{L}{PE} - \frac{UE}{PE}
\]  

(7-4)

The modified ratio of underwriting profit (MRUP) under the modified SAP is obtained by dividing equation (7-2) by the premiums earned (PE). The result is written as follows:

\[
13 \text{ Most policies are written for a period no longer than a year, at the present time. In the general case when a few policies are written for more than a year this modification is determined as follows:}
\]

\[
GUP_t = PE_t - L_t - UE_t + PUE_t - PUE_{t-1} - PUE_{t-2} - \cdots - PUE_{t-n}
\]

(7-3A)

where \( GUP_t \) = Modified underwriting profits for the current year \( t \), under the GAAP.

The time index is \( t \), \( t \) represents the current year, \( t-1 \) the previous year, \( t-2 \) two years ago, etc.

\( PUE_{t-1}, \) etc., = previous underwriting prepaid expenses that have not been deducted from the statutory underwriting profit \( t-1, t-2 \ldots, t-n \) years ago. In the current year \( t \) these expenses should be matched with revenues recognized from these policies which have written \( t-1, \ldots t-n \) years ago.
The prepaid underwriting expenses, that apply to future periods, are obtained by calculating the change in the unearned premiums reserve ($\Delta UPR$), and then multiplying this change by the ratio of underwriting expenses (UE) to premiums written during the current year (PW). Then:

$$PUE = \Delta UPR \left( \frac{UE}{PW} \right)$$  \hspace{1cm} (7-6)$$

Thus, equation (7-5) is rewritten as follows:

$$MRUP = 1 - \frac{L}{PE} - \frac{UE}{PE} + \frac{\Delta UPR \left( \frac{UE}{PW} \right)}{PE}$$  \hspace{1cm} (7-7)$$

It is assumed that the premiums are earned pro rata over the period that the policies are in force. The change in the unearned premium reserve is written as:

$$\Delta UPR = PW - PE$$  \hspace{1cm} (7-8)$$

Thus it follows that prepaid underwriting expense, equation (7-6), is rewritten as follows:

$$PUE = \Delta UPR \left( \frac{UE}{PW} \right) = (PW - PE) \left( \frac{UE}{PW} \right) = \frac{PW \cdot UE - PE \cdot UE}{PW}$$  \hspace{1cm} (7-9)$$

and the last term in equation (7-7) is rewritten as follows:

$$\frac{\Delta UPR \left( \frac{UE}{PW} \right)}{PE} = \frac{UE - PE \cdot UE}{PW \cdot PE} = \frac{UE}{PW} - \frac{UE}{PW}$$  \hspace{1cm} (7-10)$$

If equation (7-10) is substituted into equation (7-7), then equation (7-7) can be rewritten as follows:

---

14 This modification is based on Bachman [19, p. 15], see also Kross [97, p. 477].
Hence, the modified ratio of underwriting profits (MRUP) is **unity minus the combined trade ratio** \( \frac{L}{PE} + \frac{UE}{PW} \).

This modification of the statutory underwriting profit ratio (SRUP) is applied in Chapter V and will be reexamined in the empirical Chapters VIII and IX. An analysis of the MRUP variability across time is included. The average ratio for each company across time is computed and compared with the variability of the ratio across time. The results are used for comparing solvent to insolvent companies and for prediction purposes.

As demonstrated in equations (7-3) and (7-3A) further modification is required for GAAP. Thus, based on (7-3), the underwriting profit ratio modified to GAAP (GRUP) is written as follows:

\[
GRUP_t = \frac{PE_t - L_t - UE_t + PUE_t - PUE_{t-1}}{PE_t} = 1 - \frac{L_t}{PE_t} - \frac{UE_t}{PE_t} + \frac{(PUE_t - PUE_{t-1})}{PE_t}
\]  

(7-12)

The final profitability margins (ratios), equations (7-4), (7-11) and (7-12) are examined and compared empirically in Chapter IX. The average profitability margins (ratios) and the standard deviations over time is examined for each company in the sample. It is expected that insolvent insurers will demonstrate lower ratio of a mean divided by standard deviation, coefficient of stability (COS). The purpose is to investigate which equation will demonstrate the most efficient predictability power:

Rewriting equations (7-2) and (7-3) for a period \( t \) shows:

\[
MUP_t = PE_t - L_t - UE_t + PUE_t
\]

(7-2A)
\[ GUP_t = PE_t - L_t - UE_t + PUE_t - PUE_{t-1} \] (7-3B)

Bachman [19, p. 16] argues that equation (7-2) follows the GAAP. Thus by using equation (7-6) one may approach the modified underwriting profit (MUP\textsubscript{t}) through equations (7-8) and (7-9) as follows:

\[ MUP_t = PE_t - L_t - UE_t + PUE_t = PE_t - L_t - UE_t + \Delta UPR_t \left( \frac{UE_t}{PW_t} \right) = PE_t - L_t - UE_t \]

\[ + \frac{PW_t \cdot UE_t + PE_t \cdot UE_t}{PW_t} = PE_t - L_t - UE_t + UE_t - \frac{PE_t \cdot UE_t}{PW_t} = PE_t - L_t - \frac{PE_t \cdot UE_t}{PW_t} \] (7-2B)

However, in general the modified underwriting profits (MUP) differs from GAAP underwriting profits (GUP), MUP\textsubscript{t} \neq GUP\textsubscript{t}, since PUE\textsubscript{t} \neq PUE\textsubscript{t-1}, unless PUE\textsubscript{t-1} = 0 (e.g., for the first year of modification). Bachman's claim is correct only if the premiums earned are a constant proportion (K) of the premiums written: PE\textsubscript{t} = (1-K)PW\textsubscript{t-1} + KPW\textsubscript{t}, (0 \leq K \leq 1); and the underwriting expenses are a constant portion (C) of the premiums written: UE\textsubscript{t} = CPW\textsubscript{t}; (0 < C < 1). Only under these conditions does MPU\textsubscript{t} = GPU\textsubscript{t}. Otherwise, these two modification of SAP underwriting profits (SUP) differ. The following section illustrates the differences between the methods.

**Underwriting Profits, and Profit Margin on Premiums: Two Illustrations**

Assuming that a new company started to write P-L insurance in 1977. All the policies are written for one year and premius are earned pro rata over the year.

Using SAP, the results are illustrated as follows:

\[ 15 \text{ A mathematical proof is presented in Appendix A2.} \]
Example 1:

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>UPR*</td>
<td>UPR</td>
<td>ΔUPR</td>
<td>Premiums</td>
<td>Premiums</td>
<td>Loss</td>
<td>Underwriting</td>
<td>Underwriting</td>
<td></td>
</tr>
<tr>
<td></td>
<td>beg.</td>
<td>End</td>
<td>Written</td>
<td>Earned</td>
<td>Incurred</td>
<td>Expenses</td>
<td>Profits</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$</td>
<td>$</td>
<td>$(PW)</td>
<td>$(PE)</td>
<td>$(L)</td>
<td>$(UE)</td>
<td>$(SUP)</td>
<td></td>
</tr>
<tr>
<td>1977</td>
<td>0</td>
<td>600</td>
<td>600</td>
<td>1200</td>
<td>600</td>
<td>300</td>
<td>400 (-100)</td>
<td></td>
</tr>
<tr>
<td>1978</td>
<td>600</td>
<td>900</td>
<td>300</td>
<td>1800</td>
<td>1500</td>
<td>900</td>
<td>500 100</td>
<td></td>
</tr>
<tr>
<td>1979</td>
<td>900</td>
<td>1100</td>
<td>200</td>
<td>2200</td>
<td>2000</td>
<td>1400</td>
<td>600 0</td>
<td></td>
</tr>
<tr>
<td>1980</td>
<td>1100</td>
<td>800</td>
<td>(-300)</td>
<td>1600</td>
<td>1900</td>
<td>1200</td>
<td>500 200</td>
<td></td>
</tr>
<tr>
<td>1981</td>
<td>800</td>
<td>0</td>
<td>(-800)</td>
<td>0</td>
<td>800</td>
<td>540</td>
<td>0 260</td>
<td></td>
</tr>
<tr>
<td>5 years totals</td>
<td>6800</td>
<td>$6800</td>
<td>$4340</td>
<td>$2000</td>
<td>$460</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*UPR = Unearned Premium Reserve at the beginning of year column (1) and at the end of the year column (2).

The company stops writing P-L insurance at the end of 1980 and voluntarily retired at the end of 1981. Following equation (7-2) as well as equations (7-4) through (7-11), the modified underwriting profits (MUP) and the modified underwriting profit ratio are written as follows:

Example 1B:

<table>
<thead>
<tr>
<th></th>
<th>SUP</th>
<th>PUE</th>
<th>MUP</th>
<th>GUP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(Equation</td>
<td>(Equations</td>
<td>(Equation</td>
<td>(Equation</td>
</tr>
<tr>
<td></td>
<td>(1))</td>
<td>(6), or (9)</td>
<td>(2)</td>
<td>(3A))**</td>
</tr>
<tr>
<td>1977</td>
<td>$ (-100)</td>
<td>600(400/1200) = $200.00</td>
<td>$100.00</td>
<td>$100.00</td>
</tr>
<tr>
<td>1978</td>
<td>100</td>
<td>300(500/1800) = 83.33</td>
<td>183.33</td>
<td>150.00</td>
</tr>
<tr>
<td>1979</td>
<td>0</td>
<td>200(600/2200) = 54.54</td>
<td>54.54</td>
<td>50.00</td>
</tr>
<tr>
<td>1980</td>
<td>200</td>
<td>(-300)(500/1600)= -93.75</td>
<td>106.25</td>
<td>150.00</td>
</tr>
<tr>
<td>1981</td>
<td>260</td>
<td>(-300) 0 = 0</td>
<td>0 260.00</td>
<td>10.00</td>
</tr>
<tr>
<td>Total</td>
<td>460</td>
<td>244.12*</td>
<td>704.12*</td>
<td>460.00</td>
</tr>
</tbody>
</table>

*Under the modified method an adjustment is made only in 1981. The modified underwriting profits should be adjusted by the total changes in the prepaid underwriting expenses. These $244.12 make the modified underwriting profit for 1981 $260-244.12 = $15.88.

**The GUP is calculated under the assumption that half of the underwriting expenses of every year belong to current year and the second half to the following year. This assumption is realistic if premiums are earned pro rata over the year.
The main purpose of the last illustration is to demonstrate that modified underwriting profit MUP (equation 2) is not equal to GUP (equation 3). As demonstrated in the example, the MUP overstates the underwriting profit, and a modification is necessary at the end of 1981, when the company retires.

The modified underwriting profit is equal to the underwriting profit under GAAP only for the first year (1977). The example clarifies that the combined-trade ratio is not the necessary modification required under GAAP (equation 7-2 vs. equation 7-3A, or equation 7-11 vs. equation 7-12).

A second example illustrates the same results based on a going concern principle. Consider the following assumptions.

(1) A company starts to modify the underwriting results in 1975.

(2) Premiums are earned pro rata over the year.

(3) Policies are written only for one year.

(4) The company has a cycle of growth and decline in the underwriting premiums.

(5) Losses incurred are 2/3 of premium earned in each period.

Assumptions (4) and (5) may be relaxed.
Example 2:

<table>
<thead>
<tr>
<th>Year</th>
<th>Premiums Written</th>
<th>Premiums Earned</th>
<th>Losses Incurred</th>
<th>Underwriting Expenses</th>
</tr>
</thead>
<tbody>
<tr>
<td>1975</td>
<td>$600</td>
<td>$900</td>
<td>$300</td>
<td>$1800</td>
</tr>
<tr>
<td>1976</td>
<td>900</td>
<td>1200</td>
<td>300</td>
<td>2400</td>
</tr>
<tr>
<td>1977</td>
<td>1200</td>
<td>1800</td>
<td>600</td>
<td>3600</td>
</tr>
<tr>
<td>1978</td>
<td>1800</td>
<td>2000</td>
<td>200</td>
<td>4000</td>
</tr>
<tr>
<td>1979</td>
<td>2000</td>
<td>1600</td>
<td>-400</td>
<td>3200</td>
</tr>
<tr>
<td>1980</td>
<td>1600</td>
<td>1500</td>
<td>-100</td>
<td>3000</td>
</tr>
<tr>
<td>1981</td>
<td>1500</td>
<td>1200</td>
<td>-300</td>
<td>2400</td>
</tr>
</tbody>
</table>

Since the company starts to modify the SUP in 1975 the results for this year are the same under the modified method and under GAAP.

The final statutory underwriting profit compared with the modified underwriting profit and the underwriting profit under GAAP are summarized as follows:

Example 2A:

<table>
<thead>
<tr>
<th>Year</th>
<th>SUP</th>
<th>PUE</th>
<th>MUP</th>
<th>GUP (Equation 3A)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1975</td>
<td>$50</td>
<td>300(450/1800) = $75</td>
<td>$125</td>
<td>$275</td>
</tr>
<tr>
<td>1976</td>
<td>100</td>
<td>300(600/2400) = 75</td>
<td>175</td>
<td>175</td>
</tr>
<tr>
<td>1977</td>
<td>100</td>
<td>500(900/3600) = 150</td>
<td>250</td>
<td>250</td>
</tr>
<tr>
<td>1978</td>
<td>150</td>
<td>200(1115/4000) = 59</td>
<td>209</td>
<td>257.50</td>
</tr>
<tr>
<td>1979</td>
<td>750</td>
<td>-400(983/3200) = -123</td>
<td>-627</td>
<td>684.</td>
</tr>
<tr>
<td>1980</td>
<td>-100</td>
<td>-100(1113/3000) = -38</td>
<td>-138</td>
<td>-25.</td>
</tr>
<tr>
<td>1981</td>
<td>-150</td>
<td>-300(1050/2400) = -131.25</td>
<td>-281.25*</td>
<td>-191.50*</td>
</tr>
<tr>
<td>Total</td>
<td>900</td>
<td>66.75</td>
<td>966.75*</td>
<td>1425*</td>
</tr>
</tbody>
</table>

*Data are not adjusted in 1981 since the insurer continued operation.

The last example demonstrates that usually GUP differs from MUP, and that both differ from SUP.

Assume that earned premiums and underwriting expenses are constant proportion of premiums written (K=1/2, and C=1/4 respectively) then \( UE_t = \frac{1}{4}PW_t \) and \( PE_t = \frac{1}{2}PW_t + \frac{1}{2}PW_{t-1} \), and MUP=GUP. Thus the last example is written as follows:
Example 3:

<table>
<thead>
<tr>
<th>Year</th>
<th>EU</th>
<th>SUP</th>
<th>PUE</th>
<th>MUP</th>
<th>GUP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1975</td>
<td>$450</td>
<td>$50</td>
<td>300(450/1800) = $ 75</td>
<td>$125*</td>
<td>$275*</td>
</tr>
<tr>
<td>1976</td>
<td>600</td>
<td>100</td>
<td>300(600/2400) = 75</td>
<td>175</td>
<td>175</td>
</tr>
<tr>
<td>1977</td>
<td>900</td>
<td>100</td>
<td>600(900/3600) = 150</td>
<td>250</td>
<td>250</td>
</tr>
<tr>
<td>1978</td>
<td>1000</td>
<td>265</td>
<td>200(1/4) = 50</td>
<td>315</td>
<td>315</td>
</tr>
<tr>
<td>1979</td>
<td>800</td>
<td>933</td>
<td>-400(1/4) = -100</td>
<td>833</td>
<td>833</td>
</tr>
<tr>
<td>1980</td>
<td>750</td>
<td>283</td>
<td>-100(1/4) = -25</td>
<td>258</td>
<td>258</td>
</tr>
<tr>
<td>1981</td>
<td>600</td>
<td>300</td>
<td>-300(1/4) = -75</td>
<td>225</td>
<td>225</td>
</tr>
</tbody>
</table>

*Not adjusted.

It is demonstrated in Example 2A that when the assumption of fixed proportion across time is violated, GUP≠MUP.

Underwriting Profits and Investment Earnings and Gains

The previous equations and illustrations are based on two primary assumptions: (1) premiums are written pro rata over the year; (2) policies are written only for one year, otherwise equation (7-3A) and not (7-3) should be applied.

The reconciliation of net income in conformity with GAAP is presented by P.B. Lukens [107, pp. 316-319], and AICPA Industry Audit Guide [11, pp. 60-61].

All investment earnings and realized capital gains on stocks and bonds are recorded by SAP and included in the determination of statutory net income. Although unrealized gains on stocks are not included on a flow-thru basis in the income statements, they are recorded on a separate statement and treated as direct credits or charges to surplus.16

16 For a brief discussion, see AICPA [11, pp. 56-57].
Thus the statutory accounting profits (SP), including investments gains (IG), are determined by adding the statutory underwriting profits (SUP) (Equation 7-1) to the statutory investment gains as follows:

\[ SP = SUP + IG = (PE - L - UE) + (IE + RG + UGS) \]  

where
- \( IE \) = Investment earnings
- \( RG \) = Realized capital gains on stocks and bonds
- \( UGS \) = Unrealized capital gains on stocks

Where modified SAP is applied, the modified profits (MP) would be:

\[ MP = MUP + IG = (PE - L - UE + PUE) + (IE + RG + UGS) \]  

where \( MUP \) = Modified underwriting profits (equation 7-2).

Whenever GAAP earnings are considered, both the statutory underwriting profits and the investments gains are modified (e.g., unrealized capital gains are excluded). Thus, the GAAP profits (GP) for year \( t \) are determined as follows:

\[ GP_t = GUP_t + IE + RG_t = (PE_t - L_t - UE_t + PUE_t + PUE_{t-1}) + IE_t + RG_t \]  

where \( GUP_t \) is defined as in equation (7-3).

If the unrealized gains under the market value of assets (MVA) procedure are considered, equation (7-13) must be modified and the market value profits (MVP) are written as follows:

---

17 The underwriting GAAP profit is obtained by assuming that policies are written pro rata over the year. Therefore, 50 percent of the written premiums as well as 50 percent of the underwriting expenses, are recorded as UPR and PUE, \( k = 1/2 \). Several sources estimate that the PUE should be only about 40 percent, \( K = 40 \); e.g., AICPA [11, p. 55].
\[ MVP = SP + UGB = SUP + IG + UGB = (PE - L - UE) + (IE - RG + UGS) + UGB \]  \hspace{0.5cm} (7-16) \\

where \( UGB \) = Unrealized capital gains on bonds.

All these equations will apply in the empirical analyses.

**Accounting Procedures and Stability Measures for Prediction of Insolvency**

Stability of financial ratios over time is a major phenomenon examined in this study. The stabilities of the profitability ratios are examined under four different accounting procedures. At the first step, the statutory profits \( SP \) (equation 13) are divided by the premiums earned, the GAAP profits, \( GP \) (equation 7-15) are also divided by the premiums earned. The modified profitability, \( MP \) (equation 7-14) is developed farther through equation (7-11), and investment gains are divided by premium written. The MVP (equation 7-16) is divided by premiums earned, as well as by premiums written. \(^{18}\)

Profitability ratios on surplus (rather than on premiums) also apply. Each surplus is the one calculated by the appropriate accounting procedure. Therefore, four profitability ratios on four different surpluses are examined. In summary, four profitability measures are transformed to profitability ratios. Four profitability ratios on premiums and four profitability ratios on surplus are determined for every insurer in each period.

The next step is to calculate the coefficient of stability (COS) for each ratio for all companies over time, one and three years prior to solvency. The COS rather than the financial ratios are employed

\(^{18}\)See also equation (5-10).
for the accounting procedures and univariate analysis is used for insolvency predictions.

The next step is to compare the stability of the financial statements when the four different accounting practices are employed. The liabilities decomposition measures and the assets decomposition measures (Dl and Da) will be determined from the four different financial statements of each insurer in the sample. New decomposition measures (NDl and NDa) and square-proportions (SP1 and SPa) are also computed from the data sets.

In the last step, multidiscriminant analyses and 0-1 linear regression models are employed for insolvency classifications. Each multivariate method is examined under the four accounting procedures. All univariate and multivariate indices are compared. The major purpose is to find which accounting practice is more accurate than the other procedures for prediction of insolvency.

Curtis and Smith [42] apply a comparison of General Price level (GPL) and historical cost financial statements in the prediction of bankruptcy among industrial firms. Financial ratios are computed from both traditional and GPL financial statements, and MDA was used for bankruptcy classification. Little difference is found in the bankruptcy prediction; the GPL data are shown to be consistently as accurate as historical data (GAAP) for prediction of bankruptcy. Hermelink's study [67] indicates that there are no significant differences in the ability of conventional accounting (SAP) and a modification toward GAAP (valuation of investment in stocks on cost basis) in predicting the degree of solvency among P-L insurers as measured by
Best's policyholders' rating (BPF). It will be of interest to demonstrate whether or not the empirical results of this study indicate a superiority of any accounting procedure to predict insolvency (see Chapter IX). A major conclusion may be related to SAP, since the primary justification for the use of SAP is that it may be a better measurement tool for monitoring solvency.

Summary

Four accounting practices are explored in this chapter: 1) SAP, 2) modified SAP, 3) GAAP, and 4) the MVA procedure. The impact of these four accounting practices on valuation of assets and measures of profits among P-L insurers, is examined. Profitability ratios are derived from all four financial statements. The COS of each ratio are used as univariate variables. The stability of the four financial statements are ascertained by decomposition measures (DM), the new decomposition measures (NDM), and the square-proportion (SP). Multivariate models integrate all the univariate variables. The predictive ability of each practice is determined, based on both the univariate and the multivariate indices. Empirical evidence on the relative merits of these accounting procedures for prediction of insolvency are presented in Chapter IX.
CHAPTER VIII
EMPIRICAL RESULTS AND DISCUSSION

This chapter presents a summary of the empirical results, as well as analysis, discussion and interpretation. The relative merits of the predictive methods are disclosed, discussed, and compared. However, the empirical results and evidences for comparing accounting procedures are discussed in the next chapter.

Methodology: Sample Selection and Procedures

The first step in the research determined those companies that failed during the period. The financial data are obtained from Best's Insurance Report [29], Best's Key Rating Guide [30], Best's company files (unpublished data), and classified material based on NAIC database. Several financial statements were also obtained from the Department of Insurance in Ohio.

Although some data are available for about 85 percent of the failed insurers, complete financial statements are available in Best's files for about 95 insolvent companies during the period 1971-1981.

Past research includes data either for the late sixties through the early seventies [155, 156, 16, 48] or the mid seventies. The most updated research, e.g., Hershbarger [73], Aentna [12] uses data from
1973-1977. Most research uses between 50 to 70 insurers together in both the solvent and insolvent groups. In contrast, this study includes 124 observations (117 in the final sample) and the period is updated through the early eighties. The research focus is on the period 1975-1980. However, four companies which failed in 1981 and four companies that nonvoluntarily dissolved between July 1 and December 31, 1974 are also included.

About 125 insurers are listed as insolvent by Best's for the period 1975-1981. However, Best's data base includes considerable data from the annual financial statements of about 62 insolvent insurers; 55 of these insurers are included in the final sample. The following table 14, summarizes the available data:

TABLE 14

Insolvent Insurers and Sample Selection

<table>
<thead>
<tr>
<th></th>
<th>Non Voluntary</th>
<th>Voluntary</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Failed insurers 1975-1981</td>
<td>74</td>
<td>51</td>
<td>125</td>
</tr>
<tr>
<td>Data available</td>
<td>46</td>
<td>12</td>
<td>58</td>
</tr>
<tr>
<td>Add Cos. (July-Dec. 74)</td>
<td>4</td>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td>Total insurers</td>
<td>50</td>
<td>12</td>
<td>62</td>
</tr>
<tr>
<td>Included in the sample</td>
<td>47</td>
<td>8</td>
<td>55</td>
</tr>
</tbody>
</table>
The following criteria for selecting insolvent P-L insurers are used: 1) insolvent companies between July 1, 1974 and December 1981; 2) availability of data: financial statements are reported to Best's for at least four years prior to insolvency. From the original sample of 62 insolvent insurers, seven are excluded from the analysis. Two companies are excluded because they were in business less than four years. The other five companies are nonactive companies and/or only partial and meaningless data are available. The inclusion of the voluntary retired companies in the sample increased the number of observations as well as made the analysis more conservative.¹

From these 55 companies 48 insurers report financial statements to Best's for at least nine years. Seven other companies report data for at least four years prior to insolvency. Forty-six insurers reported data for the NAIC-IRIS tests, or the tests are recomputed by A.N. Best or other sources [16,155], one year prior to insolvency (44 insurers three years prior to insolvency).

Sixty-two solvent firms are randomly selected out of the Best's files. The following criteria are employed: 1) P-L insurers with total asset size of less than $200 million;² 2) firms are not owned by

¹ Two voluntary retired companies retire through court procedures. Five other companies perform as insolvent companies in most variables. It might be expected that several voluntary retired companies would operate and perform more as solvent companies than as insolvent insurers, therefore type I error might be slightly inflated in the research.

² Insolvent P-L insurers are not extremely large firms. Only one failed insurer had about $200 million in assets. The total asset size of failed groups were also less than $200 million, for each group.
or affiliated with other companies with more than $200 million total assets; 3) companies operate and report data to Best for the whole period; 4) firms report data to NAIC-IRIS, or the tests are recomputed by Best for at least three years.

The following insurers are excluded from the analysis: 1) very large insurers and/or groups of P-L insurers with total asset size over $200 million during the period; 2) nonactive insurers as well as new P-L firms. These two criteria exclude over one-third of the companies with data available on Best's files.

The assumption that the univariate variables are normally distributed over companies is examined. The Kolmogorov D statistics as well as tests of skewness and kurtosis are applied to variables; most are found significant, in other words not normally distributed. However, several important univariate variables appear to have a normal distribution.

A post-priori univariate analysis examines a sample of 20 very large companies, or members insurers in very large groups. All these insurers are classified as solvent by all of the primary univariate variables being employed in the research. These results indicate that excluding very large firms from the sample made the analysis more conservative, might inflate type II errors, and would increase the safety margin.

Nonactive companies are those insurers with a very low activity. The following criteria are employed in order to identify nonactive firms: 1) average net written premium to policyholders surplus (the exposure ratio) of less than 35 percent in the last three years; 2) average liabilities are less than one-quarter of the policyholders surplus in the last three years. Financial data for these insurers are either not applicable, or were not comparative. Moreover, the consequences of failures of such firms are not severe since the surplus is large enough (or more than enough) to protect the interests of the policyholders.
distribution, because the empirical tests for these variables were not significant.

Stationarity over time is examined for the Decomposition Measures (DM), employing repeated measure ANOVA as well as the Friedman distribution-free test to explore the phenomenon. The results for most variables are not statistically significant at $\alpha = .01$, indicating for some stationarity of the variables over time. Since indications for stationarity of data over time are found the sample selection procedure would be more powerful.

Univariate Empirical Findings: Best's Policyholders' Rating and NAIC-IRIS Tests

The purpose of this analysis are two: 1) to examine if Best's Policyholders' Rating (BPR) and the NAIC-IRIS tests are able to discriminate between solvent and insolvent insurers; 2) to compare the relative efficiency and effectiveness of these indices in order to have a preliminary indication of which one, if any, have more discriminatory power. Data for both Best's Rating and NAIC-IRIS tests are available for all solvent companies in the sample, the BPR is also available for all insolvent companies, but NAIC-IRIS tests are available for only 46 insolvent insurers one year prior to insolvency, and

Stationarity over time means that there are not significant differences across time for the distribution of each variable examined in the analysis.

As it was mentioned in Chapter IV the primary objectives of both methods are not prediction of insolvencies, but identifying troubled companies and being employed as selection procedures. Best's rating system even doesn't intend to disclose distressed firms, while the NAIC-IRIS primary objective is to identify troubled firms and to flag them as priority insurers, that require immediate examination.
44 insolvent insurers three years prior to insolvency. The number of
exceptional tests, outside the acceptable ranges (NAIT), and the BPR
are determined for each company. An optimal cutoff point is selected
in order to minimize the number of misclassifications, as it was
explained in Chapters IV and V.

The classification results of both methods are presented in
Table 15, for one and three years prior to insolvency. The reader can
also investigate the percent of correct classifications as well as the
number and percent of the two types of errors.

The optimal cutoff point for the NAIC-IRIS is: NAIT = 2.5 for one
year prior to insolvency. This cutoff point correctly classifies about
88 percent of the insurers, but flags about 11 percent of the solvent
firms, and 13 percent of the insolvent insurers are misclassified
(type I error). Employing this cutoff point (NAIT = 2.5) to the whole
population would flag about 13 percent of the 2000 P-L insurers
reported data to the NAIC in 1981. The NAIC standard number of ex­
ceptional tests (four) employs a cutoff point of NAIT = 3.5. Employ­
ing such a cutoff point increases the number of companies that are
misclassified; only 82 percent of the insurers are correctly predicted
one year prior to insolvency, including 28 percent of the insolvent
companies that are misclassified (type I error). Both cutoff points
misclassify about 34 percent of the insurers three years prior to
insolvency.\(^7\) By employing a cutoff point at NAIT = 3.5, 57 percent of

\(^7\)The results are in accordance with early findings by Bailey [16]
who found that 53 percent of the insolvent insurers (in the mid 70s)
are not flagged by the NAIC-IRIS three years prior to insolvency.
TABLE 15

Univariate Classification Results One and Three Years Prior to Insolvency

<table>
<thead>
<tr>
<th>Variable (Observations)</th>
<th>Actual Group</th>
<th>Predicted Group Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Solvent</td>
<td>Solvent Insolvent</td>
</tr>
<tr>
<td>NAIT1</td>
<td>(108)</td>
<td>55 7 (11%)</td>
</tr>
<tr>
<td>Cutoff Point: 2.5</td>
<td>Percent Correctly Classified: 87.9%</td>
<td></td>
</tr>
<tr>
<td>NAIT1</td>
<td>(108)</td>
<td>56 6 (10%)</td>
</tr>
<tr>
<td>Cutoff Point: 3.5</td>
<td>Percent Correctly Classified: 82.4%</td>
<td></td>
</tr>
<tr>
<td>NAIT3</td>
<td>(106)</td>
<td>45 17 (27%)</td>
</tr>
<tr>
<td>Cutoff Point: 2.5</td>
<td>Percent Correctly Classified: 66.0%</td>
<td></td>
</tr>
<tr>
<td>NAIT3</td>
<td>(106)</td>
<td>51 11 (18%)</td>
</tr>
<tr>
<td>Cutoff Point: 3.5</td>
<td>Percent Correctly Classified: 66.0%</td>
<td></td>
</tr>
<tr>
<td>BPR1</td>
<td>(117)</td>
<td>56 6 (10%)</td>
</tr>
<tr>
<td>Cutoff Point: 3.5</td>
<td>Percent Correctly Classified: 92.3%</td>
<td></td>
</tr>
<tr>
<td>BPR1</td>
<td>(117)</td>
<td>58 4 (7%)</td>
</tr>
<tr>
<td>Cutoff Point: 4.5</td>
<td>Percent Correctly Classified: 89.7%</td>
<td></td>
</tr>
<tr>
<td>BPR3</td>
<td>(117)</td>
<td>45 17 (26%)</td>
</tr>
<tr>
<td>Cutoff Point: 2.5</td>
<td>Percent Correctly Classified: 80.3%</td>
<td></td>
</tr>
<tr>
<td>BPR3</td>
<td>(117)</td>
<td>52 10 (16%)</td>
</tr>
<tr>
<td>Cutoff Point: 3.5</td>
<td>Percent Correctly Classified: 80.3%</td>
<td></td>
</tr>
</tbody>
</table>
the insolvent companies are misclassified in the research (43 percent with a cutoff point of NAIT = 2.5) three years prior to insolvency.

The results support the conclusions of Meador and Thornton [155] and Hershbarger [73] about the large number of misclassifications by the NAIC-IRIS, and the poor performance of the system two and more years prior to the actual failures. Recalling that the NAIC anticipated 96 percent of the insolvent insurers to be flagged as priority companies one year before insolvency and 82 percent three years prior to insolvency, it may be argued that the results fall short of expectations. It appears that the system does not adequately discriminate between solvent and insolvent insurers, at least three years before insolvency.

Best's, BPR, performs with better accuracy. The BPR classify correctly 93 percent of the insurers one year before failure with a cutoff point of 3.5; about 90 percent are correctly classified when the cutoff point was 4.5. A cutoff point of 3.5 flags all insurers with a rate B or less. However, only about 8 percent of the total insurers in Best's files have ratings of B, C+, or C. In addition, about 17 percent are not rated (including above 4 percent with "rating omitted"). The best classification with a cutoff point of 3.5, correctly predicting about 80 percent on the insurers three years before insolvency. 8

---

8Employing averages for ratings by Best and NAIC-IRIS for one and three years does not improve the prediction results of the two methods. Averages are employed for BPR and NAIT, for one year before insolvency average ranks of the years one through three; for three years prior to insolvency the average ranks are for the years three through five.
Only two of the insolvent insurers have "zero" exceptional ratios, also two insolvent insurers have a "A+" rating three years prior to insolvency. None have NAIT = 0, and only one voluntary retired insurer has A+ rating one year prior to insolvency. These results indicate that, to some extent, insuring with "A+" or "NAIT = 0" companies might be a safety strategy.

The relative efficiency and effectiveness of BPR and NAIT as classification procedures are measured in Tables 16 and 17. However, this examination is a rough one since the statistical tests that are employed and the null hypotheses examined are sensitive to large samples (as one with 117 observations). A t-test as well as the Wilcoxon Rank Sum two sample test are employed. Both tests examine the significance of differences between groups (means).\(^9\) The general null hypothesis in Table 16 is that there are no differences between the mean of the solvent group E (S) and the mean of the insolvent insurers E (I), as follows:

\[ H_0: \mu_1 = \mu_2 \]

\[ H_a: \mu_1 \neq \mu_2 \]

\(^9\)Because several variables are normally distributed, a t-test is applied. However, because most variables are not normally distributed the Wilcoxon Rank Sum test is also applied. The general null hypothesis for the Wilcoxon Rank Sum test is no difference between the population distributions of the variables, \( F (S) = F (I) \), while \( H_a: F (S) \neq F (I) \); where \( F (S) \) is the distribution of a variable over the solvent companies, and \( F (I) \) is the distribution of the variable over the insolvent companies. If the null hypothesis is true then the expected ranks of the two groups are equal. If the null hypothesis is rejected the only conclusion is that the two distributions are not identical. The null hypothesis can be converted to an hypothesis about mean differences if the distributions are symmetrical. For further information see Sigel [141], and Marascuilo and McSweeney [109].
### TABLE 16

Profile Analysis: Statistical Characteristics of the Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Solvent Companies</th>
<th>Insolvent Companies</th>
<th>t Value</th>
<th>Z-Wilcoxon+</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Mean</td>
<td>Std. Dev.</td>
</tr>
<tr>
<td>BPR₁</td>
<td>1.871</td>
<td>1.859</td>
<td>6.963</td>
<td>2.027</td>
</tr>
<tr>
<td>BPR₂</td>
<td>2.177</td>
<td>1.912</td>
<td>5.563</td>
<td>2.500</td>
</tr>
<tr>
<td>NAIT₁</td>
<td>0.935</td>
<td>1.458</td>
<td>5.065</td>
<td>2.150</td>
</tr>
<tr>
<td>NAIT₂</td>
<td>1.774</td>
<td>1.769</td>
<td>3.591</td>
<td>2.336</td>
</tr>
</tbody>
</table>

+ Z-Wilcoxon Rank Sum Test
* Significant at .0001
** Significant at .0002

### TABLE 17

Classification Effectiveness and Significance

<table>
<thead>
<tr>
<th>Variable</th>
<th>Cutoff Point</th>
<th>Percent Correctly Classified</th>
<th>t-Test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Solvent Companies</td>
<td>Insolvent Companies</td>
<td>Total</td>
</tr>
<tr>
<td>BPR₁</td>
<td>3.5</td>
<td>90</td>
<td>94</td>
</tr>
<tr>
<td></td>
<td>4.5</td>
<td>93</td>
<td>85</td>
</tr>
<tr>
<td>BPR₂</td>
<td>2.5</td>
<td>73</td>
<td>89</td>
</tr>
<tr>
<td></td>
<td>3.5</td>
<td>84</td>
<td>76</td>
</tr>
<tr>
<td>NAIT₁</td>
<td>2.5</td>
<td>89</td>
<td>87</td>
</tr>
<tr>
<td></td>
<td>3.5</td>
<td>90</td>
<td>72</td>
</tr>
<tr>
<td>NAIT₂</td>
<td>2.5</td>
<td>73</td>
<td>57</td>
</tr>
<tr>
<td></td>
<td>3.5</td>
<td>82</td>
<td>43</td>
</tr>
</tbody>
</table>

* Significant at .005
** Significant at .0005
\[ \text{Ho: } E(I) = E(S) \]
\[ \text{Ha: } E(I) > E(S) \]

This presentation is accurate for the t-test. All the results in Table 16 for both tests are significant, this is an indication that the distributions of the variables over the insolvent group differ from their distributions over the solvent group.

Neither the t-test nor the Wilcoxon test measure the discriminate power of each univariate variable; this was examined in Table 15. A rough measurement of the effectiveness of each variable is examined in Table 17. Most variables (for one of three years) demonstrate classifications that were significantly different than chance at .0005 level; the variable NAIT (for three years) is significant at .005 level. The variables produce significant discriminatory power which might compensate for any research bias.

A final phase is to compare the NAIT with BPR for one and three years before insolvency. The purpose is to examine whether or not the better results produced by BPR are statistically significant. A proportion Z test is employed. The results are demonstrated in Table 18.

The results indicate that there is no significant difference between the two variables, in their ability to predict insolvency one year prior to insolvency. However, BPR is found to produce a better prediction than NAIT three years prior to insolvency.

---

10 The table examined only the hypotheses that classifications by the univariate variables are different than classifications by chance (0.50).
TABLE 18
Comparisons for Overall Predictive Ability

<table>
<thead>
<tr>
<th>Variable</th>
<th>NAIT_1</th>
<th>BPR_1</th>
<th>NAIT_3</th>
<th>BPR_3</th>
</tr>
</thead>
<tbody>
<tr>
<td># of observations</td>
<td>108</td>
<td>117</td>
<td>106</td>
<td>117</td>
</tr>
<tr>
<td>Percent correctly classified</td>
<td>87.9%</td>
<td>92.3%</td>
<td>66.0%</td>
<td>80.3%</td>
</tr>
<tr>
<td>Proportion Z Value for Differences</td>
<td>1.11 n.s.</td>
<td></td>
<td>2.42**</td>
<td></td>
</tr>
</tbody>
</table>

NOTES: The proportion Z test employed is

\[ Z = \frac{P_1 - P_2}{\sqrt{\left(\frac{1}{n_1} + \frac{1}{n_2}\right) \hat{P}(1-\hat{P})}} \]

where \( P_1 \) = overall proportion correctly classified by NAIT
\( P_2 \) = overall proportion correctly classified by BPR

and \( \hat{P} = \frac{P_1(n_1) + P_2(n_2)}{n_1 + n_2} \)

\( n_1 = \) observations in NAIT, \( n_1 = 108 \)
\( n_2 = \) observations in BPR, \( n_2 = 117 \)

n.s. = not significant
** = Significant at .01

Both the NAIC-IRIS and Best's rating classify correctly about 90 percent of the insurers one year before insolvency. However, BPR is a better tool for three years' prediction before insolvency. BPR method classifies correctly only about 80 percent of the insurers three years before insolvency; the NAIT variable classifies correctly only 66 percent of the insurers three years prior to insolvency. This poor performance demonstrates the need for better methods for prediction of insolvencies.
Univariate Empirical Findings: The Decomposition Measures and the Square-Proportions

This analysis examines: 1) whether the decomposition measures (DM) and the square proportions (SP) are able to discriminate between solvent and insolvent insurers; 2) the effectiveness of the DM and SP as predictive variables; 3) the predictive ability of DM and SP compared with NAIT and BPR.

The classification results of the DM and SP are presented in Table 19 for one and three years before insolvency. The best results are produced while employing the DM on the liability size, Liabilities Decomposition Measures (DL) and New Liabilities Decomposition Measures (NDL).

The assets decomposition measures (DA and NDA), and the square proportions on assets (SPA), predict correctly about 75 percent of the insurers one year before insolvency, and less than 70 percent three years prior to insolvency. It appears that the decomposition measures and squared proportions shere applied to asset side are less applicable to predict financial insolvencies, while having only a modest discriminatory power.

The DA, NDA, and SPA fluctuate among insurers and over time and have large standard deviations. The major reasons for the poor performance are: 1) dependency on investment decisions which are affected by fluctuations in interest rates and conditions in the stock markets (on the average over 80 percent of the assets are invested in bonds and stocks); 2) the SAP under which stocks are recorded based on market values; 3) frequent changes in credit policies (fluctuations in agents' and premiums' balances).
TABLE 19

Univariate Classification Results: DM and SP

<table>
<thead>
<tr>
<th>Variable</th>
<th>Actual Group</th>
<th>Predicted Group Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Solvent</td>
<td>Insolvent</td>
</tr>
<tr>
<td></td>
<td>One Year Prior</td>
<td></td>
</tr>
<tr>
<td>DL₁</td>
<td>55 (9%)</td>
<td>7 (11%)</td>
</tr>
<tr>
<td>NDL₁</td>
<td>56 (7%)</td>
<td>4 (10%)</td>
</tr>
<tr>
<td>SPL₁</td>
<td>55 (9%)</td>
<td>7 (11%)</td>
</tr>
<tr>
<td>AVDL₁₃</td>
<td>56 (7%)</td>
<td>4 (10%)</td>
</tr>
<tr>
<td>AVNDL₁₃</td>
<td>56 (7%)</td>
<td>4 (10%)</td>
</tr>
<tr>
<td>AVSPL₁₃</td>
<td>54 (2%)</td>
<td>1 (3%)</td>
</tr>
<tr>
<td>Three Years Prior</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DL₃</td>
<td>52 (10%)</td>
<td>10 (16%)</td>
</tr>
<tr>
<td>NDL₃</td>
<td>51 (16%)</td>
<td>11 (18%)</td>
</tr>
<tr>
<td>SPL₃</td>
<td>49 (28%)</td>
<td>13 (21%)</td>
</tr>
</tbody>
</table>

Cutoff Point: .01800, Percent Correctly Classified: 87.7%

Cutoff Point: .14700, Percent Correctly Classified: 91.5%

Cutoff Point: .00140, Percent Correctly Classified: 89.7%

Cutoff Point: .01560, Percent Correctly Classified: 91.5%

Cutoff Point: .1300, Percent Correctly Classified: 92.3%

Cutoff Point: .00140, Percent Correctly Classified: 92.3%

Cutoff Point: .01350, Percent Correctly Classified: 79.5%

Cutoff Point: .1170, Percent Correctly Classified: 82.9%

Cutoff Point: .00110, Percent Correctly Classified: 79.5%
### Table 19 (Continued)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Actual Group</th>
<th>Predicted Group Membership</th>
<th>Cutoff Point</th>
<th>Percent Correctly Classified</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVDL\textsubscript{35}</td>
<td>Solvent</td>
<td>53</td>
<td>9 (15%)</td>
<td>0.02000</td>
</tr>
<tr>
<td></td>
<td>Insolvent</td>
<td>12 (22%)</td>
<td>43</td>
<td>0.02000</td>
</tr>
<tr>
<td>AVNDL\textsubscript{35}</td>
<td>Solvent</td>
<td>53</td>
<td>9 (15%)</td>
<td>0.12000</td>
</tr>
<tr>
<td></td>
<td>Insolvent</td>
<td>9 (16%)</td>
<td>46</td>
<td>0.12000</td>
</tr>
<tr>
<td>AVSPL\textsubscript{35}</td>
<td>Solvent</td>
<td>49</td>
<td>13 (21%)</td>
<td>0.00160</td>
</tr>
<tr>
<td></td>
<td>Insolvent</td>
<td>6 (11%)</td>
<td>49</td>
<td>0.00160</td>
</tr>
</tbody>
</table>

**NOTES:**

1) Only variables with at least 76% correct classification are included.

2) The notation 1 represents values for one year prior to insolvency; 3 represents values for three years prior to insolvency.

3) The notation 13 represents average values for years one through three and the notation 35 represent average values for years three through five.

4) List of variables (abbreviations):

   - **DM** - Decomposition Measures (either on the liabilities (L) the assets size (A) or both)
   - **DL** - Decomposition Measures on the liability size (DA - on Assets)
   - **NDL** - New Decomposition Measures on the liability size
   - **SPL** - Square of proportion on the liability size
   - **AVDL\textsubscript{13}** etc., - Average value of DL for the year 1 through 3 prior to insolvency.
The NDL classifies correctly 91.5 percent of the insurers in the sample one year before insolvency compared with 89.7 percent by either DL₁ or SPL₁. The NDL demonstrates a better predictive ability for three years prior to insolvency, 82.9 percent correct classification compared with 79.5 percent correct classification by either DL₃ or SPL₃. However, the differences in the overall predictive ability of the three measures as well as the differences in the predictive ability for insolvent companies only, are not statistically significant even for three years prior to insolvency.

The average DM for the last three years before insolvency are also presented in Table 19. Slight improvements in the predictive ability are demonstrated, but the improvements are not statistically significant. The same statement is correct for three years prior to insolvencies, when the averages of years three through five are employed.

The relative effectiveness of the DM and SP are roughly measured in Tables 20 and 21. The observed t-tests as well as the observed Wilcoxon Rank Sum tests are statistically significant for all the variables. The DL, NDL and SPL demonstrate ability to discriminate between solvent and insolvent insurers. Moreover, the largest significant results are generally demonstrated by NDL, this may be an indication that the NDL is a more effective measure for predicting insolvencies among insurers than the other DM, and SP.¹²

¹²Other interesting findings are: 1) all DM as well as SP have high positive correlations with one another; 2) the DM usually have negative correlation with the companies size (as measured by total assets or policyholders' surplus), for both groups of insurers larger
### TABLE 20

Profile Analysis: Statistical Characteristics for DM and SP

<table>
<thead>
<tr>
<th>Variable</th>
<th>Solvent Companies</th>
<th>Insolvent Companies</th>
<th>Observed</th>
<th>Observed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Mean</td>
<td>Std. Dev.</td>
</tr>
<tr>
<td>DL1</td>
<td>0.01006</td>
<td>0.01954</td>
<td>0.11693</td>
<td>0.12666</td>
</tr>
<tr>
<td>AVDL13</td>
<td>0.00865</td>
<td>0.00838</td>
<td>0.10310</td>
<td>0.12452</td>
</tr>
<tr>
<td>NDL1</td>
<td>0.08486</td>
<td>0.06143</td>
<td>0.31399</td>
<td>0.18862</td>
</tr>
<tr>
<td>AVNDL13</td>
<td>0.08155</td>
<td>0.03079</td>
<td>0.28808</td>
<td>0.18659</td>
</tr>
<tr>
<td>SPL1</td>
<td>0.00106</td>
<td>0.00231</td>
<td>0.01464</td>
<td>0.02179</td>
</tr>
<tr>
<td>AVSPL13</td>
<td>0.00856</td>
<td>0.00104</td>
<td>0.01158</td>
<td>0.01385</td>
</tr>
<tr>
<td>DL3</td>
<td>0.00878</td>
<td>0.01045</td>
<td>0.07442</td>
<td>0.10409</td>
</tr>
<tr>
<td>AVDL35</td>
<td>0.1217</td>
<td>0.01235</td>
<td>0.13229</td>
<td>0.20121</td>
</tr>
<tr>
<td>NDL3</td>
<td>0.08547</td>
<td>0.04482</td>
<td>0.24121</td>
<td>0.19818</td>
</tr>
<tr>
<td>AVNDL35</td>
<td>0.09774</td>
<td>0.04314</td>
<td>0.31010</td>
<td>0.26901</td>
</tr>
<tr>
<td>SPL3</td>
<td>0.00078</td>
<td>0.00084</td>
<td>0.00864</td>
<td>0.01658</td>
</tr>
<tr>
<td>AVSPL35</td>
<td>0.00126</td>
<td>0.00145</td>
<td>0.01268</td>
<td>0.01795</td>
</tr>
</tbody>
</table>

Note: All results are significant at less than .0005.

### TABLE 21

Classification Effectiveness and Significance

<table>
<thead>
<tr>
<th>Variable</th>
<th>Percent Correctly Classified</th>
<th>Observed t Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Insolvent</td>
<td>Solvent</td>
</tr>
<tr>
<td>DL1</td>
<td>91</td>
<td>89</td>
</tr>
<tr>
<td>AVDL13</td>
<td>93</td>
<td>90</td>
</tr>
<tr>
<td>NDL1</td>
<td>93</td>
<td>90</td>
</tr>
<tr>
<td>AVNDL13</td>
<td>95</td>
<td>90</td>
</tr>
<tr>
<td>SPL1</td>
<td>91</td>
<td>89</td>
</tr>
<tr>
<td>AVSPL13</td>
<td>98</td>
<td>87</td>
</tr>
<tr>
<td>DL3</td>
<td>75</td>
<td>84</td>
</tr>
<tr>
<td>AVDL35</td>
<td>78</td>
<td>85</td>
</tr>
<tr>
<td>NDL3</td>
<td>84</td>
<td>82</td>
</tr>
<tr>
<td>AVNDL35</td>
<td>84</td>
<td>85</td>
</tr>
<tr>
<td>SPL3</td>
<td>80</td>
<td>79</td>
</tr>
<tr>
<td>AVSPL35</td>
<td>89</td>
<td>79</td>
</tr>
</tbody>
</table>

Note: All results are significant at less than .0005.
It appears that the DM, NDM and SP, where they employed on the liability size are useful effective and efficient tools for prediction of insolvencies among P-L insurers. The DM improve predictiveability compared with NAIT, the differences with BPR are not statistically significant.

Univariate Classification: Stability of the Profitability Ratios and the Quasi-Systematic Risk

The stability of financial ratios over time and profitability results compared with the overall industry performance are examined in this section. Following the discussion in Chapter V the analysis will concentrate on the coefficients of stability (COS) of the financial ratios over time and how they perform for prediction of insolvencies.

Stability of Underwriting Profitability Ratios

The modified ratio of underwriting profits (MRUP = 1 - combined trade ratio), and the modified ratio of underwriting profits on surplus (MPUS), are examined in the study. These ratios classify correctly about 80 percent of the insurers one year prior to insolvency. However, the correct predictability is only about 70 percent for three years before insolvencies. Inclusion of investment income and gain improve the predictive ability of the ratios. The modified profitability ratio (MPR), which includes the investment results, companies have smaller DM, these results support the conservative approach in the sample selection (very large insurers were excluded); 3) the DM appears to be stationary over time.
classified correctly about 85 percent of the insurers one year before insolvency, but only about 75 percent three years prior to insolvency. Rather than investigating the ratios themselves the research focuses on the stability of these financial ratios over time. The primary parameter is the coefficient of stability (COS), which is the mean divided by the standard deviation (St. D), of the ratios over time.

Employing the COS for underwriting profits (COSMRUP), slightly improve the classification results. It appears that the COS of the underwriting profits ratios are better variables to be used for prediction of insolvencies, than the mean or standard deviations of these ratios, or the ratios themselves. Nevertheless, it can be argued that underwriting profits parameters over time classified correctly less than 80 percent of the firms three years prior to insolvency, therefore further investigation should be applied.

The Effect of Investment Income

Investment income and gain are included in the profitability ratios' means, standard deviations, and COS over time. Then the parameters of the modified profitability are examined. The COS for both ratios demonstrate outstanding predictive ability for one year before insolvency, and the best results for three years prior to insolvency. The extreme values for both COS for the solvent and the insolvent groups one year prior to insolvency are presented in Table 22.

The classification results of the parameters of the modified profitability ratios are presented in Table 23, for one and three
TABLE 22
COS Values for the Extreme Observation in the Two Groups

<table>
<thead>
<tr>
<th>Insolvent Group</th>
<th>COSMPR(^1)</th>
<th>COSMPRS(^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 Highest Values</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5093</td>
<td>0.3352</td>
<td></td>
</tr>
<tr>
<td>0.5131</td>
<td>0.3521</td>
<td></td>
</tr>
<tr>
<td>0.5184</td>
<td>0.4183</td>
<td></td>
</tr>
<tr>
<td>0.6722</td>
<td>0.4384</td>
<td></td>
</tr>
<tr>
<td>0.8928</td>
<td>0.7860</td>
<td></td>
</tr>
<tr>
<td>Solvent Group</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 Lowest Values</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5037</td>
<td>0.4033</td>
<td></td>
</tr>
<tr>
<td>0.5794</td>
<td>0.5711</td>
<td></td>
</tr>
<tr>
<td>0.6639</td>
<td>0.5802</td>
<td></td>
</tr>
<tr>
<td>0.7378</td>
<td>0.6036</td>
<td></td>
</tr>
<tr>
<td>0.7478</td>
<td>0.6138</td>
<td></td>
</tr>
</tbody>
</table>

\(^1\)Coefficient of stability over time of the modified profitability ratio on premiums.

\(^2\)Coefficient of stability over time of the modified profitability ability ratio on surplus.

- Both ratios include investment income and gain.

years prior to insolvency. Table 24 presents the mean and standard deviations of the variables and tests the significance. The results of both tables indicate the effectiveness of the parameters for predicting insolvencies. The best single variable COSMPRS correctly classifies 98.3 percent of the insurers one year before insolvency, and 85.5 percent three years prior to insolvency. Almost the same results are demonstrated by COSMPR, both variables have the strongest predictive ability better than all other univariate variables.
## TABLE 23

Univariate Classification Results: Stability Parameters for Profitability Ratios

<table>
<thead>
<tr>
<th>Variable</th>
<th>Actual Group</th>
<th>Predicted Group Membership</th>
<th>Cutoff Point</th>
<th>Percent Correctly Classified</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Solvent</td>
<td>Insolvent</td>
<td></td>
</tr>
<tr>
<td><strong>COSMPR</strong>&lt;sub&gt;1&lt;/sub&gt;</td>
<td>Solvent</td>
<td>59</td>
<td>3 (5%)</td>
<td>.540</td>
</tr>
<tr>
<td></td>
<td>Insolvent</td>
<td>1 (2%)</td>
<td>54</td>
<td></td>
</tr>
<tr>
<td><strong>COSMPS</strong>&lt;sub&gt;1&lt;/sub&gt;</td>
<td>Solvent</td>
<td>61</td>
<td>1 (2%)</td>
<td>.510</td>
</tr>
<tr>
<td></td>
<td>Insolvent</td>
<td>1 (2%)</td>
<td>54</td>
<td></td>
</tr>
<tr>
<td><strong>COSMPR</strong>&lt;sub&gt;3&lt;/sub&gt;</td>
<td>Solvent</td>
<td>54</td>
<td>8 (13%)</td>
<td>.778</td>
</tr>
<tr>
<td></td>
<td>Insolvent</td>
<td>10 (18%)</td>
<td>45</td>
<td></td>
</tr>
<tr>
<td><strong>COSMPS</strong>&lt;sub&gt;3&lt;/sub&gt;</td>
<td>Solvent</td>
<td>55</td>
<td>7 (11%)</td>
<td>.710</td>
</tr>
<tr>
<td></td>
<td>Insolvent</td>
<td>10 (18%)</td>
<td>45</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Percent Correctly Classified</th>
<th>Number of Companies</th>
<th>Percent of Type I Error</th>
<th>Percent of Type II Error</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MEMPR</strong>&lt;sub&gt;1&lt;/sub&gt;</td>
<td>88.9</td>
<td>13</td>
<td>16</td>
<td>7</td>
</tr>
<tr>
<td><strong>MEMPR</strong>&lt;sub&gt;3&lt;/sub&gt;</td>
<td>94.9</td>
<td>6</td>
<td>7</td>
<td>3</td>
</tr>
<tr>
<td><strong>SDMPR</strong>&lt;sub&gt;1&lt;/sub&gt;</td>
<td>83.8</td>
<td>19</td>
<td>18</td>
<td>27</td>
</tr>
<tr>
<td><strong>SDMPR</strong>&lt;sub&gt;3&lt;/sub&gt;</td>
<td>84.6</td>
<td>18</td>
<td>14</td>
<td>16</td>
</tr>
<tr>
<td><strong>MEMPR</strong>&lt;sub&gt;3&lt;/sub&gt;</td>
<td>81.2</td>
<td>22</td>
<td>29</td>
<td>10</td>
</tr>
<tr>
<td><strong>MEMPR</strong>&lt;sub&gt;3&lt;/sub&gt;</td>
<td>78.6</td>
<td>25</td>
<td>20</td>
<td>14</td>
</tr>
<tr>
<td><strong>SDMPR</strong>&lt;sub&gt;3&lt;/sub&gt;</td>
<td>73.5</td>
<td>31</td>
<td>35</td>
<td>19</td>
</tr>
<tr>
<td><strong>SDMPR</strong>&lt;sub&gt;3&lt;/sub&gt;</td>
<td>70.9</td>
<td>34</td>
<td>40</td>
<td>19</td>
</tr>
</tbody>
</table>
TABLE 24

Profile Analysis: Statistical Characteristics of the Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Solvent Companies</th>
<th>Insolvent Companies</th>
<th>Observed t Value</th>
<th>Observed Z Wilcoxon</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Mean</td>
<td>Std. Dev.</td>
</tr>
<tr>
<td>COSMPR&lt;sub&gt;1&lt;/sub&gt;</td>
<td>1.695</td>
<td>.832</td>
<td>-.159</td>
<td>.554</td>
</tr>
<tr>
<td>COSMPR&lt;sub&gt;1&lt;/sub&gt;S</td>
<td>1.723</td>
<td>1.163</td>
<td>-.275</td>
<td>.495</td>
</tr>
<tr>
<td>COSMPR&lt;sub&gt;3&lt;/sub&gt;</td>
<td>1.703</td>
<td>1.040</td>
<td>.099</td>
<td>1.004</td>
</tr>
<tr>
<td>COSMPR&lt;sub&gt;3&lt;/sub&gt;S</td>
<td>1.693</td>
<td>1.212</td>
<td>-.047</td>
<td>1.430</td>
</tr>
<tr>
<td>MEMPR&lt;sub&gt;1&lt;/sub&gt;</td>
<td>.1214</td>
<td>.060</td>
<td>.011</td>
<td>.838</td>
</tr>
<tr>
<td>MEMPR&lt;sub&gt;1&lt;/sub&gt;S</td>
<td>.228</td>
<td>.084</td>
<td>-1.01&lt;sup&gt;+&lt;/sup&gt;</td>
<td>2.879</td>
</tr>
<tr>
<td>MEMPR&lt;sub&gt;3&lt;/sub&gt;</td>
<td>.115</td>
<td>.066</td>
<td>.140</td>
<td>1.377</td>
</tr>
<tr>
<td>MEMPR&lt;sub&gt;3&lt;/sub&gt;S</td>
<td>.211</td>
<td>.086</td>
<td>-.245</td>
<td>1.432</td>
</tr>
<tr>
<td>SDMPR&lt;sub&gt;1&lt;/sub&gt;</td>
<td>.076</td>
<td>.028</td>
<td>.493</td>
<td>1.485</td>
</tr>
<tr>
<td>SDMPR&lt;sub&gt;3&lt;/sub&gt;</td>
<td>.160</td>
<td>.081</td>
<td>1.315</td>
<td>2.791</td>
</tr>
<tr>
<td>SDMPR&lt;sub&gt;3&lt;/sub&gt;S</td>
<td>.076</td>
<td>.033</td>
<td>.384</td>
<td>1.349</td>
</tr>
<tr>
<td>SDMPR&lt;sub&gt;3&lt;/sub&gt;S</td>
<td>.158</td>
<td>.091</td>
<td>.487</td>
<td>1.344</td>
</tr>
</tbody>
</table>

+ - not significant.
* - significant at .05.
** - significant at .025.
*** - significant at .005.
All other results are significant at less than .0001.

Table 24 demonstrates with respect to group means, that only the COS had high significant results, while other parameters were either moderately significant or not significant. This is another indication for the superiority of the predictive ability of the COS over other parameters.

The COS of the profitability ratios without investment earnings and gains are compared with the COS of profitability ratios with investment earnings and gains. These comparisons are presented in Table 25. COSMPRS and COSMPR predictive ability out-perform the predictive ability of the COS of these ratios without investment.
TABLE 25
Comparisons of the Predictive Ability of COS

<table>
<thead>
<tr>
<th>Variables Compared</th>
<th>Percent Correctly Classified</th>
<th>Proportion Z Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>COSMPL vs. COSMRUL</td>
<td>96.6 vs. 87.2</td>
<td>2.635***</td>
</tr>
<tr>
<td>COSMPL vs. COSMRUL</td>
<td>84.6 vs. 77.8</td>
<td>1.33*</td>
</tr>
<tr>
<td>COSMPL vs. COSMRUL</td>
<td>98.3 vs. 86.3</td>
<td>3.44****</td>
</tr>
<tr>
<td>COSMPL vs. COSMRUL</td>
<td>85.5 vs. 74.3</td>
<td>2.12**</td>
</tr>
</tbody>
</table>

* - significant at .10 (may be interpreted either significant or not significant).
** - significant at .025
*** - significant at .005
**** - significant at .001

profits (variables COSMRUP and COSMPL), generally the differences are statistically significant.

The means vs. the variability of the ratios can also be demonstrated in the return/risk dimensions. Figures 11 and 12 demonstrate the accurate prediction of the COS while investment results are included. The COS of the underwriting profits alone, are presented in Figures 13 and 14.

Line OA (Figure 11) represents the best cutoff line where the slope of the line is the COS (e.g., 0.54 for MPR). A possible range of uncertainty (or ignorance) can also be identified (e.g., the range limited by lines OB-OC). Insurers in this range should be examined carefully by regulators.
Figure 11. Means and Temporal Standard Deviations of the Modified Profitability Ratios, Classification Procedures (one Year Prior).

1) 14 OBS hidden (e.g., a zero sign might represent two solvent companies, 1 might represent two insolvent companies).

2) The profits include investment earning and capital gains.
Means of Modified Profitability Ratio

14 CBS HIDDEN

Standard Deviation of Modified Profitability Ratio
Figure 12. Means and Temporal Standard Deviations of the Modified Profitability Ratios (Three Years Prior to Insolvency)
NOTE: 12 OBS HIDDEN
Figure 13. Means and Temporal Standard Deviations of the Underwriting Profitability Ratios (One Year Prior to Insolvency)
NOTE: 14 OBS HIDDEN

Figure 14. Means and Temporal Standard Deviations of Underwriting Profitability Ratios' (Three Years Prior to Insolvency)
Another approach is to draw a cutoff line following the formula
MEMPRS = a + b (SDMPRS).12 This line might enable regulators to
identify solvent insurers with a very small average negative profit-
ability (loss) but with a modest standard deviation. Such a possible
line is the dashed line aD (Figure 11).

In summary, the figures demonstrate the predictive ability of the
COS, which are powerful tools for accurate classification of insurers
between solvent and insolvent groups. The figures also demonstrate
the improvement in the results, when investment profits are included,
compared with the results of underwriting profits alone.

The quasi-systematic risk model did not generate any meaningful
predictive ability power. Correct classifications were less than 60
percent for most of the Betas examined in the research. As discussed
in Chapter V there might be at least four reasons for these results:
1) they are not used for spreading the risk; 2) measurement problems,
especially for choosing the industry mean as the independent variable;
3) accounting measurements of profitability (SAP Vs. GAAP); 4) Betas
are unstable.

**Multivariate Results: The Multidiscriminant Analysis (MDA)**

A MDA is applied to the data. Several models with the most power-
ful discriminatory power are employed. The purpose is to examine
whether the predictive ability of insolvency can be improved compared

---

12 This line is not the least square line, but a line that targets
to minimize the number of misclassification. This line may not
necessarily be a straight line.
with the univariate analyses. About 22 univariate variables are examined in many combinations and the most effective ones are considered. Those examinations are processed by using the Statistical Package for the Social Sciences (SPSS) [144]. Both the Direct as well as the Wilks methods are employed. The efficiency of the models is also examined; efficient models might be produced by reducing the number of variables being employed in the models. Since the research focus is not only on determining the most effective set of variables for prediction, but also to compare existing methods with new predictive variables; the relative efficiency and effectiveness of the models are compared against each other.

The results in Table 26 indicate that the most effective MDA models predicted correctly over 99 percent of the cases one year prior to insolvency. The results in Table 27 demonstrate that the most effective models predicted correctly between 89 to 92 percent of the insurers three years before insolvency. These results are considered slightly significant improvement over the predictive ability of most univariate variables, especially for early prediction.

None of the most effective models include either the means or the standard deviations of the profitability ratios over time. Whenever the quasi-systematic risk coefficients (β)s are employed they are found to be not significant. Moreover, the most effective models generally did not include averages of DM.

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13 See Chapter VI for a discussion.
**TABLE 26**

MDA Classification Results One Year before Insolvency

| Model 1: \( Z = -0.6371 + 3.7966 \text{DL}_1 - 4.3066 \text{NDL}_1 - 0.0727 \text{BPRI} \\ -0.1330 \text{NAIT}_1 - 0.1912 \text{COSMPR}_1 + 0.3412 \text{CSVMPR}_1 \\ +0.1118 \text{CSVMPRS}_1 \) |
|-------------------|-------------------|
| Eigenvalue: 7.9032, Wilks Lambda = 0.1123, \( \chi^2 = 243.7 \) (significant at .0001) |

<table>
<thead>
<tr>
<th>Actual Group</th>
<th>Predicted Group Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td>solvent</td>
<td>62</td>
</tr>
<tr>
<td>insolvent</td>
<td>1 (1.8%)</td>
</tr>
</tbody>
</table>

99.1% correctly classified

| Model 2: \( Z = -1.3242 + 3.0319 \text{NDL}_{11} + 0.2276 \text{BPRI} + 0.1649 \text{NAIT}_1 \\ -0.7774 \text{COSMPR}_1 \) |
|-------------------|-------------------|
| Eigenvalue: 3.7352, Wilks Lambda = 0.2112, \( \chi^2 = 175.7 \) (significant at .0001) |

<table>
<thead>
<tr>
<th>Actual Group</th>
<th>Predicted Group Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td>solvent</td>
<td>61</td>
</tr>
<tr>
<td>insolvent</td>
<td>1 (1.8%)</td>
</tr>
</tbody>
</table>

98.3% correctly classified

| Model 3: \( Z = 0.0948 + 6.4520 \text{DL}_1 - 7.4834 \text{NDL}_1 + 1.1612 \text{COSMPR}_1 \) |
|-------------------|-------------------|
| Eigenvalue: 2.5582, Wilks Lambda = 0.2810, \( \chi^2 = 144.1 \) (significant at .0001) |

<table>
<thead>
<tr>
<th>Actual Group</th>
<th>Predicted Group Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td>solvent</td>
<td>61</td>
</tr>
<tr>
<td>insolvent</td>
<td>0</td>
</tr>
</tbody>
</table>

99.1% correctly classified

| Model 4: \( Z = 0.2015 - 3.9834 \text{NDL}_1 + 1.1749 \text{COSMPR}_1 \) |
|-------------------|-------------------|
| Eigenvalue: 2.4201, Wilks Lambda = 0.2924, \( \chi^2 = 140.1 \) (significant at .0001) |

<table>
<thead>
<tr>
<th>Actual Group</th>
<th>Predicted Group Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td>solvent</td>
<td>61</td>
</tr>
<tr>
<td>insolvent</td>
<td>0</td>
</tr>
</tbody>
</table>

99.1% correctly classified
TABLE 26 (Continued)

Model 5: \( Z = -2.3505 + 0.4403 \text{BPR}_1 + 0.1900 \text{NAIT}_1 \)

Eigenvalue: 2.0870, Wilks Lambda = 0.3239 \( \chi^2 = 128.5 \) (significant at .0001)

<table>
<thead>
<tr>
<th>Actual Group</th>
<th>Predicted Group Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td>solvent</td>
<td>57  5 (8.1%)</td>
</tr>
<tr>
<td>insolvent</td>
<td>4   (7.2%)  50</td>
</tr>
</tbody>
</table>

92.3% correctly classified

TABLE 27

MDA Classification Results Three Years Prior

Model 1: \( Z = -0.6331 - 15.2206 \text{DL}_3 + 9.1719 \text{NDL}_3 + 0.1617 \text{BPR}_3 
-0.1045 \text{CSVMPRS} + 6.3388 \text{SPA}_3 \)

Eigenvalue: 1.5984, Wilks Lambda = 0.3848, \( \chi^2 = 106.9 \) (significant at .0001)

<table>
<thead>
<tr>
<th>Actual Group</th>
<th>Predicted Group Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td>solvent</td>
<td>59  3 (4.8%)</td>
</tr>
<tr>
<td>insolvent</td>
<td>8   (14.5%)  47</td>
</tr>
</tbody>
</table>

90.6% correctly classified

Model 2: \( Z = -1.6701 - 13.7089 \text{DL}_3 + 10.9466 \text{NDL}_3 - 24.9967 \text{SPL}_3 
+ 0.2702 \text{BPR}_3 - 0.4523 \text{COSMPR}_3 \)

Eigenvalue: 1.2797, Wilks Lambda = 0.4386 \( \chi^2 = 92.7 \) (significant at .0001)

<table>
<thead>
<tr>
<th>Actual Group</th>
<th>Predicted Group Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td>solvent</td>
<td>55  7 (11.3%)</td>
</tr>
<tr>
<td>insolvent</td>
<td>6   (10.9%)  49</td>
</tr>
</tbody>
</table>

88.9% correctly classified

Model 3: \( Z = 0.3064 - 13.3171 \text{DL}_3 - 9.7684 \text{NDL}_3 + 0.7524 \text{COSMPR}_3 \)

Eigenvalue: 0.8681, Wilks Lambda = 0.5353 \( \chi^2 = 70.9 \) (significant at .0001)

<table>
<thead>
<tr>
<th>Actual Group</th>
<th>Predicted Group Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td>solvent</td>
<td>57  5 (8.1%)</td>
</tr>
<tr>
<td>insolvent</td>
<td>6   (10.9%)  49</td>
</tr>
</tbody>
</table>

90.6% correctly classified
**TABLE 27 (Continued)**

Model 4: \( Z = -0.1922 - 3.4724 \text{NDL}_3 + 0.7732 \cos\text{SPR}_3 \)

Eigenvalue: 0.7939, Wilks Lambda = 0.5574, \( \chi^2 = 66.6 \) (significant at .0001)

<table>
<thead>
<tr>
<th>Actual Group</th>
<th>Predicted Group Membership</th>
<th>Solvent</th>
<th>Insolvent</th>
</tr>
</thead>
<tbody>
<tr>
<td>solvent</td>
<td></td>
<td>57</td>
<td>5 (8.1%)</td>
</tr>
<tr>
<td>insolvent</td>
<td></td>
<td>8 (14.5%)</td>
<td>47</td>
</tr>
</tbody>
</table>

88.9% correctly classified

Model 5: \( Z = 1.7056 + 0.4534 \text{BPR}_3 - 0.0015^* \text{NAIT}_3 \)

Eigenvalue: 0.5962 Wilks Lambda = 0.6265 \( \chi^2 = 53.3 \) (significant at .0001)

<table>
<thead>
<tr>
<th>Actual Group</th>
<th>Predicted Group Membership</th>
<th>Solvent</th>
<th>Insolvent</th>
</tr>
</thead>
<tbody>
<tr>
<td>solvent</td>
<td></td>
<td>52</td>
<td>10 (16.1%)</td>
</tr>
<tr>
<td>insolvent</td>
<td></td>
<td>13 (23.6%)</td>
<td>42</td>
</tr>
</tbody>
</table>

80.3% correctly classified

*not significant.

Model 1, with seven variables correctly classifies 99.1 percent of the insurers one year prior to insolvency. Almost the same model with six variables predict correctly 90.6 percent of the insurers three years before insolvency. Model 2 (which also includes BPR and NAIT for one year before insolvency) correctly classifies 98.3 and 88.9 percent of the insurers one and three years respectively, prior to insolvency.

The efficiency of the models are examined by reducing the number of variables in each model. Models 3 and 4 with three and two variables, respectively, present the same predictive ability as models 1 and 2.\(^{14}\) All the parameters of models 1 through 4 have been significant.

\(^{14}\)These results are based on the optimal cutoff point. A discussion about using the midpoint between groups' centroids will follow.
The last two models might be considered effective as well as the most efficient models in the analysis. Several other results are examined in Appendix C.

Model 5 with two variables (NAIT and BPR) predicted correctly about 91 percent of the cases in the sample for one year before insolvency, but only about 80 percent of the insurers for three years prior to insolvency. This model possessed significantly less predictive ability compared with models 3 and 4, as demonstrated in Table 28.

<table>
<thead>
<tr>
<th>TABLE 28</th>
</tr>
</thead>
<tbody>
<tr>
<td>A Comparison of the Overall Classification Power Models 3 and 4 Vs. Model 5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Models</th>
<th>Classification Percent and Observed</th>
<th>Z-values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>One year prior</td>
<td>three years prior</td>
</tr>
<tr>
<td>Model 3 Vs.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 5</td>
<td>(99.1% Vs. 92.3) 2.589***</td>
<td>(90.6% Vs. 80.3%) 2.234**</td>
</tr>
<tr>
<td>Model 4 Vs.</td>
<td>(99.1% Vs. 92.3) 2.589***</td>
<td>(88.9% Vs. 80.3%) 1.822*</td>
</tr>
</tbody>
</table>

* - significant at .05
** - significant at .01
*** - significant at .005
Validation and Cutoff Points

The absence of an ex-ante validation sample is a common ground for criticism on most previous research for predicting of insolvencies. Most studies fail to examine the sensitivity of the parameters to time span, although several studies examine the predictive ability of the models on independent sample of firms. Two types of validation samples are examined in the research. The first one employs a random uniform-distribution procedure to split the overall sample into two independent groups with a holdout sample of about 60 percent of the insurers. The second procedure uses the observations from 1974-1975 for a running-on sample and cases from 1976-1981 as an independent-holdout sample. The parameters for the 1974-1975 cases were used in the models to predict insolvencies for the years 1976-1981. The results are presented in Appendix C. Over 97 and 88 percent correct prediction, respectively, are demonstrated by models 3 and 4 for years one and three prior to insolvency. The evidences suggest that the results are valid and stationary over time. Moreover, the process enables to establish a real world setting, since parameters of the MDA models based on past results (1974-1975) are employed on independent and recent data (1976-1981). These results provide a test of stationary of the model's parameters over time and increase the confidence in the models.

As discussed in previous chapters the optimal cutoff point was used throughout the analysis. The criterion being employed was minimizing the probability of misclassifications. This classification
procedure is preferred to the alternative classification rule of the midpoint cutoff between the mean of the solvent group and the mean of the insolvent group.\textsuperscript{15} When the first criterion is compared with the second: midpoint (between the two groups' centroids), moderate improvements are achieved for most of the models. The results also are summarized in Appendix C along with the two different cutoff comparisons for the major univariate variables. A significant improvement of the discriminatory power is demonstrated by employing the first criterion: minimizing the number of misclassification compared with the midpoint criterion, when both were employed to univariate variables. (However, generally only modest improvement when MDA were employed.)

**MDA Assumptions**

Although most COS are approximately normally distributed, several univariate DM, SP, BPR and NAIT are not found to be normally distributed.\textsuperscript{16} Since most univariate variables are not univariate normal together they cannot be assumed as multivariate normal. Moreover, for most models the variance/covariance matrices of the two groups are not equal. Thus violations of the basic assumptions of the MDA are suggested. However, in practice the violations may be considered irrelevant since the MDA is considered a robust technique.

\textsuperscript{15}As explained in previous chapters cost considerations were not employed in the research.

\textsuperscript{16}The Kolmogornov D statistics as well as tests for skewness and Kurtosis were employed. A sample of the 62 solvent companies and 4 insolvent companies (which might represent the overall population) is examined.
Nevertheless the conservative Lachenbrach "Jacknight" technique are employed and the probability of misclassification was reexamined.\textsuperscript{17}

Table 29 presents the classification results for model 3 while the Lachenbruch's procedure was employed. It seems that the results for the standard linear MDA are not biased significantly upward, since a very small increase in the misclassification percentage is observed. For further results see Appendix C.

The evidences suggested that the MDA with the two or three stability variables is an efficient and accurate explanations of insolvencies for current and for early prediction.

\textbf{TABLE 29}

Classification Results for Model 3 Lachenbruch Procedure Vs. Linear MDA

<table>
<thead>
<tr>
<th></th>
<th>Predicted Group Membership</th>
<th>Linear Model</th>
<th>Quadratic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Group</td>
<td></td>
<td>solvent</td>
<td>insolvent</td>
</tr>
<tr>
<td>1 year</td>
<td>solvent</td>
<td>61</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>insolvent</td>
<td>1</td>
<td>54</td>
</tr>
<tr>
<td>percent correctly classified</td>
<td>98.3%</td>
<td></td>
<td>98.3%</td>
</tr>
<tr>
<td>3 years</td>
<td>solvent</td>
<td>56</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>insolvent</td>
<td>6</td>
<td>49</td>
</tr>
<tr>
<td>percent correctly classified</td>
<td>89.7%</td>
<td></td>
<td>88.6%</td>
</tr>
<tr>
<td>Linear MDA (employed in the research)</td>
<td>solvent</td>
<td>61</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>insolvent</td>
<td>0</td>
<td>55</td>
</tr>
<tr>
<td>percent correctly classified</td>
<td>99.1%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 years</td>
<td>solvent</td>
<td>57</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>insolvent</td>
<td>6</td>
<td>49</td>
</tr>
<tr>
<td>percent correctly classified</td>
<td>90.6%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\textsuperscript{17}See Chapter VI, for a discussion on the linear and quadratic MDA assumptions, and the Lachenbruch's procedure.
Multivariate Results: Multiregression Analysis

A multiregression zero-one model is regressed on the same independent variables. The dependent variable is group (0 = solvent, 1 = insolvent). The independent variables are selected by using forward and backward stepwise regression. Proc Stepwise and GLM analyses generated by the Statistical Analysis System (SAS) [137] are employed. Two cutoff points were examined: a midpoint cutoff value of 0.50 for the dependent zero-one variable group), and the optimal cutoff points which minimize the number of misclassifications. The major empirical results are summarized in Table 30. The best significant model 1 (presented in Appendix C) with six variables and a cutoff point of 0.41 classified correctly about 92 percent of the firms three years prior to insolvency, a slight and not significant improvement over the best MDA. However, the MDA possessed slightly better results (although nonsignificant) than the zero-one regression model for the efficient models 3 and 4. Further results are presented in Appendix C.

Although the results for model 5 (with BPR and NAIT as independent variables) are not presented in Table 30, they are slightly but not significantly better than the MDA.

It appears that both the MDA and the zero-one regression model possess about the same predictive ability for the best models.\(^{16}\) For the most efficient models, the MDA demonstrates slightly better classification power, but the differences in the classification accuracy are not statistically significant.

\(^{16}\) However, all the parameters of the MDA are statistically significant, several parameters of the zero-one regression models are not statistically significant.
TABLE 30

Classification Results: Models 3 and 4 under Multiregression (0,1) Model

<table>
<thead>
<tr>
<th>Model 3 (one year prior): $Y = .4486 - 1.4601 DL_1 + 1.6935 NDL_1 - .2628 COSMPR_1$</th>
<th>$R^2 = .719, F = 96.3$ significant at less than .0001</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Group</td>
<td>Predicted Group Membership</td>
</tr>
<tr>
<td>solvent</td>
<td>Insolvent</td>
</tr>
<tr>
<td>61</td>
<td>1 (2%)</td>
</tr>
<tr>
<td>0</td>
<td>55</td>
</tr>
<tr>
<td>percent correctly classified: 99.1%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model 3 (three years prior): $Y = .3931 - 34387 DL_3 + 3.2523 NDL - .1889 COSNPR_3$</th>
<th>$R^2 = .465, F = 32.7$ (.0001)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Group</td>
<td>Predicted Group Membership</td>
</tr>
<tr>
<td>solvent</td>
<td>Insolvent</td>
</tr>
<tr>
<td>55</td>
<td>7 (11%)</td>
</tr>
<tr>
<td>5 (9%)</td>
<td>50</td>
</tr>
<tr>
<td>percent correctly classified: 89.7</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model 4 (one year prior): $Y = -.5162 + .9122 NDL_1 - 2691 COSMPR_1$</th>
<th>$R^2 = .708, F = 137.9$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Group</td>
<td>Predicted Group Membership</td>
</tr>
<tr>
<td>solvent</td>
<td>Insolvent</td>
</tr>
<tr>
<td>62</td>
<td>0</td>
</tr>
<tr>
<td>1 (2%)</td>
<td>54</td>
</tr>
<tr>
<td>percent correctly classified: 99.1%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model 4 (three year prior): $Y = .5181 + .8563 NDL_3 - .1933 COSMPR_3$</th>
<th>$R^2 = .443, F = 45.3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Group</td>
<td>Predicted Group Membership</td>
</tr>
<tr>
<td>solvent</td>
<td>Insolvent</td>
</tr>
<tr>
<td>53</td>
<td>9 (15%)</td>
</tr>
<tr>
<td>5 (9%)</td>
<td>50</td>
</tr>
<tr>
<td>percent correctly classified: 88.0%</td>
<td></td>
</tr>
</tbody>
</table>
Summary

The coefficient of stability for the profitability ratios (over time) out-perform all other univariate variables in their predictive ability. However, liabilities decomposition measures also possess powerful predictive ability, while asset decomposition measures have very little classification ability. Both types of stability measures (DL and COS) generally classified solvent and insolvent companies better than the Best's rating (BPR), the NAIC-IRIS (NAIT) and financial ratios especially for early prediction. The evidences suggest that the multivariate models do a better job for predicting insolvencies than the univariate variables, primarily for early prediction. Both the MDA and the zero-one multiple regression analysis are shown to be accurate models for predictions of insolvencies among P-L insurers. Follow-up classification results for univariate and multivariate analyses are present in the summary Table 31.
<table>
<thead>
<tr>
<th>Variable</th>
<th>One Year Prior</th>
<th>Three Years Prior</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Overall % Type</td>
<td>Overall % Type</td>
</tr>
<tr>
<td></td>
<td>Correctly I %</td>
<td>Correctly I %</td>
</tr>
<tr>
<td></td>
<td>Classified</td>
<td>Classified</td>
</tr>
<tr>
<td></td>
<td>Error</td>
<td>Error</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COSMPR</td>
<td>97 2 5</td>
<td>85 18 13</td>
</tr>
<tr>
<td>COSMPRS</td>
<td>98 2 2</td>
<td>85 18 11</td>
</tr>
<tr>
<td>DL</td>
<td>90 9 11</td>
<td>79 25 17</td>
</tr>
<tr>
<td>NDL</td>
<td>91 7 10</td>
<td>83 16 18</td>
</tr>
<tr>
<td>SPL</td>
<td>90 9 11</td>
<td>79 20 21</td>
</tr>
<tr>
<td>AVDL</td>
<td>91 7 10</td>
<td>82 22 15</td>
</tr>
<tr>
<td>AVNDL</td>
<td>92 5 10</td>
<td>85 16 15</td>
</tr>
<tr>
<td>MDA</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1</td>
<td>99 2 0</td>
<td>91 15 5</td>
</tr>
<tr>
<td>Model 3</td>
<td>99 2 0</td>
<td>91 11 8</td>
</tr>
<tr>
<td>Model 4</td>
<td>99 0 2</td>
<td>89 14 8</td>
</tr>
<tr>
<td>(0,1) Regress</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1</td>
<td>99 0 2</td>
<td>92 13 2</td>
</tr>
<tr>
<td>Model 3</td>
<td>99 0 2</td>
<td>90 9 11</td>
</tr>
<tr>
<td>Model 4</td>
<td>98 2 2</td>
<td>88 9 15</td>
</tr>
</tbody>
</table>
CHAPTER IX
DIFFERENT ACCOUNTING PRACTICES: EMPIRICAL RESULTS FOR INSOLVENCY PREDICTION

The objective of this chapter is to compare the ability of stability measures computed from SAP financial statements to predict insolvency with the ability of stability measures computed from three other accounting practices to do likewise. Four different accounting practices are employed: 1) SAP, 2) modified SAP, 3) GAAP, and 4) the MVA procedure (assets are recorded at market value). All these practices are discussed in Chapter VII. Empirical evidence on the relative merit of these accounting practices for prediction of insolvency is presented in this chapter.

Predictive Ability Hypotheses

Predictions of insolvencies among P-L insurers are developed using univariate analyses, MDA, and 0-1 linear regression models. Four sets of stability measures are developed for one and three years prior to insolvency. The first data set is based on SAP financial statements, the other sets are based on modified SAP financial statements, GAAP financial statements, and the MVA financial statements.

The general hypothesis being tested is:

Ho: There are no differences in the ability of stability measures computed with data developed according to different accounting practices to predict insolvencies among P-L insurers.
This null hypothesis can also be stated as follows: modification of insurers' SAP financial statements to other accounting practices will not affect the ability of the stability measures to predict insolvencies among P-L insurers.

Six pairs of hypotheses may be tested for each period, because there are four different practices. Perhaps, the most interesting pair of hypotheses is:¹

**Ho:** The percentage of correct classification with stability measures computed from SAP is equal to the percentage of correct classification of stability measures computed from GAAP.

**Ha:** The percentage of correct classification is higher with stability measures computed from SAP. This alternative hypothesis is in accordance with arguments that have been promoted by regulators since the 1870s.

### Predictions Using Univariate Stability Measures

Testing the predictive power of each stability measure is accomplished by the same procedures which are employed in the previous chapters. The correct classification of the stability measures computed from the four accounting practices are presented in Table 32.²

---

¹The same pairs of comparisons are also useful to compare SAP with modified SAP, and SAP with the MVA procedure. A comparison between GAAP and the MVA, and a comparison of GAAP with modified SAP, are also useful. A sixth comparison may be to compare modified SAP with MVA procedure.

²Only univariate variables with over 85 percent correct classification for one year prior to insolvency are shown in Table 32.
TABLE 32
Percentage of Insurers Correctly Classified by the
Four Accounting Practices: Univariate Analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>SAP Insolvent</th>
<th>SAP Solvent</th>
<th>Modified SAP Insolvent</th>
<th>Modified SAP Solvent</th>
<th>GAAP Insolvent</th>
<th>GAAP Solvent</th>
<th>MVA Insolvent</th>
<th>MVA Solvent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Overall</td>
<td>Overall</td>
<td>Overall</td>
<td>Overall</td>
<td>Overall</td>
<td>Overall</td>
<td>Overall</td>
<td>Overall</td>
</tr>
<tr>
<td>One Year</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>DL</td>
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<td>91</td>
<td>89</td>
<td>80</td>
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<td>78</td>
<td>90</td>
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<tr>
<td></td>
<td>89.7</td>
<td>89.7</td>
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<td>84.6</td>
<td>84.6</td>
<td></td>
<td></td>
<td></td>
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<tr>
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<td>93</td>
<td>90</td>
<td>82</td>
<td>89</td>
<td>76</td>
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<td>86.3</td>
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<tr>
<td>SPL</td>
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<td>89</td>
<td>84</td>
<td>82</td>
<td>84</td>
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</tr>
<tr>
<td></td>
<td>89.7</td>
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<td>82.9</td>
<td>84.6</td>
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<tr>
<td>AVDL</td>
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<td>84</td>
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<td>95</td>
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<td>84</td>
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</tr>
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<tr>
<td>SPL</td>
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</tbody>
</table>
TABLE 32 (Continued)

<table>
<thead>
<tr>
<th>Variable</th>
<th>SAP Insolvent Overall</th>
<th>SAP Solvent Overall</th>
<th>Modified SAP Insolvent Overall</th>
<th>Modified SAP Solvent Overall</th>
<th>GAAP Insolvent Overall</th>
<th>GAAP Solvent Overall</th>
<th>MVA Insolvent Overall</th>
<th>MVA Solvent Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>COS(P)</td>
<td>91 81 85.5</td>
<td>82 87 84.6</td>
<td>85 82 83.8</td>
<td>91 84 87.2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COS(S)</td>
<td>89 82 85.5</td>
<td>82 89 85.5</td>
<td>84 84 83.8</td>
<td>91 82 86.3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes
1) Total number of observations 117, including 55 insolvent insurers.
2) Abbreviations
DL - Liability decomposition measures.
NDL - Liabilities new decomposition measures.
SPL - Liabilities square-proportion measures.
AVDL - Average liabilities decomposition measures (averages over years 1 through 3 for one year prior to insolvency, and averages over years 3 through 5 for 3 years prior to insolvency).
AVNDL - Average liabilities new decomposition measures.
AVSPL - Average liabilities square-proportion measures.
COS(P) - Coefficient of stability of overall profitability ratios on premiums. Mean divided by the standard deviation over time.
COS(S) - Coefficient of stability of overall profitability ratios on surplus.
The first column for each practice presents the percentage of insolvent insurers correctly classified, and the last column for each practice represents the percentage of solvent insurers correctly classified. The overall percentage of insurers correctly classified by each practice is presented in the middle column.

The results indicate\(^3\) that the overall percentage of insurers correctly classified by SAP stability measures is better than the overall classification by GAAP stability measures for one year prior to insolvency. However, the overall percentages of insurers correctly classified by modified SAP are similar to the classification results by SAP; therefore, the two methods should be considered similar procedures. The MVA procedure produces about the same classification results as the correct classification produced by SAP (or modified SAP), but the classification results produced by SAP decomposition measures and the square-proportion methods are better than the classification results produced by those methods when computed from MVA financial statements.

All four practices produce similar classification results three years prior to insolvency. The results indicate that the overall percentage of insurers correctly classified by SAP stability measures are only slightly better than the percentage of insurers correctly classified by GAAP stability measures. It is difficult to draw any meaningful conclusion about the differences among the classification

\(^3\)The coefficients of stability of the overall profitability ratios (COS) correctly classify more insurers than the decomposition measures and the square-proportion methods. These classification results are the same over all four accounting practices.
results of the four accounting practices for three years prior to insolvency.

**Statistical Significance**

All major univariate stability measures computed from the four different accounting practices demonstrate effective ability to discriminate between the solvent and the insolvent groups of insurers. Both the "t" tests and the Wilcoxon Rank-Sum tests are significant for all major variables. Thus, there are strong indications that the solvent group of insurers differs from the insolvent group of insurers for all major variables computed from the four different accounting procedures.

The major purpose of this section is to measure the statistical validity of the classification results are computed from the different accounting practices. The differences in the classification results are evaluated using statistical tests. Two statistical tests, a proportion Z test and a distribution free \( \chi^2 \) for two-by-two contingency tables are employed. Because SAP, modified SAP, and the MVA

---

4 Both tests are explained in the previous chapter.

5 The proportion Z test is described in the previous chapter, see the bottom of Table 18. For a general discussion of these tests, see Marascuilo and McSweeney [109, Ch. 5]. The \( \chi^2 \) test is based on the statistic "T" which is computed from the following contingency table

<table>
<thead>
<tr>
<th></th>
<th>0_{11}</th>
<th>0_{12}</th>
</tr>
</thead>
<tbody>
<tr>
<td>0_{21}</td>
<td>0_{21} + 0_{22}</td>
<td></td>
</tr>
</tbody>
</table>

\[ N = n_1 + n_2 \]

Where
demonstrate similar results, the primary comparison is between SAP stability measures and GAAP stability measures. The significant results are presented in Table 33.

The null hypothesis cannot be rejected for all univariate variables when SAP is compared with modified SAP or the MVA procedure one or three years prior to insolvency. When GAAP is compared with SAP (or modified SAP) the null hypothesis can be rejected for several variables one year prior to insolvency. Table 33 shows that the null hypothesis can be rejected for the coefficients of stability of the overall profitability ratios (COS), and for the liabilities new decomposition measure (NDL), one year prior to insolvency. When the predictive ability is examined for the insolvent group only, the null hypothesis can be rejected for additional two variables (see Table 33).

All comparisons are not statistically significant for three years prior to insolvency. Thus, the results indicate that there are no

\[
0_{11} = \text{number of insurers correctly classified with practice \#1} \\
0_{12} = \text{number of insurers incorrectly classified with practice \#1} \\
0_{21} = \text{number of insurers correctly classified with practice \#2} \\
0_{22} = \text{number of insurers incorrectly classified with practice \#2} \\
0 = \frac{N(0_{11}0_{22} - 0_{12}0_{21})^2}{n_1n_2(0_{11} + 0_{21})(0_{12} + 0_{22})} \\
T = \text{The observed } T \text{ is compared with critical values of } \chi^2 \text{ with 1 degree of freedom. In this research } n_1 = n_2 = 117, \text{ and } N = 234. \text{ For further discussion, see Elam [52, pp. 35-7].}
\]
### TABLE 33

Comparisons of Predictive Ability One Year Prior to Insolvency, GAAP Vs. SAP

<table>
<thead>
<tr>
<th>Variable</th>
<th>Percent Correctly Classified</th>
<th>Z-proportion Score</th>
<th>T Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Predictive Ability</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COS(P)</td>
<td>97.4 Vs. 91.5</td>
<td>1.971***</td>
<td>3.991***</td>
</tr>
<tr>
<td>COS(S)</td>
<td>96.6 Vs. 90.6</td>
<td>1.875**</td>
<td>3.490***</td>
</tr>
<tr>
<td>NDL</td>
<td>91.5 Vs. 84.5</td>
<td>1.459*</td>
<td>2.051*</td>
</tr>
</tbody>
</table>

Insolvent Insurers' Predictive Ability

<table>
<thead>
<tr>
<th>Variable</th>
<th>Percent Correctly Classified</th>
<th>Z-proportion Score</th>
<th>T Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>COS(P)</td>
<td>98.2 Vs. 90.9</td>
<td>1.678**</td>
<td>2.821**</td>
</tr>
<tr>
<td>COS(S)</td>
<td>96.4 Vs. 89.1</td>
<td>1.476*</td>
<td>2.157*</td>
</tr>
<tr>
<td>DL</td>
<td>90.9 Vs. 80.0</td>
<td>1.621*</td>
<td>2.633*</td>
</tr>
<tr>
<td>NDL</td>
<td>92.7 Vs. 81.8</td>
<td>1.714**</td>
<td>2.946**</td>
</tr>
<tr>
<td>AVSPL</td>
<td>94.5 Vs. 78.2</td>
<td>2.490****</td>
<td>6.253****</td>
</tr>
</tbody>
</table>

* - significant at .10 (may be interpreted either significant or not significant based on the preferences of the reader).
** - significant at .05
*** - significant at .025
**** - significant at .01

All other differences are not significant.
statistically significant differences between stability measures computed from the four accounting practices in their ability to predict insolvency three years prior to insolvency.

In summary, SAP, modified SAP and the MVA stability measures produce approximately similar classification results. The Z score and the T score indicate that SAP data improve the prediction ability of the stability measures compared with GAAP data one year before insololvency. However, SAP practice does not make the predictive variables significantly more powerful for three years prior to insolvency.

Multivariate Stability Measures Prediction

The effect of different accounting practices on the predictive ability of insolvency is tested in this section by employing multivariate models. Only five multivariate models are discussed, but many other models are examined. The stability measures computed from the different accounting practices, the BPR and the NAIT are selected by stepwise techniques and the significant variables are employed in the MDA and the 0-1 regression analyses. This procedure is repeated for one and three years prior to insolvency for each of the four accounting practices. Thus, the first model is established and examined four times for each period. The second model, II, employs the coefficient of stability COS(P), the liabilities new decomposition measure (NDL), BPR and NAIT. All other three multivariate models include only

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6 Twenty-two variables are included in the analysis. The variables are the stability measures, the NAIC-IRIS test (NAIT) and the Best's policyholders' rating (BPR); all three variables are discussed in Chapters V, VI, and VII.
stability measures. Model III includes three stability measures NDL, DL, and COS(P) (see abbreviations at the bottom of Table 32). Model IV includes only two variables NDL, and COS(P). Model V is similar to model III except that the average decomposition measures over time (AVDL, AVNDL) substitute for DL and NDL. The last three models are considered more efficient, because only two or three variables are employed. 7

The classification results of the five multivariate models computed from the four accounting practices are presented in Tables 34 and 35. The results indicate that all multivariate models computed from the accounting practices demonstrate abilities to discriminate between the solvent and the insolvent groups. Models computed from SAP, modified SAP, and the MVA produce similar results one year prior to insolvency. The efficient models III and IV correctly classify 99.1 percent of the insurers when computed from these accounting practices one year prior to insolvency. The overall percentage of insurers correctly classified by SAP models is better than the overall percentage of insurers correctly classified by GAAP models for one year before insolvency. All four practices show similar results three years prior to insolvency; models computed from SAP data

7All two or three coefficient of the variables employed in each multivariate model are usually statistically significant. Cutoff points with the smallest error classification rates are employed for each model. This may explain the slightly better results sometimes achieved by model IV with only two variables included in the models.
<table>
<thead>
<tr>
<th>Model</th>
<th>SAP</th>
<th>Modified SAP</th>
<th>GAAP</th>
<th>MVA</th>
</tr>
</thead>
<tbody>
<tr>
<td>One Year</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>100</td>
<td>98</td>
<td>98</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>99.1(6)</td>
<td>99.1(7)</td>
<td>94.8(9)</td>
<td>100(7)</td>
</tr>
<tr>
<td>II(4)</td>
<td>98</td>
<td>96</td>
<td>98</td>
<td>98</td>
</tr>
<tr>
<td></td>
<td>97.4</td>
<td>98.3</td>
<td>94.0</td>
<td>98.3</td>
</tr>
<tr>
<td>III(3)</td>
<td>100</td>
<td>98</td>
<td>100</td>
<td>98</td>
</tr>
<tr>
<td></td>
<td>99.1</td>
<td>99.1</td>
<td>94.0</td>
<td>99.1</td>
</tr>
<tr>
<td>IV(2)</td>
<td>100</td>
<td>98</td>
<td>100</td>
<td>98</td>
</tr>
<tr>
<td></td>
<td>99.1</td>
<td>99.1</td>
<td>91.4</td>
<td>99.1</td>
</tr>
<tr>
<td>V(3)</td>
<td>98</td>
<td>100</td>
<td>98</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>99.1</td>
<td>99.1</td>
<td>94.8</td>
<td>99.1</td>
</tr>
<tr>
<td>Three Years</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>84</td>
<td>96</td>
<td>86</td>
<td>95</td>
</tr>
<tr>
<td></td>
<td>90.6(7)</td>
<td>90.6(6)</td>
<td>88.9(8)</td>
<td>91.5(6)</td>
</tr>
<tr>
<td>II(4)</td>
<td>86</td>
<td>94</td>
<td>89</td>
<td>89</td>
</tr>
<tr>
<td></td>
<td>89.7</td>
<td>88.9</td>
<td>88.0</td>
<td>89.7</td>
</tr>
<tr>
<td>III(3)</td>
<td>91</td>
<td>87</td>
<td>89</td>
<td>92</td>
</tr>
<tr>
<td></td>
<td>88.9</td>
<td>90.6</td>
<td>86.3</td>
<td>89.7</td>
</tr>
<tr>
<td>IV(2)</td>
<td>85</td>
<td>92</td>
<td>85</td>
<td>92</td>
</tr>
<tr>
<td></td>
<td>88.9</td>
<td>88.9</td>
<td>86.3</td>
<td>87.2</td>
</tr>
<tr>
<td>V(3)</td>
<td>89</td>
<td>92</td>
<td>84</td>
<td>90</td>
</tr>
<tr>
<td></td>
<td>85.5</td>
<td>87.2</td>
<td>83.8</td>
<td>88.9</td>
</tr>
</tbody>
</table>

Notes: (1) Model I includes 6 to 9 variables, computed through the stepwise procedure.
(2) The numbers of variables appear in the parentheses.
### TABLE 35

Percentage of Insurers Correctly Classified by the Four Accounting Practices: 0-1 Multiregression Analysis

<table>
<thead>
<tr>
<th>Model</th>
<th>SAP Insol-vent Overall</th>
<th>Modified SAP Insol-vent Overall</th>
<th>GAAP Insol-vent Overall</th>
<th>MVA Insol-vent Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>98 100</td>
<td>99.1(6)</td>
<td>98 95</td>
<td>97 98 100</td>
</tr>
<tr>
<td>II</td>
<td>98 98</td>
<td>98.3</td>
<td>98.3</td>
<td>94.8 98</td>
</tr>
<tr>
<td>III(3)</td>
<td>100 98</td>
<td>99.1</td>
<td>99.1</td>
<td>94 98 100</td>
</tr>
<tr>
<td>IV(2)</td>
<td>100 98</td>
<td>99.1</td>
<td>99.1</td>
<td>91 94 100</td>
</tr>
<tr>
<td>V(3)</td>
<td>98 100</td>
<td>99.1</td>
<td>99.1</td>
<td>94.8 99.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Three Years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>98 94</td>
<td>87 97</td>
<td>82 95</td>
<td>85 97 90.6(6) 92.3(6)</td>
</tr>
<tr>
<td>II(4)</td>
<td>87 92</td>
<td>88 93</td>
<td>84 93</td>
<td>82 95 89.7 88.9</td>
</tr>
<tr>
<td>III(3)</td>
<td>97 89</td>
<td>91 89</td>
<td>82 90</td>
<td>89 94 89.7 86.3</td>
</tr>
<tr>
<td>IV(2)</td>
<td>85 95</td>
<td>91 85</td>
<td>78 95</td>
<td>85 90 90.6 88.0</td>
</tr>
<tr>
<td>V(3)</td>
<td>89 84</td>
<td>86 90</td>
<td>84 85</td>
<td>87 94 86.3 88.0</td>
</tr>
</tbody>
</table>

Note: The numbers of variables appear in the parentheses.
correctly classified only about 2 percent more insurers than the correct classification by GAAP models.

The statistical significance of the results are shown in Table 36. Models computed from SAP data differ significantly from the models computed by GAAP data one year prior to insolvency and the null hypothesis can be rejected. However, all comparisons are not statistically significant for the early predictions. All four accounting practices demonstrate similar results and the null hypotheses cannot be rejected for three years prior to insolvency. In general,

<table>
<thead>
<tr>
<th>Model</th>
<th>Percent Correctly Classified</th>
<th>Z-proportion Score</th>
<th>T Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>I, V (MDA)</td>
<td>99.1 Vs. 94.8</td>
<td>1.913**</td>
<td>3.682**</td>
</tr>
<tr>
<td>III (MDA)</td>
<td>99.1 Vs. 94.0</td>
<td>2.130***</td>
<td>4.659***</td>
</tr>
<tr>
<td>IV (MDA)</td>
<td>99.1 Vs. 91.4</td>
<td>2.769****</td>
<td>7.727****</td>
</tr>
<tr>
<td>I (0-1)</td>
<td>99.1 Vs. 95.7</td>
<td>1.634*</td>
<td>2.737*</td>
</tr>
<tr>
<td>III, IV (0-1)</td>
<td>99.1 Vs. 94.0</td>
<td>2.130***</td>
<td>4.659***</td>
</tr>
<tr>
<td>V (0-1)</td>
<td>99.1 Vs. 94.8</td>
<td>1.913**</td>
<td>3.682**</td>
</tr>
</tbody>
</table>

* - significant at .10 (may be interpreted either significant or not significant based on preferences of the reader).
** - significant at .05
*** - significant at .025
**** - significant at .005
for three years the overall percentages of insurers correctly classified are so similar that it is difficult to draw any meaningful conclusion, except that the models perform equally well. No clear advantage exists for any accounting practice in terms of accurate early prediction.

Several further considerations may be useful for comparing the effect of the multivariate models computed from different accounting practices in the prediction of insolvency. The weighted standard coefficients of the models, the overall F of each model, and the multiple coefficient of determination, $R^2$, may also be useful. However, close examination reveals approximately the same coefficients, when each model is computed four times under the different accounting practices.

**Discussion and Interpretations**

The SAP are required by regulatory agencies. Regulators design the SAP in order to determine whether their objectives are being met. Monitoring solvency is considered the primary objective of insurance regulators, who argue that SAP is a better procedure than GAAP for accomplishing this purpose. The empirical results indicate that the conventional experience of regulators and their argument are justified for one year prior to insolvency. Stability measures computed from SAP data show more accurate predictive ability than stability measures computed from GAAP data for current prediction of insolvency. However, the empirical evidence does not support the argument for early prediction; data furnished by SAP are not significantly better than data
furnished by GAAP. It appears that SAP is not a better accounting practice than GAAP for the purpose of early prediction of insolvency.

Stability measures from MVA data produce approximately the same results as stability measures computed from SAP data. For most variables SAP data produce slightly better predictive power than MVA data, but the differences are not statistically significant. Two explanations can be advanced for these results. First, recording bonds at market values causes fluctuations in the value of bonds' portfolio as market conditions change over time. The volatility of interest rates affects the prices of bonds. Both the solvent and the insolvent insurers are affected approximately the same by these fluctuations. Secondly, municipal and local governments' bonds often do not have market values; therefore, a significant portion of the bond portfolio is recorded at amortized value when the MVA is applied.\(^8\) Thus, the differences between the value of bonds when recorded at MVA, and when recorded at SAP are smaller than it would be expected, and both groups of insurers are affected approximately the same by the recorded adjustments.

The modified SAP results are similar to results furnished by SAP data. The adjustments for the modified SAP are too small to affect the stability of financial statements over time. Stability measures computed from SAP are similar to stability measures computed from the modified SAP, and both differ from the stability measures computed from GAAP data one year prior to insolvency. The results

\(^8\) For a comprehensive discussion see Chapter VII.
also indicate that research employing modified SAP as an approximation to GAAP may be misleading (e.g., Kross [97], Bachman [19]).

**Summary and Concluding Remarks**

Stability measures computed from SAP are found to be very similar to stability measures computed from the modified SAP and the MVA one and three years prior to insolvency. Stability measures computed from SAP are shown to be consistently better than stability measures computed from GAAP, for prediction of insolvency one year prior to the event. However, stability measures computed from SAP are not found to be more accurate than stability measures computed from GAAP in predicting insolvencies three years prior to insolvency. Thus, the null hypothesis that SAP furnishes equal data as GAAP furnishes for computing stability measures (for prediction of insolvency) cannot be rejected for three years prior to this event.

In general, the study cannot conclude that one accounting practice is better than other accounting practices for P-L insurers, rather than providing empirical evidence on the usefulness of these practices for predicting insolvencies. GAAP financial statements and MVA financial statements may be very important and useful for other purposes not examined in this research.
CHAPTER X
SUMMARY AND CONCLUSIONS

Review

This study is designed to develop new statistical methods for predicting of insolvencies among P-L insurers. The failure of existing methods to predict insolvencies among P-L insurers is reexamined empirically. Previous studies concentrated on examining existing methods (e.g., the NAIC-IRIS tests or the Best's ratings) or utilized financial ratios for insolvency prediction. Those studies that examined early prediction had results that fell short of expectations.

This research applies new stability measures to predict insolvencies among insurers. Methods developed in the study allow earlier predictions of insolvency than do methods currently in use. The stability measures are developed and tested empirically. The results are found to be superior both to existing methods and to direct analyses of financial ratios.

In most other industries the question of insolvency prediction focuses on methods. In the insurance industry prediction of insolvency is also concerned with measuring and recording the data. Regulators prefer the SAP as an accounting practice for measuring and monitoring insolvencies. This study provides empirical evidence on the validity of this preference by determining which accounting practice supplies the best data for predicting of insolvencies. Four different
accounting procedures are compared, their effects on the predictive power of the stability measures are determined.

The study opens with a discussion and a survey of major theories and models for identification of insolvency. The basic assumptions upon which the research is undertaken are based upon accounting and finance theory and applications. Models for identifying insolvencies, criteria for determining when they exist, and definitions of insolvencies are analyzed, but methods discussed in the survey are not developed to a point where they have widespread practical implications. The insolvency record and factors that may lead to insolvency are discussed and analyzed. A comprehensive literature review on general business failure prediction and prediction of insolvencies among P-L insurers is also presented.

**Development of New Statistical Methods for Prediction of Insolvency**

Five groups of univariate variables are developed and tested in this research. The stability of components on the balance sheet are measured by three variables (1) the decomposition measures (DM) that have already been examined by previous research, but only on industrial firms; (2) the new decomposition measures (NDM) which are developed in this study; (3) the square-proportion (SP) which is also developed in the study, and is a simpler model than the other two.

The stability of financial ratios over time is also examined. The discussion concentrates on the stability of the profitability ratios over time. First, the average return and the temporal standard deviation of each ratio are computed. Then the average return
is divided by the temporal standard deviation to determine the COS for each insurer. The covariabilities of the profitability ratios of each insurer with the overall profitability of the industry are examined over time. This association is termed as the quasi-systematic risk $\beta$, or the accounting beta. It is expected that insolvent insurers may have larger betas, and therefore beta may be used to discriminate between solvent and insolvent insurers. Unfortunately, there are measurement and other problems that may hamper the validity of the beta analysis.

Multivariate models that employ the five groups of univariate stability measures are discussed in the research. The MDA, a fairly robust procedure, is compared with the 0-1 linear regression model. Alternative probabilistic models are also presented.

In summary, the new univariate and multivariate stability measures are tested in the study and compared with one another to see if significant differences in the classifications power for insolvency prediction can be found between the variables.

**Empirical Results and Conclusions**

The variables and methods developed in this study have accomplished what was originally planned. The results indicate strong predictive ability for the stability measures. Existing methods fail to accomplish the task of early prediction; the stability measures are found significantly better than the NAIC-IRIS, Best's ratings, and financial ratios, for current and early prediction of insolvency.

The stability measures are also compared with one another to see if significant differences in predictive power can be found among them.
The COS of the profitability ratios are judged significantly stronger than the DM, the NDM, and the SP for current prediction. The COS also demonstrate better results for early predictions, but the differences in predictive ability are not statistically significant. The quasi-systematic risk (accounting beta) is weaker than all other methods for prediction of insolvencies. Measurement problems may hamper and distort the results.

When the COS of the underwriting profitability ratios and the COS of the profitability ratios with investment earnings and gains are compared with one another, the latter are found to be significantly better for current and early prediction. This is an indication of the importance of the investment results in the P-L insurance industry. The role of investment earnings and gains is essential for predicting insolvencies. Underwriting profits alone are not strong enough indicators for possible future deliquency.

No clearly superior multivariate model emerges from the analysis. The efficient models employ three variables (COS, NDL, and DL), or two variables (COS, and NDL). Both models classify correctly 99 percent of the insurers one year prior to insolvency and about 90 percent of the insurers three years before insolvency. The most effective model (with five variables) classifies correctly about 92 percent of the insurers three years prior to insolvency.

Both the MDA and the 0-1 regression models are shown to be accurate and similar for prediction of insolvency. Employing holdout samples demonstrates that the parameters (coefficients) are stationary over observations and stable over time. The evidence suggests
that the multivariate models do a better job than the univariate models, especially for early prediction.

Finally, the results indicate that the new methods should be used by regulators in order to predict and monitor insolvency. The study does not argue for abolishing the existing method (NAIC-IRIS), but the new models may gradually substitute for and/or supplement existing techniques.

The Effect of Different Accounting Practices

The second research question centers around whether or not different accounting practices affect the predictive ability of the stability measures employed by this research. Four different accounting practices are examined: (1) SAP, (2) Modified SAP, (3) GAAP, and (4) MVA. Modifications and adjustments required for the four different accounting practices are presented, discussed, and computed. Based on the four different accounting practices, four different sets of stability measures are employed for prediction of insolvency. Empirical evidence on the relative merits of these accounting practices for prediction of insolvency is presented.

The hypothesis that different accounting practices provide similar prediction results cannot be rejected for early prediction. This discovery may lead to the conclusion that SAP and GAAP furnish similar data for the purpose of early prediction. Stability measures computed from SAP data are not more powerful and accurate than stability measures computed from GAAP data three years prior to insolvency. The null hypotheses are rejected, however, for current prediction one year
prior to insolvency. Stability measures computed from SAP data perform significantly better than stability measures based on GAAP data one year prior to insolvency. Thus, it seems that SAP furnishes better data than GAAP does for current prediction of insolvencies.

No recommendation to abolish the SAP can be advocated based on this research because the results are nonconclusive. The NAIC-IRIS tests computed from SAP data fail to perform for early predictions. Other accounting practices may or may not improve the results. However, complete data for recomputing these tests are not available. This subject is one of the topics discussed in the following section.

Directions for Future Research

Several issues are worthy of future investigations as a result of this study. Each distinct topic that warrants more intense study is numbered.

1. The analysis limits itself to several groups of stability measures. Other stability measures may also be useful. The COS are measured only on profitability ratios. The stability measures' performance may be improved through the use of more extensive examinations of COS of other financial ratios (e.g., the surplus ratio, or the policyholders' surplus ratio). Decomposition measures are employed only on the balance sheets of P-L insurers. DM analyses of other parts of the financial statements may be useful.

The quasi-systematic risk method should be reexamined with sample averages rather than industry means as independent variables. In this way, the effect of large and stable insurers would be excluded.
COS of the 11 tests that are used by the NAIC-IRIS may be very useful. Perhaps they may substitute for the current acceptable/exceptional ranges for each test as criteria for a flagged test.

2. Financial ratios may also be included in the multivariate analyses. Those ratios that are pointed out in previous research (e.g., [12], [48], [130], [156]) may be employed. Integrating other financial ratios may increase the predictive ability of the multivariate models, but the efficiency of the models would be reduced because more variables are included in the analyses.

3. The analysis of the coefficient of stability as a classification procedure may also be improved through the extension and development of new classification models (e.g., a linear classification rule based on the mean and standard deviation of the modified profitability ratio may apply: \( \text{MEMPR} = \alpha + \beta \text{SDMPR} \)). This statement is also concerned with all other new stability measures developed in the study.

4. Future multivariate analyses may employ probability models for prediction of insolvency. Logit and/or probit models may be used, and the results should be compared with the results of the MDA and 0-1 regression analyses.

5. The question whether or not SAP is the best accounting practice for early monitoring of delinquent insurers and early prediction of failures among P-L insurers should be investigated further. Additional study is necessary before a final recommendation can be applied. Because this research does not examine the NAIC-IRIS tests under the four accounting practices due to unavailability of data, more studies
are necessary. The tests are based on SAP data, and have a very little discriminatory power for early prediction of insolvencies. It is worthy to examine the impact of other accounting practices on these tests. There is no doubt, however, that stability measures should be introduced as methods for predicting insolvencies.

6. This study limits itself to the P-L insurance industry. A final suggestion is to use the stability measures in other industries. The methods developed here must not be restricted to the P-L insurance industry, and can be extended to life insurance companies, financial institutions, and industrial firms. However, different ratios, components of the balance sheets, and profit measures may need to be applied in other industries.
APPENDIX A

STATUTORY ACCOUNTING PROCEDURES (SAP) VS. GENERALLY ACCEPTED ACCOUNTING PRINCIPLES (GAAP)

More than a hundred years has passed since the first uniform statement blank was drafted for fire insurance companies by a special committee of the National Convention of Insurance Commissioners. Almost thirty years ago a new fire and casualty annual statement blank was adopted by The National Association of Insurance Commissioners (NAIC). With a few additional schedules this annual statement is still in use for property and liability (P-L) insurers, and it is uniform across all P-L companies.

The main differences between GAAP and the statutory accounting are considered in this appendix. The focus is on: 1) Matching revenues and expenses. 2) Nondadmitted assets. 3) Annual statement blank. 4) Asset evaluation, including liquidation value of assets and investment regulation. 5) The reserve accounts— including surplus and voluntary reserves, unearned premium reserves, and loss reserves.

The following issues are not discussed in this appendix:

1) Classification of the financial statement as well as the large number of required schedules.

2) Discussion on underwriting income, investment income as well as realized and unrealized investment and other capital gains (losses).
3) Treatment of dividends to policyholders and stockholders.
4) Tax allocation and recording.
5) Consolidated financial statements.
6) Statement of changes in financial position.

These issues are not considered in the appendix because either study does not emphasize all issues and problems in P-L insurance accounting, or the issues are considered in Chapter VII (e.g., #2). In the first stage of the empirical study, the figures on the financial statements are taken directly from insurance company reports. However, in Chapters VII and IX adjustments for GAAP as well as for other procedures are considered for the purposes of the research. Figures are adjusted to GAAP, NVA, and modified SAP in order to compare the predictive ability of the models under SAP vs the predictability power of the models under GAAP and the other procedures. The purpose of this appendix is to introduce more insight into SAP (the accounting procedure used in the P-L industry) and to compare it with GAAP.

**Essential Considerations in Statutory Accounting**

**Why Statutory Accounting Differs from GAAP**

The accounting techniques used by property and liability insurers differ from those which are used by most other industries. Most industries use accounting techniques under the generally accepted accounting principles (GAAP).

J.S. Pieringer [129, pp. 926-938] argues that P-L accounting violates many of the accounting principles used by other business, but
there is a reason for each variation. Insurance, although a private enterprise, is vested with a public interest, and is subject to strict regulation that determines the applicable accounting principles and procedures. The primary concern is maintenance of solvency of insurers and the reporting requirements are designed to present the financial position of each company strictly on this basis, and not on the basis of going concern. Pieringer considers three variations: 1) Nonadmission of assets; 2) No deferral expenses; and 3) Liquidation values for assets.

J.L. Henss [75, pp. 53-61] supports introducing GAAP because it would enable sophisticated users to determine the realistic financial position of the company.

In summary, the main reasons for using statutory accounting in P-L insurance are:

1) Statutory accounting is concerned with maintenance of solvency. The primary objective of statutory accounting is to guarantee the solvency of the company, while GAAP are based on the going concern concept.

2) In order to protect the policyholders' claims against the company's assets, statutory accounting is based on liquidation. A conservative approach is traditionally taken.

3) The statutory accounting procedures prescribed by the regulatory authorities are "time tested and provide sound, reliable, comparable, and uniform financial and operating information. The principles carefully developed over a period of one hundred years by
qualified individuals—experienced and knowledgeable in the industry, they may be conservative because of the nature of the business...^1

4) The insurance industry is generally more concerned about all phases of its operation. The regulatory bureaus traditionally have used the financial statements including their schedules for regulation. Statutory accounting may be considered more appropriate for the regulation purpose.

5) The individual states' commissioners fulfill their duties under certain constraints. In 1978, only 4.2 percent of the 2.9 billion dollars premium taxes and fees paid by the insurance companies in the U.S. were spent for operation of the departments. Consequently many departments are understaffed and the statutory accounting serves as tools for easier and quicker examination of the companies.

6) The evaluation of financial statements for a policyholder differs from evaluation from a stockholder position. The stockholder position is more concerned with GAAP-based reports.

Matching Revenues and Expenses

One primary objective of GAAP is to match revenues and related expired costs. Costs incurred during the period are examined to determine their relationship to the revenues. Costs which are of the same period are charged against the revenue in order to determine the profit (or loss) of the company. Costs that cannot be identified with the

^1Statement by fire and casualty insurance industry (#16/38; p. 56).
the period are accrued as prepaid expenses or deferred charges and considered valuable assets.

Under statutory P-L accounting: commissions, underwriting acquisition and related general expenses, premium taxes, and fees must all be treated as current expenses.

The purpose of charging the deferred costs immediately is to reduce assets (thus, excluding accounts as prepaid expenses), therefore maintaining smaller policyholders' surplus (equity). The conceptual rationale is that future is uncertain and deferred costs may not provide future benefits. A short illustration might explain the difference.

Assume a one-year policy is written on Dec. 1, 1980 with no loss claims during the policy term and afterwards. Acquisition expenses (including commissions) are $72.

<table>
<thead>
<tr>
<th>Date</th>
<th>Statutory accounting</th>
<th>GAAP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>premium earned</td>
<td>premium earned</td>
</tr>
<tr>
<td></td>
<td>incurred (loss)</td>
<td>incurred (loss)</td>
</tr>
<tr>
<td>Dec. 1, 1980</td>
<td>240</td>
<td>240</td>
</tr>
<tr>
<td>Dec. 31, 1980</td>
<td>72 ($72)</td>
<td>20 6</td>
</tr>
<tr>
<td>Jan. 1981</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>Feb.</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>Nov.</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>Total</td>
<td>$240</td>
<td>$240</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Date</th>
<th>Premium expenses gain (loss)</th>
<th>GAAP premium expenses gain (loss)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>earned</td>
<td>incurred</td>
</tr>
<tr>
<td>Dec. 1, 1980</td>
<td>240</td>
<td>240</td>
</tr>
<tr>
<td>Dec. 31, 1980</td>
<td>72 ($72)</td>
<td>20 6</td>
</tr>
<tr>
<td>Jan. 1981</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>Feb.</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>Nov.</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>Total</td>
<td>$240</td>
<td>$240</td>
</tr>
</tbody>
</table>
On Dec. 31, 1980 the statutory accounting would show $52 loss compared with $14 profit under the GAAP accounting.

Nonadmitted Assets

Statutory regulation prohibits insurance companies from including many assets such as equipment and furniture, agents' balances over three months due (account receivable), etc. These assets are considered admitted by most other businesses and carried at cost less accumulated depreciation (for fixed assets) under GAAP. These assets are charged directly as costs against surplus (equity) under statutory accounting. Premiums over 90 days due are considered nonadmitted and excluded from assets under statutory accounting no matter who owes the premiums. Using GAAP might increase the total stockholders' surplus (equity) by substantial amounts.

The entry for adjustment of nonadmitted assets under GAAP might illustrate as the following:

<table>
<thead>
<tr>
<th>Debit</th>
<th>Credit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agents' balances over 90 days due</td>
<td>$200,000</td>
</tr>
<tr>
<td>Advances to contractors and others</td>
<td>50,000</td>
</tr>
<tr>
<td>Bills receivable</td>
<td>20,000</td>
</tr>
<tr>
<td>Other receivable</td>
<td>30,000</td>
</tr>
<tr>
<td>Furniture and equipment</td>
<td>400,000</td>
</tr>
<tr>
<td>Stockholders equity (surplus)</td>
<td>$700,000</td>
</tr>
</tbody>
</table>

Nonadmitted assets of a company not recognized by the insurance commissioners may include the following:

---

2G.H. Huff [82, p. 26].
1. Agents' balances or uncollected premiums over three months due.

2. Equipment, furniture and supplies (other than electronic computers).


4. The company's stock held as treasury stock.

5. Loans on the company's stock.

6. Deposits in suspended banks, less estimated amount recoverable.

7. Bills receivable, past due, taken for premiums.

8. Excess of bills receivable, not past due, taken for risks over the unearned premiums.

9. Bills receivable, not taken for premiums.

10. Loans on personal security, endorsed or not.

11. Advances to contractors.

12. Advances for travel and expenses.

13. Leasehold improvements.

14. Other assets that are not admitted and which should be itemized.

**Asset Valuation**

**Liquidation Value of Assets and Investment Regulation**

Insurance companies must invest their funds only on various types of securities and other admitted assets. States post limitations on the ways funds can be invested. The laws vary widely from state to state. They are concerned with both qualitative and quantitative...
restrictions and deal with such matters as: 1) Authorized types of investments (media); 2) Portfolio distribution among various types of approved investment (media); 3) The amount of security required for an authorized type of media to qualify as an acceptable investment; 4) The percentage of the outstanding common stock of a corporation which may be held; 5) The percentage assets that may be invested in the securities of a single corporation, in order to achieve diversification of investments. Several states require P-L insurers to restrict the investment of assets equal to their minimum required capital and surplus. Other states restrict investments equal to the required unearned premium and loss reserves. The main reasons for all these restrictions are to protect the interests of policyholders in the insurer solvency, and to monitor the liquidity of the investments. Other reasons are to discourage concentration of economic power, and to encourage the commitment of funds for socially desirable purposes. 3

The investments are usually valued at the amount for which they could be liquidated. Real estate items might be carried at appraisal value but often carried at book value. Bonds secured and not in default are valued by the process of amortization of premium or discount, depending on whether they were purchased at a price above or below par; their value gradually approaches par as they age to maturity. Investment in stocks are carried at market value, as if they might immediately be liquidated. 4

3[116, p. 109].

4Bonds are about 60% of the insurer's assets, while stocks are about 23% (compared with about 40% in the late 60s).
Asset valuation; Major Considerations

The main subjects to consider while analyzing the assets of P-L companies are: 1) Liquidity, 2) Distribution or diversification, 3) The quality of the assets. It is necessary to ascertain that assets are sound for reasons mentioned in the previous section.

1) Liquidity means ease with which assets can be converted to cash. The objective is to guarantee the ability of an insurer to liquidate its assets in order to meet the policyholder and/or stockholders claims. The flexibility of this procedure is very important. The higher the liquidity the more the security that the insurer would be able to meet claims of policyholders.

2) The distribution or diversification of assets. The larger the overall diversification the less the risk.

3) The quality of the assets should be examined in order to be sure that the portfolio does not include speculative assets. The emphasis is on quality as well as marketability.

G.W. Huff [82, pp. 15-27] classifies the assets to four classes: 1) Ledger assets are those assets recorded on the book of the insurer. 2) Nonledger assets are not recorded on the books, although taken into account in the balance sheet (e.g., excess of market value over cost of stocks owned). 3) Admitted assets are recognized by the state insurance department. 4) Nonadmitted assets are not recognized by the state insurance department.

Assets are reported on the balance sheet by the following types:

1. Bonds—Usually valued on amortized basis listings in special Schedule D. Bonds are the major investment of insurance companies.
The quality of a bond portfolio should be considered; the portfolio should be without speculative bonds. The goal is to assure maximum security without default risk, and maximizing expected rate of return for a given risk.

2. Common and preferred stocks—valued on market values listed in Schedule D. Relatively small amount is invested in preferred stocks. The objective is to gain maximum rate of return for a given risk. Diversification usually reduces the risk. The statutory requirement usually restricts the investment in a single corporation. Existence of subsidiary companies usually reduces the liquidity of the parent company. Investments in subsidiary companies have increased in the last 20 years. The analyst might use consolidated balance sheets. However, for statutory purposes each separate company should file also its own report.

3. Real Estate—The total value of offices and other admitted property, usually valued on book value at cost plus capital improvement less depreciation, sometimes maintained at appraisal value, and listed in Schedule A. Real estate was less than 2% of total assets in most P-L companies in 1980. For purpose of analyzing and evaluating the insurer they might be appraised at market value.

4. Mortgage loans and collateral loans—listed in Schedules B and C respectively were less than 1/2 percent of total assets in P-L companies.

5. Cash and bank deposits—listed individually in Schedule N., about 1.7% of total assets in 1980.
6. Miscellaneous assets—includes premium balances, accrued interest and association accounts listed separately on the balance sheet, were less than 10 percent of total assets. The main asset was premium balances, about 7.9 percent of total assets and about 15 percent of annual written premiums in 1980. These uncollected premiums represent accounts receivable from agents and policyholders less commission.

7. Other assets—including funds held or deposited with ceding reinsurance, bills and notes receivable, etc., about 3 percent of total assets.

Liquidation, distribution and diversification, and the quality of assets of any company should be compared to its liabilities. H.G. Krogh [96, p. 914] has considered that the nature and use of P-L insurance company assets are not unduly difficult to understand. Liabilities are another matter, however, and require considerable more attention.

**Evaluating the Liabilities**

The liabilities of P-L insurance company may be categorized into four major groups: 1) primary unpaid losses; 2) unpaid expenses; 3) deferred income, and 4) funds withheld for the accounts of others.\(^5\)

The surplus varies from the owner's equity accounts found in other business organizations. In a stock insurance company the capital stock, contributed capital, and retained earnings are separated accounts regarded as capital and policyholders surplus. The policyholders' surplus of a mutual or reciprocal insurers represent

\(^5\) [75, p. 3].
debt financing when the insurer is established, retained earnings are developed through operations.

The Reserve Accounts: Definitions and General Considerations

A reserve was defined in accounting as a part of surplus set aside for a special purpose. Reserves in accounting have a few meanings: 1) An offset to an asset. 2) An estimated liability of indefinite or uncertain amount. 3) A restriction of dividend—paying power which has a subdivision in the retained income.

Reserves in P-L insurance are liabilities required by law. These liabilities must hold because not all premiums have been immediately earned, and losses immediately paid. The insurer must hold sufficient funds (assets) to offset these reserves. The three main types of reserves are: 1) Unearned Premium Reserve (U.P.R). 2) Loss Reserves. 3) Voluntary Reserves.

Not all premiums are immediately earned, part of them must maintain as liabilities to cover future claims and expenses. Those liabilities are called reserves. Ruth Salzmann [134; p. 29] prefers to use the term "estimated liabilities," since the term reserve has a variety of meanings causing considerable confusion.

The main subjects to consider while analyzing the liabilities of P-L companies are: 1) Solvency and strength; 2) Adequate reserves, and 3) The contingency nature of the reserves.

1. Solvency and strength—Often the higher the surplus as to total liabilities the more the solvency and strength of a company.

2. Adequate Reserves—The reserves should not be too high but not too low. The loss reserves should be sufficient to absorb all
claims, and UPR reserves should be adequate. If the reserves are too high, surplus is understated and reported underwriting gains are less favorable than actual results. If the reserves are too low, surplus is overstated and reported underwriting results are more favorable than actual.

3. The contingency nature of the reserves is important. The reserves are based on estimations and evaluations. The loss and loss adjustment expense liabilities are estimated by the use of statistical and actuarial techniques. There is much uncertainty and unknown about future factors such as the climate in the courts, the amount of recovery, the economic conditions, inflation, and so on.

Surplus and Voluntary Reserves

Policyholders' surplus in a stock P-L company includes capital contributed and retained earnings. Total surplus includes capital paid in, net surplus, voluntary reserves, and treasury stock (against surplus). The surplus in mutual companies includes guarantee funds, net surplus and voluntary reserves. As mentioned at the beginning of this section, the guarantee funds represent debt financing issued when the insurer was established although it is treated as capital stock. The net surplus in both types of companies is the retained earnings developed through operations. These are the net gains developed from underwriting, investment, and other operations. Additional sources of retained earnings are: 1) Net capital gains realized from sale or maturity of investments; 2) Unrealized gain (or losses) derived from difference between cost and market values of stocks; 3) Changes in
loss reserves over the actual performance, etc.

For stock companies, most states require that all stock be issued at a premium as to create paid-in balances as well as a capital stock balance, the effect is to buttress the assets and equity of the company before it begins underwriting operations.6

In addition to the statutory required reserves, the Reserves for taxes, dividends, and contingencies are voluntary reserves that may be a subdivision of the surplus.

The Unearned Premium Reserve (UPR)

The UPR is required by the laws of all states, and must be equal to the unearned portion of the gross premium of all the policies of the company outstanding at the time when financial statements are prepared. The income from premiums is reported pro rata over the policy term. The insurance company must provide a liability for deferred income in the amount which would have to be refunded if all of the policies in force were cancelled by the insurer on the balance sheet date. The insurer must maintain a UPR for each policy according to the fraction of the premium on policy term that has not expired. For each policy the UPR reflects the difference between the net written premium and the accumulated earned premium.

The reason for this legal requirement is that an insurer collects the premium or the right to the whole premium in advance, while the claims might be paid during the policy term, which may be a long period

6 H.C. Krogh [96, pp. 918-919].
The purpose of the UPR is to insure the financial solvency, stability and solidity of the insurer. "The UPR is based on the theory that if the premium is sufficient to pay losses and expenses and provide a margin of profit over the term of the policy, the pro rata part of the premium representing the unexpired term, should be adequate to pay the losses and expenses which will be incurred during the unexpired term."  

If the premiums written are stable the UPR will remain constant. If the insurer's premium volume is expanding, the UPR will increase, and if the premium volume is declining the UPR will decrease.

Evaluating the Loss Reserves

The loss reserves are the estimated liabilities for claims and for loss adjustment expenses. Because the amounts of claims are not known, these liabilities are called reserves. If the exact liabilities' amount were known, it probably would be called: accrued claims payable [64, p. 618].

The loss reserves in P-L insurance includes the following amounts:

1) Liability for claims reported and adjusted, but have not yet been paid. 2) Liabilities for claims filed and estimated but have not yet been adjusted. 3) Estimated liabilities of claims incurred but have not yet been reported. Each kind of these liabilities includes: a) The claims themselves—or at least the estimated amounts; and b) The estimated amounts of the expenses of adjusting these claims [116, p. 105].

---

7 J.S. Pieringer [129, p. 930].
When a claim is closed, it is excluded from the reserves and recorded as an incurred loss. The incurred losses for the period are equal to the paid losses for the period plus loss reserves at the end of the period minus the loss of reserves at the beginning of the period.

Estimation of the loss reserves that are reported but not yet adjusted is difficult for the following reasons: a) The reported claims might be doubtful claims; b) Losses require investigations and appraisals; c) They might be unusual claims which will be settled after a long period of time; and d) Claims in a few lines might need a special examination, like a medical examination in personal injury and workers' compensation cases.

Losses incurred but not yet reported are very difficult to estimate. Usually, they are determined by formulas based on data and statistics from prior periods, and modified trend factors. The loss-adjusted expenses for the three kinds of loss reserves are often estimated by formulas and ratios.
A proof that Modified Statutory Underwriting Profits are equal to GAAP underwriting profits, MUP = GUP, if underwriting expenses and earned premiums both are fixed proportions of premiums written.

Assume that: (1) The premiums earned are a fixed proportion (K) of the premiums written, PE\textsubscript{t} = (1-K)PW\textsubscript{t-1} + KPW\textsubscript{t}. K = the proportion earned at the current year, and 1-K = the proportion deferred for the next year. (2) The underwriting expenses are a fixed proportion (C) of the premiums written, UE\textsubscript{t} = CPW\textsubscript{t}. (3) Thus the prepaid underwriting expenses are: PUE\textsubscript{t} = (1-K)UE\textsubscript{t} = (1-K)CPW\textsubscript{t}. (4) The constants are: 0 ≤ K ≤ 1, and 0 ≤ C ≤ 1.

For simplification we assume that all policies are written for one year, and K proportions of the policies are earned in the current year.

The following table summarized the assumptions

<table>
<thead>
<tr>
<th>UPR beg.</th>
<th>UPR end</th>
<th>ΔUPR</th>
<th>PW</th>
<th>PE</th>
<th>UE\textsubscript{t}</th>
<th>PUE\textsubscript{t}</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1-K)PW\textsubscript{t-1}</td>
<td>(1-K)PW\textsubscript{t}</td>
<td>(1-K)(PW\textsubscript{t} - PW\textsubscript{t-1})</td>
<td>PW\textsubscript{t}</td>
<td>(1-K)PW\textsubscript{t-1} + KPW\textsubscript{t}</td>
<td>CPW\textsubscript{t}</td>
<td>(1-K)CPW\textsubscript{t}</td>
</tr>
</tbody>
</table>

The modified profits under GAAP are:

\[ GUP\textsubscript{t} = PE\textsubscript{t} - L\textsubscript{t} - UE\textsubscript{t} + PUE\textsubscript{t} - PUE\textsubscript{t-1} = (1-K)PW\textsubscript{t-1} + KPW\textsubscript{t} - L\textsubscript{t} - CPW\textsubscript{t} + (1-K)CPW\textsubscript{t-1} \]

\[ = PW\textsubscript{t-1}[(1-K) - (1-K)C] + PW\textsubscript{t}[K-C+(1-K)C] - L\textsubscript{t} \]

\[ = PW\textsubscript{t-1}(1-K-C+CK) + PW\textsubscript{t}(K-KC) - L\textsubscript{t} \]

Using equations (7-2), (7-6) and (7-9) the modified underwriting profits (modified SAP, MUP) are:
The last term on the right hand side of the equation can be further developed as follows:

\[
\frac{[(1-K)PW_{t-1}+KPW_t](CPW)}{PW_t} = \frac{(1-K)CPW_{t-1}}{PW_{t-1}} + \frac{KPW_t}{PW_t}
\]

Thus

\[
MPU_t = (1-K)PW_{t-1} + KPW_t - (1-K)CPW_{t-1} - KCPW_t - L_t
\]

\[
= PW_{t-1}[(1-K)-(1-K)C] + PW_t(K-KC) - L_t
\]

\[
= PW_{t-1}(1-C+KC) + PW_t(K-KC) - L_t = GUP_t
\]

Q.E.D.
APPENDIX B

THE DECOMPOSITION MEASURES MODELS' PROPERTIES AND RELATIONSHIP TO INFORMATION THEORY

Properties of the DM

The decomposition measures belong to the family of statistical dispersion measures as the variance and the standard deviation. Garner and McGill [62] analyzed the relationship between the decomposition measures and the analysis of variance (ANOVA). Lev [104, p. 58] argues that DM seem to be better for analysis of financial statements than other measures of dispersion (including ANOVA) which assume that the random variation is normal. He underlines the following reasons:

1. The DM are distributed-free and less restricted than other tools of variance analysis.
2. The DM can be applied to nominal variables.
3. The DM are scaled free, changes of the value of the variable alone do not affect the measures.

There are four main mathematical properties of the decomposition measures:

1. When there is no change in the relative fraction of items, the measures will be at their minimum, and take the value zero (e.g., if \( P_i = Q_i \) for all \( i \), or \( P_{gi} = Q_{gi} \) for all \( gi \)).
2. The larger the changes in the consecutive relative fractions (the larger the difference between \( Q_i \) and \( P_i \)), the larger the value of the DM.
3. Lev [102, p. 71] proves that the expected value of new information (as measured in formula, 5-3) is always nonnegative. The same proof may apply to equation 5-4; the DM are always nonnegative.

4. The DM obey the mathematical property of additivity. Lev [104, p. 54] points out that the usefulness of this property enables the disaggregation which leads to equation 5-4, and the including fact that Dbs is the arithmetic average of Dl and Da. The weighted arithmetic logarithmic function of Qi log \( \frac{Q_i}{P_i} \) is the main reason for this property.

Apart from the last mathematical property there is also an important practical implication for the use of this weighted logarithmic function which might not be considered by Lev. There are several items which are small compared with all other items. An absolute increase in dollars term may increase the influence of this component, proportionally to its small fraction.\(^1\) The weighted logarithmic function enables to weight each change in a component (i) relative to its importance (fraction) in the total assets and/or liabilities.

\(^1\)An item i may be 1 percent of the total assets \( P_i = .01 \), this item might triple over the accounting period, then \( Q_i = .03 \). Without using the weighted function this change may overwhelm all other changes, even in more important items. If formula (5-3) was \( \Sigma \log \frac{Q_i}{P_i} \) then the previous change would be \( \log_e \frac{.03}{.01} = \log_e 3 \approx 1 \) nits; while a change of another important component from .25 to .50 would be only \( \log_e \frac{.50}{.25} = \log_e 2 \approx .69 \) nits.
Several other properties of the DM are: (1) They may be designed to examine the stability of a firm's (e.g., an insurer) liabilities, assets, or both over time. (2) The DM may apply to other parts of the financial statements and measure changes in income statements, and schedules in the context of P-L insurers. (3) The DM may be considered complements to financial ratios analysis. The financial ratios apply to specific items (e.g., net income over equity), whereas the DM focus on decomposition of financial statement; Lev [103, p. 120]. The DM indicate variation in financial statement over time while financial ratios are measured at a point of time over a single period.

The main disadvantages of the DM are: (1) The DM indicate distance rather than directions they are unable to distinguish whether a change is toward an optimal position. (2) DM focus on something that happened rather than what has been happened. (3) There is a need to further analysis of the components in order to examine the reasons for the change. Complementary accounting and management control techniques might be used; Lev [104].

Relationship to Information Theory

Theil [151; 152] and Lev [102] discuss the implication of information theory for financial statement analysis. The information content of a new modified message is explained. Assuming an event E with an original probability P of occurrence, when a nondefinite new message occurs the original probability P (0 < P < 1) is replaced by Q (0 < Q < 1). They defined the original information received as \( h(P) = -\log P \), and the revised information \( h(Q) \), as \( h(Q) = -\log (Q) \). The
information content of the nondefinite message is the difference between the two, as defined in equation (1):

\[ h(P) - h(Q) = -\log (P) + \log (Q) = \log \frac{Q}{P} \]  

(1)

In the special case where \(Q = 1\), \(\log Q/P = -\log P\); and when \(Q = P\), \(\log Q/P = \log 1 = 0\), no additional information content is received by the definite message.

Assume that there are \(n\) mutually exclusive events \(E_1, \ldots, E_n\) each one with a relevant probability \(P_1, \ldots, P_n\);

\[ \sum_{i=1}^{n} P_i = 1. \]

When a new nondefinite message arrived the probabilities are transformed to \(Q_1, \ldots, Q_n\). For a new definite message the information content is \(\log \frac{Q_1}{P_1}\). However, the probability that event \(E_i\) will occur and also the probability that \(\log \frac{P_i}{Q_i}\) is the information received, are both \(Q_i\). Therefore "the expected information content of a new non-definite message is, \(I\),

\[ I = Q_1 \log \frac{Q_1}{P_1} + \ldots + Q_n \log \frac{Q_n}{P_n} = \sum_{i=1}^{n} Q_i \log \frac{Q_i}{P_i} \]

(2)

The expected information is always nonnegative, it is zero if \(P_i = Q_i\) for all \(i\). As \(P_i \neq Q_i\) for some \(i\) the measure will be positive, and larger the discrepancies between the \(P_i's\) and the \(Q_i's\) the larger the measure" Lev [102].

For further development and possible application for evaluating conditional logit models, see Judge, Griffith, etc. [89, pp. 601-605].
Both Lev and Theil apply the expected information to the development of DM. Lev [102] interprets the use of the probabilistic presentation. Portions of items on the balance sheet are parallel to probability distribution. Both have the same two requirements: (1) the individual probabilities (portions) will be nonnegative, and (2) the probabilities (portions) will be sum to one.

While employing the new decomposition measures (NDM), the expected information content might be weakened. Equation 3 demonstrate the expected information content under the new development.

\[ NI = \sum_{i=1}^{n} Qi \left| \log \frac{Q_i}{P_i} \right| \]  

We may assume that information content of the message is modified. Thus equation (1) can be rewritten as follows:

\[ |h(P) - h(Q)| = |-\log(P) + \log(Q)| = \left| \log \frac{Q}{P} \right| \] (1a)

---

_3 Assuming the following Assets_

<table>
<thead>
<tr>
<th>i</th>
<th>Pi (proportion, or fraction)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Cash &amp; Securities 800 P1 = .80</td>
</tr>
<tr>
<td>2</td>
<td>Fixed Assets 200 P2 = .20</td>
</tr>
<tr>
<td></td>
<td>Total Assets $1000; \Sigma P_i = 1.00</td>
</tr>
</tbody>
</table>

The probabilistic interpretation would be that the proportion Pi is the probability that a dollar picked at random from the assets belonged to an asset i. For example, the probability that a dollar picked at random belongs to fixed assets is .20.
B-II  A Proof that the Square-Proportions, SP
is $0 \leq SP \leq 1$

The square proportions was defined in equation (5-6) as:

$$SP = \sum_{i=1}^{n} Qi (Qi-Pi)^2$$

(1) SP cannot be negative since for each proportion (component), i
are positive, $Pi > 0$, $Qi > 0$, and $(Qi-Pi)^2 > 0$ by definition.
Since both terms cannot be negative the sum of their multipli-
cations cannot also be negative. \(\therefore\) SP $\geq 0$
SP is zero only if $Qi = Pi$ for all i.

(2) SP $\leq 1$

It is given that $Qi \leq 1$ and $Pi \leq 1$
and also $\Sigma Qi = 1$ (as well as $\Sigma Pi = 1$)
proof: Since $(Qi-Pi)^2 \leq 1$,
therefore for all $i$ $Qi \geq Qi \cdot (Qi-Pi)^2$,
and since $\Sigma Qi = 1$
\(\therefore\) $\Sigma Qi (Qi-Pi)^2 \leq \Sigma Qi = 1$
APPENDIX C

ADDITIONAL EMPIRICAL RESULTS

This appendix presents additional empirical results, and introduces more insight to the interpretations. All these results are related to Chapter VIII.

Additional multivariate results based on MDA and LRM are presented in Table 37. Holdout validation results are summarized in Table 38. Additional classification results are demonstrated in Table 39, and the Lachenbruch procedure is employed. Finally, optimal cutoff points are compared with midpoints cutoff (between means, groups' centroids, and .50 for the 0-1 LRM), these results are summarized in Table 40.
TABLE 37

MDA and 0-1 LRM Additional Classification Results

MDA, one year prior

Model 6: \( Z = 0.1722 + 4.2633 \, DL_1 - 7.7258 \, NDL_1 + 16.3792 \, SPL_1 + 1.1361 \, COSMPR_1 \)

Eigenvalue: 2.5915, Wilks Lambda = 0.2784 \( \chi^2 = 144.48 \) (significant at .0001)

<table>
<thead>
<tr>
<th>Actual Group</th>
<th>Predicted Group Membership</th>
<th>Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solvent</td>
<td></td>
<td>Solvent</td>
</tr>
<tr>
<td></td>
<td></td>
<td>61</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1 (1.6%)</td>
</tr>
<tr>
<td>Insolvent</td>
<td></td>
<td>Insolvent</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>55</td>
</tr>
</tbody>
</table>

99.1% Correctly Classified

LRM, One Year Prior

Model 1: 6 variables, \( R^2 = 0.895 \) \( F = 133.46 \)

Percent correctly classified: 99.1%, type I errors = 0%, type II errors = 1.6%

LRM, Three Years Prior

Model 1: 6 variables, \( R^2 = 0.6416 \) \( F = 32.86 \)

Percent correctly classified: 92.3% type I error = 12.7%, type II error = 3.2%
### TABLE 38

**MDA: Holdout Validation Results**

<table>
<thead>
<tr>
<th>Model</th>
<th>Running-On Sample</th>
<th>Holdout Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Predicted Group Membership</td>
<td>Predicted Group Membership</td>
</tr>
<tr>
<td><strong>One Year (uniform)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I, IV</td>
<td>Solvent 26 0</td>
<td>Solvent 36 0</td>
</tr>
<tr>
<td>Insolvent 0 26</td>
<td>Insolvent 1(3.4%) 26</td>
<td></td>
</tr>
<tr>
<td>percent correctly classified: 100%</td>
<td>98.5%</td>
<td></td>
</tr>
<tr>
<td><strong>Three Years (uniform)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>Solvent 26 1(3.7%)</td>
<td>Solvent 34 1(2.9%)</td>
</tr>
<tr>
<td>Insolvent 2(9.5%) 19</td>
<td>Insolvent 8(23.5%) 26</td>
<td></td>
</tr>
<tr>
<td>percent correctly classified: 93.7%</td>
<td>86.7%</td>
<td></td>
</tr>
<tr>
<td>IV</td>
<td>Solvent 30 0</td>
<td>Solvent 32 0</td>
</tr>
<tr>
<td>Insolvent 5(27%) 13</td>
<td>Insolvent 11(29.7%) 26</td>
<td></td>
</tr>
<tr>
<td>percent correctly classified: 89.6%</td>
<td>84.8%</td>
<td></td>
</tr>
<tr>
<td><strong>One Year (Time)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>Solvent 25 0</td>
<td>Solvent 37 0</td>
</tr>
<tr>
<td>Insolvent 0 23</td>
<td>Insolvent 1(3.1%) 31</td>
<td></td>
</tr>
<tr>
<td>percent correctly classified: 100%</td>
<td>98.6%</td>
<td></td>
</tr>
<tr>
<td>IV</td>
<td>Solvent 25 0</td>
<td>Solvent 36 1(2.7%)</td>
</tr>
<tr>
<td>Insolvent 0 23</td>
<td>Insolvent 1(3.1%) 31</td>
<td></td>
</tr>
<tr>
<td>percent correctly classified: 100%</td>
<td>97.1%</td>
<td></td>
</tr>
<tr>
<td><strong>Three Years (Time)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>Solvent 25 0</td>
<td>Solvent 37 0</td>
</tr>
<tr>
<td>Insolvent 3(13%) 20</td>
<td>Insolvent 8(25%) 24</td>
<td></td>
</tr>
<tr>
<td>percent correctly classified: 93.7%</td>
<td>88.4%</td>
<td></td>
</tr>
<tr>
<td>IV</td>
<td>Solvent 24 1(4%)</td>
<td>Solvent 36 1(2.5%)</td>
</tr>
<tr>
<td>Insolvent 6(26%) 17</td>
<td>Insolvent 7(22%) 25</td>
<td></td>
</tr>
<tr>
<td>percent correctly classified: 85.4%</td>
<td>88.4%</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:**
1) Uniform - the sample is randomly split through the use of a uniform distribution, about 40 percent of the observations are included in the running-on sample.
2) Time - Observations from 1974-5 are used for the running-on sample, as follows:

<table>
<thead>
<tr>
<th></th>
<th>Running-on (1974-5)</th>
<th>Holdout (1976-81)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solvent</td>
<td>25</td>
<td>37</td>
<td>62</td>
</tr>
<tr>
<td>Insolvent</td>
<td>23</td>
<td>32</td>
<td>55</td>
</tr>
<tr>
<td></td>
<td>48</td>
<td>69</td>
<td>117</td>
</tr>
</tbody>
</table>

3) Cutoff point is based on midpoint between groups centroids.

TABLE 39

Classification Results for Models I and IV Linear Vs. Quadratic, and Lachenburch Procedure

<table>
<thead>
<tr>
<th>Model</th>
<th>Lach. Linear Model</th>
<th>Lach. Quadratic Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Percent Correctly Classified</td>
<td>Percent Correctly Classified</td>
</tr>
<tr>
<td></td>
<td>Overall Solvent Insolvent</td>
<td>Overall Solvent Insolvent</td>
</tr>
<tr>
<td>One Year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>98.3 98 98</td>
<td>98.3 98 98</td>
</tr>
<tr>
<td>IV</td>
<td>98.3 98 98</td>
<td>97.4 98 97</td>
</tr>
<tr>
<td>Three Years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>89.7 94 86</td>
<td>88.0 90 85</td>
</tr>
<tr>
<td>IV</td>
<td>88.9 92 85</td>
<td>86.3 89 84</td>
</tr>
</tbody>
</table>
TABLE 40

Classification Results: Optimal Cutoff Points
Vs. Midpoints Cutoff

<table>
<thead>
<tr>
<th>Variable/ Model</th>
<th>One Year</th>
<th>Three Years</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Optimal Cutoff Point</td>
<td>Midpoints Cutoff</td>
</tr>
<tr>
<td></td>
<td>Percent Correctly Classified</td>
<td>Percent Correctly Classified</td>
</tr>
<tr>
<td></td>
<td>Overall Solvent</td>
<td>Insolvent</td>
</tr>
<tr>
<td>COS</td>
<td>96.6</td>
<td>95</td>
</tr>
<tr>
<td>DL</td>
<td>89.7</td>
<td>89</td>
</tr>
<tr>
<td>NDL</td>
<td>91.5</td>
<td>90</td>
</tr>
<tr>
<td>SPL</td>
<td>89.7</td>
<td>89</td>
</tr>
<tr>
<td>I(MDA)</td>
<td>99.1</td>
<td>100</td>
</tr>
<tr>
<td>IV(MDA)</td>
<td>99.1</td>
<td>98</td>
</tr>
<tr>
<td>I(LRM)</td>
<td>99.1</td>
<td>98</td>
</tr>
<tr>
<td>IV(LRM)</td>
<td>99.1</td>
<td>100</td>
</tr>
</tbody>
</table>

Notes: 1) Optimal cutoff point minimizes the number of misclassifications.
2) Midpoint cutoff is the middle point between groups' means or centroids.
3) The midpoint for the 0-1 LRM is 0.50.
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