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THE PREDICTION OF SMALL BUSINESS INSTABILITY--LOAN NONCOMPLIANCE: A DISCRIMINANT ANALYSIS APPROACH

The Louisiana State University and Agricultural and Mechanical Col. PH.D. 1982

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THE PREDICTION OF SMALL BUSINESS INSTABILITY--LOAN NONCOMPLIANCE: A DISCRIMINANT ANALYSIS APPROACH

A Dissertation

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

in

The Department of Accounting

by
Charles Thomas Moores
B.S., University of Arkansas, 1977
M.S., Louisiana State University, 1978
December 1982

ACKNOWLEDGEMENTS

To acknowledge all those who made completion of the doctroral program and this dissertation possible is inconceivable. The faculty in the Department of Accounting provided an environment that was not only conducive to learning, but also required application of the knowledge acquired. My fellow graduate students provided encouragement as well as positive criticism.

My Dissertation Committee, Professors Trapnell, Hartman, Curatola, Hair and Willis, steered me through this project with patience and skill. They were always available with the necessary guidance when a question or problem arose. Jerry Trapnell, the chairman, was particularly adept at helping me bring everything together. He was always there when I needed the encouragement to continue.

Many thanks go to Carol Marr of Fidelity National Bank, without her ideas and help at the onset I would not have been able to acquire data for the research. Also, to the numerous banks that took the time to supply the data.

A special note of thanks to my parents. Throughout my life they have provided me with a consistent set of standards by which to lead my life. They have always been there when they were needed; providing encouragement, support, confidence, and most of all love. I hope that I can provide these for their grandchild as well as they provided them for me.

To my daughter, Christi, who has provided many hours of enjoyment and relief. She was always willing to provide a break when times were trying.

Finally, there is one person who made the last five years bearable. Her patience, encouragement, support and love were needed more than she knows. When I was weak, she was strong. To Becky, my wife and friend, many thanks.

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ABSTRACT

The purpose of this study was to determine if a small business' tendency towards loan noncompliance could be ascertained from the business' financial information. By developing linear discriminant models a firm's tendency towards loan noncompliance was accurately determined.

For the objectives of this study loan noncompliance was defined as the borrower not complying with the terms of the original loan agreement. Examples of loan noncompliance are: (1) alteration of the loan agreement to the disadvantage of the lending institution, (2) late payment, and missing an interest and/or principal payment.

Data for this research was obtained from Robert Morris Associates (RMA) member banks. The information received from each bank was their RMA Data Submission Forms. On each form the bank indicated whether the firm was, or was not, in compliance with their original loan agreement at the end of the firm's fiscal year. A total of 347 firms were received resulting in 51 matched pairs.

The discriminant models were developed using a stepwise procedure and the Lachenbruch-Mickey leaving-one-out (LM) validation technique. Additional validation was provided by employing a hold-out sample of complying firms. The model that was most effective at determining a firm's tendency towards non-compliance consisted of: (1) earnings before taxes to total liabilities, (2) cash to current liabilities, and (3) current liabilities to cash flow. The accuracy of

the model was 76.5 percent employing the LM validation technique and 62.1 percent based on the holdout sample of complying firms. This shows that a small business' tendency towards loan noncompliance can be effectively determined based on financial ratios. The inclusion of industry and economic data did not enhance the financial ratios ability to indicate the tendency towards noncompliance.

Improved specification of the model to include nonfinancial information is likely to be difficult. If qualitative information could be obtained (e.g., number of employees, education of owner, integrity of management, etc.) a better model could possibly be developed. The question of coefficient stability and variable relationship stability could be evaluated by employing inter-temporal testing.

CHAPTER I

INTRODUCTION

Small businesses have always had a strong influence on the American economy. During 1980 small businesses employed more persons and generated more revenues than large businesses. Dun and Bradstreet reported in the Census of American Business - 1980 that of the nearly 4.5 million firms reporting, 56.5 percent employed four or fewer persons and 88 percent had less than twenty employees. Of the more than 3.5 million firms reporting their sales, 15.4 percent had sales of less than $50,000 and 77.2 percent reported sales of less than $500,000 [23].

From 1955 through 1963, the small business' share of the Gross National Product (GNP) was a relatively stable 43 percent, however, by 1976 small business' share of the GNP had declined to 39 percent [76]. During this period business bankruptcies increased from 16,357 in 1967 to 35,201 in 1976 [76]. During 1980, more than 39,000 businesses filed for bankruptcy. Through July 1981 the bankruptcy rate among small businesses was averaging 313 per week, up from 220 per week for the same period in 1980 [30]. As the number of small business bankruptcies increased, their percentage contribution to the GNP was decreasing.

Creditors of a failed firm can be the hardest hit. When a business fails the creditors may receive only a fraction of what they are owed. Dun and Bradstreet reported 7,564 failures in 1979. These failed firms had current liabilities exceeding $2.6 billion, which means the average loss was $353,000 [31]. The SBA's annual report, for the fiscal year ended September 30, 1980, reported 243,824 loans outstanding, for a total of $13,328.1 billion. At that time 15,206 loans (6.2 percent) were classified as delinquent, for a total of $697.2 million (5.2 percent) [76]. Since creditors are continuously doing business with hundreds of businesses of varying sizes in different industries, the ability to predict failure would be very valuable.

The American Institute of Certified Public Accountants (AICPA) in Statement on Auditing Standards (SAS) 34, issued by the Auditing Standards Board, stated that default on loan or similar agreements may be an indication that a firm is in danger of violating the going concern assumption [79], i.e., loan noncompliance could be an indication that the firm is headed for more serious financial problems, perhaps even failure. Business failure is a finality. Once a firm has failed there is little or no recourse. Prior empirical research has addressed the issue of business failure. Beaver [15], Altman [5], Deakin [29], Edmister [32], and others have provided results which indicate financial ratios are useful in foretelling failure.

Because of high interest rates, lending institutions are initially concerned with a firm's ability to meet its loan obligations. Therefore, this study will examine the ability of firms to meet their loan obligations.

Purpose of the Study

The objectives of this study are to determine if:

1. Financial ratios provide information regarding a small business' ability to meet its currently maturing debt.

2. Combinations of financial ratios and industry data can be utilized as part of an early warning system to indicate when a small business is headed for problems with its loan agreements.

3. The addition of economic data increases the effectiveness of financial ratios in predicting the ability of a small business to meet its currently maturing debt.

4. Ratios involving current maturities[1] are good indicators of a small business' ability to meet its currently maturing debt.

The purpose of this study is to develop discriminant models to accomplish these objectives. The research methodology employed to develop the models and analyze the results will be similar to the methodology employed in earlier business failure and bankruptcy studies.

For the purposes of this study, loan noncompliance is defined as the borrower not complying with the terms of the original loan agreement. One example of noncompliance is the alteration of the loan agreement to the disadvantage of the lending institution. However, formal alteration of the loan agreement is not necessary to imply noncompliance. If a borrower is tardy with the payment, they are in noncompliance, but the loan agreement has not been formally altered. Other examples of noncompliance are: (1) partial payment,

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[1] Current maturities is defined as short-term notes payable plus the maturing portion of long-term debt.

(2) missing an interest and/or principal payment, and (3) failing to reduce and renew.

The first two examples, partial payment and missing a payment, are self-explanatory. The third example, failure to reduce and renew, requires further explanation. Some financial institutions have the policy that borrowers must reduce the principal of the loan and then sign a new loan agreement every thirty, sixty, or ninety days. Therefore, failure to reduce and renew indicates the borrower did not reduce the principal of the loan, but simply renewed the loan for the same or a greater amount.

Some prior studies have been successful in predicting business failure up to five years before the occurrence [15, 29]. This may not be sufficient lead time to affect the eventual outcome, and the five-year term does not necessarily aid the lender in making a decision as to whether to grant the businessman a loan. If loan noncompliance can be regarded as a harbinger of failure, then by predicting loan noncompliance the firm can realize it is financially unstable and begin corrective procedures and the lender will have an effective tool to screen loan applications.

Definition of a Small Business

The proper yardstick for measuring the size of a business is a controversial point. Some of the most commonly observed criteria for classifying businesses according to size are: (1) total assets, (2) number of employees, (3) value of product, (4) annual sales or receipts, (5) net worth, (6) relative size within the industry, (7) dimensions of plant, (8) type of management, and (9) number of stockholders. The following table presents the measurements used by four separate organizations [17].

TABLE 1-1

MEASURES OF FIRM SIZE

Organization	Measurement
Department of the Census	Number of Employees
Dun and Bradstreet, Inc.	Net Worth
Fortune Magazine	Assets
Internal Revenue Service	Sales

If classified solely by the number of employees, a labor intensive operation would seem disproportionately large, while a capital intensive operation would appear disproportionately small. Generally, the ratio of human work to the size of operation is higher in a small business than in a large business because of automation and other labor saving devices. Therefore, using the number of employees to determine size tends to overstate the size of the firm progressively as size decreases.

Total assets would not be a reliable size measure for all businesses. For example, a professional's business might produce millions of dollars in revenues, yet have very few assets. Whereas, a manufacturing firm might have total assets equal to its annual revenues.

Employing net worth as a size measure presents a problem in that net worth can change considerably from year to year. Also, using net worth compounds the problems encountered when using assets as a size measure because net worth is a residual of assets exceeding liabilities.

The average person will think of revenues or sales when asked to determine an index to measure size. Sales may be a good measure when applied separately to different industries, i.e., a different level of sales for different industries. The sales volume of firms within the same industry should be equally affected by changes in the economy and the firms should have the same cyclical and seasonal variations. Thus, sales appears to be the common denominator to measure size.

Three definitions of a small business were considered for this research project. The first definition considered was adopted by the American Institute of Certified Public Accountants Audit Standards Committee [42]. The committee defines a small business as a firm possessing the following characteristics:

Main Characteristics

1. Manager dominance
2. Limited segregation of functions

Secondary Characteristics

1. Higher risk of management override of accounting controls
2. Limited accounting knowledge
3. Ineffective policy making body
4. Easy access to assets
5. Informal recordkeeping system

This definition was rejected because of its qualitative nature. To be able to determine these characteristics about each firm, one would have to be very intimate with the firm's organizational structure and operations. This would make acquiring an adequate sample difficult.

A second definition considered was the one employed by the Small Business Administration (SBA) [50]. To qualify as a small business according to the SBA size standards, a business concern must pass five tests. The business must be:

1. independently owned and operated
2. not dominant in its field of operations
3. and its: (UNIT OF MEASURE)
   - employees
   - annual receipts
   - assets
   - net worth
   - net income
4. do not exceed: (AMOUNT)
   - number
   - dollars
5. for assistance under (PROGRAM)
   - financial assistance
   - procurement assistance
   - management assistance
   - SBIC assistance
   - other assistance programs

Items 1 and 2 above, are fixed requirements, while items 3, 4 and 5 are allowed to vary from industry to industry. Table 1-2 shows current size standards for air transporters [50].

As can be seen, a change in the type of assistance desired requires a change in the unit of measure, in the amount, or in both. Even for the same assistance and same two-digit SIC code the unit of measure can change. The SBA size standards system has incorporated five different units of measure into eight different definitions of a small business. This causes considerable difficulty in defining a small business for research purposes. For these reasons the SBA

TABLE 1-2

EXAMPLE OF SBA VARYING UNITS OF MEASURE

		TYPE OF ASSISTANCE	
SIC	Description	Financial Assistance	Procurement Assistance
4511	Certified Carriers	1000 empl.	1500 empl.
4521	Noncertified Carriers	1000 empl.	1500 empl.
4582	Airports and Flying Fields	\$1.5 mil. annual sales	500 empl.
4583	Airport Terminal Service	\$1.5 mil. annual sales	500 empl.

definition of a small business was rejected for use in this research project.

When Congress enacted the Small Business Act of 1953, creating the Small Business Administration, a small business was defined as:

> SEC.3. For purposes of this Act, a small-business concern ... shall be deemed to be one which is independently owned and operated and which is not dominant in its field of operations. In addition to the foregoing criteria the Administrator, in making a detailed definition may use these criteria, among others: Number of employees and dollar volume of business. Where the number of employees is used as one of the criteria in making such definition for any of the purposes of this Act, the maximum number of employees which a small-business concern may have under the definition shall vary from industry to industry to the extent necessary to reflect differing characteristics of such industries and to take proper account of other relevant factors [68].

Congress required, that if used as a criterion, the number of employees should vary according to industry membership. They also recommended using a dollar measure of business volume as a criterion, however, this measure would not have to vary according to industry membership.

Consequently, for the purposes of this study, a single definition of a small business will be employed using net sales as the size standard. This is one of the size standards recommended by Congress in 1953 and adopted by the SBA for some industries. A small business will be defined as: A business that is independently owned and operated and whose net sales do not exceed the 4-digit SIC code size standard required to receive a SBA loan. For firms whose size standards are based on the number of employees, the Census of Manufacturers, 1977 [21] was used to develop a standard. Only those firms whose net sales are less than or equal to the average sales for firms who employ the number of employees established as the SBA standard will be included. Tables 1-3 and 1-4 will aid in understanding the allowable net sales to be classified as a small business [50]. Table 1-3 shows the net sales allowed for firms in the Motor Freight Transportation and Storage classification. The procedure used to calculate a net sales size standard for an industry for which the SBA uses employees as the size standard is illustrated in Table 1-4.

TABLE 1-3

CURRENT SBA SIZE STANDARDS

Motor Freight Transportation and Storage

SIC Number	Description	Net Sales
4212	Local Trucking w/o Storage	$6.5 mil.
4213	Non-local Trucking	6.5
4214	Local Trucking w/storage	6.5
4221	Farm Product Storage	1.5
4222	Refrigerated Warehousing	6.5
4224	Household Goods Storage	6.5
4225	General Warehousing and Storage	6.5
4226	Special Warehousing and Storage	6.5
4231	Freight Trucking Terminals	1.5

TABLE 1-4

CALCULATION OF NET SALES SIZE STANDARD

SIC Code	SBA Size Standard (employees)	Census of Manufacturers (range of employees)	Sales (millions)	Number of Firms	Size Standard (Avg. sales)
2812	1000	500-1000	559.9	4	140.0
2816	1000	500-1000	532.9	7	76.1
2819	1000	500-1000	1421.2	16	88.8
3211	1000	500-1000	468.0	8	58.5
3229	750	500-1000	843.2	23	36.7
3261	500	250-500	160.0	10	16.0
3292	750	500-1000	127.3	3	42.4
3293	500	250-500	270.5	22	12.3
3693	500	250-500	341.4	17	20.1
3731	1000	500-1000	633.5	21	30.2
3999	500	250-500	292.2	24	12.2

Source: <u>Census of Manufacturers, 1977</u> [21]

<u>The Study of Small Business</u> [50]

Methodology

To accomplish the objectives set forth, the predictive ability of financial ratios and economic data must be examined. That is, can financial ratios be utilized to predict small business loan noncompliance? Then, does the addition of economic variables significantly improve the predictive ability of the financial ratios? Both questions will be answered by employing discriminant analysis. This allows for the simultaneous evaluation of all information.

The first question will be answered by constructing a discriminant model based solely on financial ratios. To resolve the second question a discriminant model will be derived that contains not only financial ratios, but also economic variables. Then the results of the two models will be compared.

The validation technique employed will be the Lachenbruch-Mickey leaving-one-out method or U Method [9, 55, 56]. The U Method holds out one observation at a time, estimates the discriminant functions based upon n_1+n_2-1 observations and classifies the held out observation.[2] This procedure is repeated for all observations in the sample. A classification error rate is determined by totaling the number of misclassifications. With this method, no observation has any effect on the discriminant function classifying it.

---

[2] The hold-out method differs from the U Method in that the hold-out method requires that a significant portion (up to fifty percent) of the sample be held back to test the validity of the discriminant function. Therefore, the discriminant function can only be estimated from part of the original sample. For small samples the hold-out method is not an appropriate procedure. The hold-out method is discussed in detail in Chapter 4.

The U method provides a technique for estimating error rates for small samples, other than classifying the original sample which results in biased and overly optimistic results. Lachenbruch and Mickey concluded that the hold-out method has no clear advantage over the U method [55].

After each model has been satisfactorily tested, the results will be analyzed to determine if financial ratios can be used to predict small business loan noncompliance. Next, the model containing both the financial ratios and economic variables will be compared to the first model to determine if the economic data does aid in the prediction of small business loan noncompliance.

Contribution of the Study

There are several potential results that may prove beneficial to small businesses and the institutions that lend to them. First, the study will determine whether there is a significant difference between the ratios of small businesses that comply with their loan agreements versus those that do not. Next, the question of whether or not financial ratios can be utilized as a device for screening loan applications will be examined. In prior studies [9, 32] financial ratios have proven useful in predicting small business failure. This study will attempt to determine if financial ratios are so sensitive that they can be used to predict small business loan noncompliance. The addition of economic data will also be investigated to determine whether such data enriches the ratios' predictive ability. This will be the initial study to examine corporations, partnerships, and proprietorships in the same study, employing a single discriminant function.

Finally, the results of this study may provide a better understanding of the underlying factors that contribute to a small business' inability to meet maturing debt. Hopefully, this will aid the small businessman in recognizing when his business is headed for financial difficulty, so that, he can initiate the necessary corrective procedures to avoid the oncoming problem and, possibly, eventual bankruptcy. The lender will be provided with a new method of screening loan applications to aid in reducing losses on loans.

Organization of the Study

Because this study examines small businesses, the first part of the study briefly examines the characteristics of a small business and its place in the American economy. Next, a review of the business bankruptcy and failure studies pertaining to this study is presented. Using these studies as the bases, the research methodology is developed as well as the operational hypotheses and variables. Finally, the results are presented including the implications and limitations of the study.

Summary

The research outlined above will answer four major questions: (1) Are financial ratios useful in predicting a small business' tendency towards loan noncompliance, (2) does the transformation of the financial ratios by their industry averages improve their predictive ability, (3) does the addition of economic data improve the predictive ability, and (4) which financial ratios are the "best" predictors of loan noncompliance, both univariately and multivariately.

The first question will be answered by constructing a discriminant function based on financial ratios of small business firms. By transforming the financial ratios by their industry averages and constructing a discriminant function based on the transformed ratios, the second question may be answered. Including economic data in the first two discriminant function will provide the answer to the third question. The fourth question will be answered by: (1) Univariate testing of the financial ratios to determine if there is a significant difference between the ratios of the complying and noncomplying firms, and (2) ranking the ratios by the partial F-values obtained when constructing the discriminant functions. The results will help in determining what financial and economic characteristics are exhibited by a noncomplying or complying small business.

CHAPTER II

LITERATURE REVIEW

Small Business: Its Problems and Contributions to the Economy

There are four major problems encountered by a small business are:

1. Too much government regulation
2. Record high inflation rates
3. Obtaining adequate financing
4. Poor management

The problems are discussed in detail in Appendix I. The effect of these problems on businesses has been an increase in the number of bankruptcies filed. Table 2-1 shows the number of bankruptcies filed from 1970 through 1979 by occupation of debtor.

In 1981, the SBA estimates that more than 15 million small businesses will file tax returns. There will be in excess of 11 million (75.4%) proprietorships and one million (8.6%) partnership returns filed. The remaining businesses will be small corporations, i.e., Subchapter S corporations and corporations that employ less than five million dollars in assets. These small businesses will account for more than 18 billion dollars in tax revenues [76].

Table 2-2 further illustrates the importance of small businesses in the economy [77]. For Table 2-2 a small business is

TABLE 2-1

BANKRUPTCIES FILED, BY OCCUPATION OF DEBTOR

	1970	1973	1974	1975	1976	1977	1978	1979
Merchants	4,003	4,492	5,317	6,048	6,124	6,533	5,553	4,177
Manufacturers	731	649	710	756	681	779	849	603
Farmers	658	431	308	550	672	736	752	592
Professionals	1,301	1,450	1,582	2,542	2,809	2,680	2,348	2,242
Others in Business	8,470	9,505	11,870	19,073	23,870	20,423	20,164	21,017
Total	15,163	16,527	19,787	28,969	34,156	31,151	29,666	28,631

Source: Statistical Abstract of the United States: 1980

TABLE 2-2

SHARE OF MARKET AS MEASURED BY BUSINESS RECEIPTS - 1975

Industry	Number of Businesses (Thousands)	Number of Businesses (Percent)	Annual Business Receipts (Billions)	Annual Business Receipts (Percent)
Agriculture, Forestry and Fishery (less farms)				
Small business	$ 256.0	93.8	$ 5.7	55.2
Large Business	16.9	6.2	4.7	44.8
Total	272.9	100.0	10.4	100.0
Mining				
Small business	75.6	88.3	25.5	39.0
Large business	10.0	11.7	39.8	61.0
Total	85.6	100.0	65.3	100.0
Contract Construction				
Small business	1,134.1	99.2	140.9	76.0
Large business	9.1	0.8	44.4	24.0
Total	1,143.2	100.0	185.3	100.0
Manufacturing				
Small business	447.4	95.4	546.9	43.6
Large business	21.5	4.6	707.5	56.4
Total	468.9	100.0	$1,254.4	100.0
Transportation, Communication, Electric, Gas and Sanitary Services				
Small business	398.2	88.0	94.6	37.9
Large business	54.3	12.0	155.0	62.1
Total	452.5	100.0	249.6	100.0

TABLE 2-2 (Continued)

Industry	Number of Businesses		Annual Business Receipts	
	(Thousands)	(Percent)	(Billions)	(Percent)
Wholesale Trade				
Small business	576.9	98.1	353.6	63.8
Large business	11.2	1.9	200.7	36.2
Total	588.1	100.0	544.3	100.0
Retail Trade				
Small business	2,298.4	99.0	428.0	72.7
Large business	23.2	1.0	160.8	27.3
Total	2,321.6	100.0	588.8	100.0
Finance, Insurance, and Real Estate				
Small business	1,584.9	99.8	69.9	31.4
Large business	3.2	0.2	152.9	68.6
Total	1,588.1	100.0	222.7	100.0
Services				
Small business	3,460.5	94.3	120.0	56.7
Large business	209.2	5.7	91.7	43.3
Total	3,669.7	100.0	211.7	100.0
All Industry (excluding farms)				
Small business	10,232.0	96.7	1,785.1	53.5
Large business	358.6	3.3	1,557.4	46.5
Total	10,590.6	100.0	$3,342.5	100.0

Source: Small Business in the Economy (December 1979).

defined as a proprietorship, partnership, or corporation that files tax form 1120S. Excluded from the totals in the table are farms for proprietorships and partnerships, and agricultural production for corporations. Small businesses outnumber large business by 28 to 1 and account for 53.5 percent of the total receipts. Small businesses are also a major employer of the workforce. Businesses with less than twenty employees employ 85 percent of the workforce, while firms with four or less employees employ 55 percent [23].

The above discussion demonstrates the relative importance of small business in the American economy. To summarize, small businesses are important because they --

1. Account for 96.7 percent of all businesses and 53.5 percent of all business receipts
2. Pay 22.6 percent of the business income tax liability
3. Employ 85 percent of all employees
4. Contribute 39 percent of the GNP

Business Failure

The reported number of business failures depends on what is considered a failure (e.g., voluntary, involuntary, corporate reorganization, arrangements). The most widely employed definition of failure is Dun and Bradstreet's:

> ... those businesses that cease operations following the assignment or bankruptcy; ceased with loss to creditors after such actions as execution, foreclosure or attachment; voluntarily withdraw leaving unpaid obligations; were involved in court actions such as receivership, reorganization or arrangement voluntarily comprised with creditors [30].

Every year several thousand firms begin operations, and almost an equal number discontinue operations. However, business failures comprise only a small portion of all discontinuances. There are many reasons other than failure for a business to discontinue operations, e.g., loss of capital, inadequate profits, ill health and retirement. If all creditors are paid in full, these discontinuances are not included as failures. Table 2-3 shows that business starts have increased steadily since 1960, with the exception of 1974. While the failure rate has decreased in all years except 1974, 1975 and 1979 [80].

Dun and Bradstreet reported that in 1979 54.5 percent (4138 firms) of the failed firms, did so within the first five years and 27.0 percent (1400 firms) had been in business between six and ten years [31]. The failure rate within the first five years has decreased since the early 1950s, but has fluctuated between 53 percent and 58 percent since 1960. The exception is 1974 when the failure rate was 59.9 percent. The failure rate for firms in business between six and ten years has increased from 19 percent in 1950 to 27 percent in 1979 [31].

The average liabilities for a failed firm in 1979 were $353,000. The total liabilities for all 7,654 failures were $2,667 million [79]. Most failed firms had liabilities under $100,000 (3930 firms or 51.9%), and only 418 firms (5.6%) had liabilities in excess of one million dollars [31].

Business failures have a serious effect on the economy. Though there are many causes of business failure, Dun and Bradstreet state:

TABLE 2-3

BUSINESS FORMATIONS AND FAILURES 1960-1979

	Business Formations (in 1,000s)	Business Failures (in 1,000s)
1960 . . .	183	15.4
1965 . . .	204	13.5
1970 . . .	264	10.7
1972 . . .	317	9.6
1973 . . .	329	9.3
1974 . . .	319	9.9
1975 . . .	326	11.4
1976 . . .	376	9.6
1977 . . .	436	7.9
1978 . . .	478	6.6
1979 . . .	525	7.6

> In nine out of ten failures, the lack of managerial experience or aptitude proved the underlying factor. This ratio holds relatively stable whether the economy is booming or falling into a recession [31].

Lack of managerial experience includes unfamiliarity with the product, incompetence, and unbalanced experience. Unbalanced experience is defined as "experience not well rounded in sales, finance, purchasing and production" [31].

Several other authors agree that poor management is a leading cause of failure [9, 23, 42, 46]. Argenti delineates five characteristics of poor management [13].

-- one-person rule

-- nonparticipating board of directors

-- unbalanced top team

-- weak finance functions

-- lack of management depth

Both poor management and management inexperience are denoted by the inability to avoid conditions that resulted in inadequate sales, competitive weaknesses, excessive fixed assets, receivables difficulties, inventory difficulties, heavy operating expenses and poor location. In 1979, these were the apparent causes of 91.9 percent of the failures [31].

Although the underlying cause of most failures is poor management, there are early warning signs that can indicate a firm is headed toward trouble. These signs are both endogenous and exogenous. However, no one list of indicators can be applied to all firms in all industries, what might be a sign of distress for one industry might be normal for another. A list of endogenous indicators would include [27, 51, 68, 85]:

1. Serious past due payment pattern
2. Request for a moratorium on payments until refinancing is arranged
3. Inadequate working capital (low current ratio)
4. Heavy debt to net worth
5. Declining cash flow
6. Erratic disposal of assets
7. Delays in releasing financial and operating data
8. Dislocation in volume or profit margin
9. High salaries or withdrawals
10. Inadequate inventory control (i.e., incorrect quantity and/or noncompetitive price)

Some exogenous indicators of trouble are [27, 31, 51, 68]:

1. Changes in the composition of the neighborhood
2. Overdependence on a major supplier or customer
3. Declining industry sales
4. Unfavorable union conditions; strikes, threatened and actual

5. Proposed and enacted legislation
6. Product obsolescence
7. Reduction in market share
8. Inability to obtain additional financing
9. Poor health of owner(s)
10. Marital difficulties

Endogenous factors are at least partially controllable by management. Though most of the endogenous problems are created by poor management, an alert management team will be aware of any potential problems and seek to remedy the problems before they become a threat to the business' existence. The financial statements are an important source of information about endogenous factors.

Exogenous factors are beyond the control of the firm. There is little evidence to indicate that these factors are unique to any one industry or firm, but instead evidence indicates that these factors affect businesses as a whole. There is recent evidence that credit rationing and the level of the national economy are correlated with the failure rates [13].

After examining the indicators of failure, if a business has prudent management, the firm should be able to avoid failure. A firm does not fail overnight, it usually has had one to three years of subpar performance [51]. Recent studies have indicated that the financial statements may reflect failure as far as five years before the occurrence [5, 15, 29].

Current Business Failure Studies

Although there have been no studies dealing specifically with the prediction of small business loan noncompliance, there have been many studies examining the usefulness of financial ratios in predicting business failure or bankruptcy. The majority of the failure studies have been based solely on financial ratios [5, 6, 7, 15, 29, 82]. A few studies have included other variables, such as dummy variables for trends (i.e., 0 or 1) [32] and economic data [9]. This research will draw heavily from the methodologies employed in earlier studies and will parallel the methodologies utilized by Beaver [15], Altman [5], and Alves [9]. Since financial ratios have played a major part in failure studies a brief review of their history is necessary.[1]

Ratio analysis began with the development of the current ratio for evaluation of credit-worthiness in the late nineteenth and early twentieth centuries and has had more impact on financial statement analysis than any other ratio. During the 1920s a multitude of publications concerning ratio analysis appeared leading to a rapid and prolific development of new ratios that has continued until today. Formal studies concerned with the prediction of business failure were present in the 1930's. A study at that time and several later ones reported that failing firms exhibit significantly different ratio measurements than going concerns. In addition, another study was concerned with ratios of large asset-size corporations that experienced difficulties in meeting their fixed indebtedness obligation [44, 59, 78]. However, until Beaver examined the efficacy of ratios in predicting bankruptcy, little effort had been expended toward the empirical verification of their usefulness.

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[1] For a succinct, but thorough, review of ratio analysis see Horrigan [45].

sification (SIC) code of the United States Department of Commerce. Total asset size was obtained from the most recent balance sheet prior to failure.

Each failed firm was pair-matched with a nonfailed firm based on industry membership, asset size, and year of financial information provided. The names of the nonfailed firms were collected from 12,000 Leading U.S. Corporations and their financial statements were obtained from Moody's.

The final sample consisted of between 117 and 158 failed and nonfailed firms with a mean asset size of $6.3 million and $8.5 million respectively. Of the 79 failed firms, 59 were bankrupt, 16 involved nonpayment of a preferred stock dividend, and one involved an overdrawn bank account. The number of firms in the sample varies because Beaver examined five years of financial data; and the availability of data for the full five year period was not a selection criterion. If this had been a selection criterion a bias would have been introduced by omitting firms that failed within their first five years; which is a significantly large number of failures [31].

Beaver calculated thirty ratios for each firm. He selected the ratios based on three criteria: (1) popularity, i.e., frequent appearance in the literature; (2) the ratios had performed well in a previous study; and (3) the ratio could be defined in terms of a cash flow concept. The ratios were divided into six "common element" groups.

The sample was randomly divided into two subsamples. To predict failure or nonfailure Beaver employed a dichomotous classification test. This test predicts failure based on the value of a single ratio (i.e., an univariate test). To predict failure or nonfailure the ratios were first arrayed in ascending order. This array was then inspected to find the optimal cutoff point, the point that would minimize the number of incorrect predictions. The actual validation test was to classify the second subsample using this cutoff point.

After each firm was classified the prediction was compared to the actual status, and the percentage of incorrect predictions computed. This was repeated for all thirty ratios. Six ratios were found to perform better than the other twenty-four. They were: (1) cash to total debt, (2) net income to total assets, (3) total debt to total assets, (4) working capital to total assets, (5) current ratio, and (6) no-credit interval.

The most accurate predictor of failure was the cash flow to total debt ratio. In the first year prior to failure only 13 percent of the firms were misclassified. The largest number of firms, 24 percent, were misclassified in the fourth year prior to failure.

One ratio from each group was selected for further analysis. The six ratios selected were the ratios that had the lowest percentage error for their group over the five year period, employing the dichomotous classification test. The next analysis performed on these ratios was a profile analysis. A profile analysis simply compares the mean values of the ratios of the failed firms with those of the nonfailed firms, it is not a predictive test.

Four *ceteris paribus* propositions were set forth to form predictions regarding the mean values of the six financial ratios. The propositions were:

1. The more liquid assets a firm has, the smaller the probability of failure.
2. The larger the net liquid-asset flow from operations, the smaller the probability of failure.
3. The larger the amount of debt held, the greater the probability of failure.
4. The larger the fund expenditures for operations, the greater the probability of failure.

By examining plots of the ratios, Beaver determined that the ratios of the nonfailed firms deviated very little over the five year period. However, there was a clear deterioration in the ratios of the failed firms over the five years preceding failure. The difference in the mean values was in the predicted direction for each ratio. This suggests that there is a difference in the ratios of failed and nonfailed firms. Nonetheless, this does not indicate that ratios have the ability to predict failure.

By constructing contingency tables Beaver showed that the ratios could not classify failed and nonfailed firms with equal success. In fact, the ratios were much better at classifying the nonfailed firms.

The last analysis undertaken by Beaver was the calculation of likelihood ratios. He constructed histograms for each ratio. The horizontal axis indicated the value of the ratio and the vertical axis showed the relative frequency with which the ratios of the failed or nonfailed firms fell into each interval. By measuring the heights of the failed and nonfailed distributions at a given value for the ratio the likelihood estimates were derived. The likelihood ratio is the ratio of the height of the failed histogram to nonfailed histogram. Thus, for each interval Beaver constructed the likelihood of failure. If the likelihood ratio was greater than one, the probability for failure was greater than the probability of non-failure and vice versa for a likelihood ratio less than one.

The results of the likelihood ratios indicated that the financial ratios conveyed useful information regarding failure for at least five years prior to failure. In each of the five years before failure the likelihood ratios had either an extremely high or low value over most of the range of the financial ratio.

Beaver's study was a landmark study in that he attempted to empirically demonstrate that financial ratios do convey information. He was successful in achieving this on an univariate basis. The biggest question he left unanswered was: "Do combinations of ratios convey more information than the ratios examined singly?" Edward Altman was the first person to address this question.

Edward Altman: "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy"

Altman employed multiple discriminant analysis (MDA) to construct a model to predict corporate bankruptcy. He defined a bankrupt firm as "a firm that is legally bankrupt and either placed in receivership or granted the right to reorganize under the provisions of the National Bankruptcy Act" [5]. This definition of bankruptcy is narrower than Beaver's definition of failure; thus, Altman had fewer bankrupt firms to analyze. His primary sample of 33 bankrupt firms was drawn from the twenty year time period 1946-1965. These firms were manufacturing firms that had filed a bankruptcy petition under Chapter X of the National Bankruptcy Act. The bankrupt firms were matched with nonbankrupt firms on the bases of industry classification, total assets, and year of financial statements. The bankrupt firms had a mean asset size of $6.4 million versus $9.6 million for the nonbankrupt firms.

Twenty-two ratios were computed for evaluation in the discriminant model. These ratios were chosen on the basis of their: (1) popularity in the literature, (2) potential relevancy to the study, and (3) a few new ratios developed by Altman specifically for the research.

Five of the original twenty-two ratios were selected as the best combination for predicting corporate bankruptcy. To select these five ratios Altman followed a four step procedure: (1) observation of the statistical significance of various alternative functions including determination of the relative contributions of each independent variable; (2) evaluation of inter-correlations between the relevant variables; (3) observation of the predictive accuracy of the various combinations of ratios; and (4) judgment of the analyst [5].

The final discriminant function included:

1. Working capital to total assets
2. Retained earnings to total assets
3. Earnings before interest and taxes to total assets
4. Market value of equity to book value of total debt
5. Sales to total assets

To test the significance of the discriminant model Altman calculated the F-value, which is the ratio of the sums-of-squares between-groups to the within-groups sums-of-squares. The F-value of 20.7 was significant at the 0.01 level. Therefore, the null hypothesis that the observations came from the same population was rejected.

Altman's discriminant model was more accurate one year prior to bankruptcy than Beaver's univariate test. The discriminant model correctly classified 96 percent of Altman's secondary sample of bankrupt firms, whereas, Beaver's classification test classified only 78 percent of the failed firms correctly. However, when classifying the nonbankrupt firms the discriminant model was correct only 79 percent of the time. Beaver was able to correctly classify 95 percent of the nonfailed firms. One must take into consideration that Altman's secondary sample of nonbankrupt firms was selected because of its resemblance to the bankrupt firms. To be included in this sample a firm must have incurred a loss in either 1958 or 1961.

Altman's overall classification error rate was 16.5 percent, while, Beaver's was only 13 percent for the year preceding failure. The two error rates are too close to say that one method is significantly better than the other. The similarity between the two error rates would be affected by the resemblance of Altman's nonbankrupt sample to the bankrupt sample. A comparable test of the model would have been to select the nonbankrupt firms on a more random basis.

The accuracy of the discriminant model was greatly reduced for long range predictions. Beaver's dichomotous classification test predicted failure or nonfailure with 78 percent accuracy five years prior to failure. Altman's discriminant model correctly predicted only 36 percent. One reason for this discrepancy is that Altman's model was constructed using ratios from the first year prior to bankruptcy. Different ratios might need to be included in the model or their coefficients revised for years other than the year preceding bankruptcy. Beaver's dichomotous classification test was based on the ratios of the year for which he was attempting to predict failure. For example, the ratios from year five were arrayed in ascending order and then the optimal cutoff point was determined. Then, based on the secondary sample's ratios from the fifth year prior to failure, failure or nonfailure was predicted. To overcome this problem Altman could have constructed a discriminant model for each year or used dummy variables to indicate the year.

Table 2-4 compares the error rates of Beaver and Altman. These error rates are biased because the firms being classified were not a hold-out sample or subsample, but the original sample used to construct the predictive models. Altman did not employ a secondary sample to test his model for the five years preceding failures. In each year, except the first year preceding failure, Beaver's dichomotous classification model out-performed Altman's discriminant model. Unexpectedly, the error rate in both studies was lower in the fifth year than in the fourth year preceding failure.

From his results Altman concluded:

-- MDA is an accurate forecaster of bankruptcy up to two years prior to bankruptcy.

-- All ratios showed a deteriorating trend over the five year period preceding bankruptcy.

TABLE 2-4

COMPARISON OF BEAVER'S AND ALTMAN'S
CLASSIFICATION ERROR RATES

Year Preceding Failure	Error Rate (%)	
	Beaver	Altman
1	10	5
2	15	28
3	21	52
4	24	71
5	22	64

-- Major changes in the values of the ratios occurred between the third and second years preceding bankruptcy.

Altman's samples of bankrupt and nonbankrupt firms may have been too small. Lindeman, Merenda and Gold recommend that the total sample size should be at least twenty times the number of independent variables upon which the classification is to be based [58]. Estes shows that the error rate deviates severely from the theoretical optimum when the ratio of sample size to variables is small [35]. Abend, Harley and Chandrasekaran's results indicated that the average probability of correct classification deteriorates as the ratio of sample size to variables decreases [2]. Therefore, since Altman's discriminant model contained five independent variables and his sample consisted of 33 bankrupt and nonbankrupt firms, he had a ratio of 6.6 firms from each classification to each independent variable. The small sample may have biased Altman's results.

Altman attempted to measure the contribution of each variable to the total discriminating power of the function. He found that the ratio of earnings before interest and taxes to total assets contributed the most. However, current research indicates that this is not a satisfactory method by which to measure the relative contribution of an independent variable in the discriminant model [34].

Altman's research crossed a new threshold in failure studies. He utilized multivariate analysis which enabled him to examine the ability of the financial ratios to predict failure jointly, rather than one ratio acting by itself.

Edward Deakin: "A Discriminant Analysis of Predictors of Business Failure"

Deakin, employing 14 of Beaver's ratios, replicated Beaver's dichomotous classification test and constructed a discriminant model for each of the five years preceding failure. Failure was said to have occurred if a firm experienced bankruptcy, insolvency, or was liquidated for the benefit of creditors [29].

Like Altman, Deakin had an extremely small sample consisting of 32 failed and nonfailed firms. These firms experienced failure between 1964 and 1970. As in prior studies the failed firms were matched with nonfailed firms on the bases of industry classification, asset size, and the year of financial information provided.

Spearman's rank-order correlation coefficient was used to indicate the order of the predictive power of the ratios. The rank-order correlation coefficients were rather high in four of the five years, the only exception was year three. This supports the results obtained by Beaver.

Deakin examined the means of the thirteen financial statement items that were used in calculating the ratios to gain insight into why the rank-order correlation coefficient was so low in the third year. This analysis indicated that the failed firms expanded rapidly in the third and fourth years prior to failure. The expansion appeared to be financed by debt and preferred stock rather than common stock or retained earnings. Because the failed firms were not generating an adequate cash flow their assets were drastically reduced from year four to year three.

Of the six ratios found by Beaver to be the most accurate at predicting failure, Deakin examined only three (cash flow to total debt, working capital to total assets, and current assets to current liabilities). These three ratios were the most accurate ratios examined by Deakin. The cash flow to total debt ratio was the most accurate predictor in both studies, but in the first year prior to failure Deakin had an error rate of 20 percent compared to Beaver's 13 percent. To improve this error rate Deakin employed discriminant analysis.

A random sample of 32 nonfailed firms was drawn from the 1962 to 1966 Moody's Industrial Manual. The 14 ratios were analyzed via discriminant analysis. Since Deakin employed 14 independent variables his sample size was too small [2, 35, 58]. One important facet of Deakin's work was the development of a discriminant model for each of the five years preceding failure.

The significance of each discriminant function was tested using Wilks' lambda. This statistic is used to test the hypothesis that the mean of the ratio vectors for each group is equal. The statistics were significant beyond the 0.001 level for the first three years preceding failure, at 0.011 for the fourth year and 0.05 for the fifth year.

Eleven failed and 23 nonfailed firms were selected at random from the 1963 and 1964 period to test the predictive ability of the model. The error rates were: first year prior to failure, 22%; second year, 6%; third year, 12%; fourth year, 23%; and the fifth year, 15%. The error rate was expected to deteriorate over the five year period, however, the error rate in the first year could not be explained by Deakin.

Deakin's classification error rate, based on the original sample, was less than Beaver's and Altman's for all five years preceding failure. As can be seen in Table 2-5, Deakin's error rate for the fifth year prior to failure was also lower than the fourth year.

Table 2-6 compares Beaver's and Deakin's classification error rates based on their secondary samples. Deakin's error rate was less in all years, except the first year preceding failure. As with the initial samples, the error rate the fifth year was less than the fourth year. No explanation was tendered for this, by either Beaver or Deakin.

Deakin's study showed considerable improvement in the error rate for the third and fifth years preceding failure. Altman's model performed better the first year prior to failure. Neither of the two

TABLE 2-5

COMPARISON OF BEAVER'S, ALTMAN'S AND DEAKIN'S ERROR RATES
(Initial Samples)

Year Preceding Failure	Error Rates (%)		
	Beaver	Altman	Deakin
1	10	5	3
2	15	28	4.5
3	21	52	4.5
4	24	71	20.5
5	22	64	17

TABLE 2-6

COMPARISON OF BEAVER'S AND DEAKIN'S ERROR RATES
(Secondary Samples)

Year Preceding Failure	Error Rates (%)	
	Beaver	Deakin
1	13	22
2	20	6
3	23	12
4	24	23
5	22	15

studies reported results as good as Beaver's for the first year prior to failure. If Deakin had used all thirty of Beaver's ratios and a stepwise discriminant analysis program his results might have been better. The key contribution made by Deakin was demonstrating the improvement in the error rates by constructing a discriminant model for each year.

Robert Edmister: "An Empirical Test of Financial Ratio Analysis For Small Business Failure Prediction"

The first attempt at predicting failure for small business was conducted by Robert Edmister in 1972 [32]. He constructed a discriminant model to predict loss or nonloss borrowing from the Small Business Administration (SBA). Edmister calculated 19 ratios to test his four hypotheses [32]:

1. A ratios level is a predictor of failure.
2. The three-year trend of each ratio is a predictor of failure.
3. The three-year average of a ratio is a predictor of failure.
4. The combination of the industry relative trend and the industry relative level for each ratio is a predictor of failure.

The first hypothesis is basically repeating what Beaver tested with his dichomotous classification test. For example, a firm with a 3:1 current ratio is less likely to fail than a firm with a 2:1 current ratio. Hypothesis two says that a ratio which moves in the same direction for three successive years may be an indication of failure (or nonfailure). The third hypothesis is self-explanatory in that an average of a ratio may be a predictor of failure. Hypothesis four allows for testing the interaction effect of two variables.

Edmister's data were gathered from the Small Business Administration and Robert Morris Associates (RMA). Because of his strenuous selection criteria his sample was limited to 42 borrowers. The loss and nonloss borrowers were not matched pairs.

Employing stepwise discriminant analysis Edmister produced a model containing seven independent variables. They were:

1. Annual funds flow to current liabilities.
2. Equity to sales.
3. Working capital to sales ratio divided by its RMA ratio.
4. Current liabilities to equity divided by its SBA ratio average.
5. Inventory to sales divided by its RMA ratio.
6. Quick ratio divided by its RMA trend.
7. Quick ratio divided by its RMA ratio.

The function correctly classified 39 of the 42 firms. This seems very accurate at first glance, however, these 42 firms were the same 42 firms used to construct the discriminant function. Therefore, these results are biased.

Edmister was concerned with multicollinearity when constructing his discriminant function. He prevented a variable from entering the discriminant function if its correlation with another variable exceeded 0.31. Eisenbeis reported that multicollinearity is a sample property that is largely an irrelevant concern in discriminant analysis except where the correlations are such that it is no longer possible to invert the dispersions matrices [34]. However, many authors feel that multicollinearity does cause problems when using discriminant analysis [24, 33, 48, 52, 64]. The main problems caused by multicollinearity are: (1) an increase in error rates when both dichomotous and continuous variables are included, and (2) incorrect rankings of individual independent variables.[2]

New ideas were added to the study of business failure by Edmister, not only did he conduct the first multivariate study dealing with small business failure, but he included trends and averages in his discriminant function.

Jeffery Alves: "The Prediction of Small Business Failure Utilizing Financial and Nonfinancial Data

In his 1978 study, Alves used Dun and Bradstreet's definition of failure. This definition is broader than the definition employed by Edmister, thereby, enabling Alves to examine a larger portion of the small business population. Using this definition Alves was not limited to firms that were SBA borrowers. A small business was defined as, "a manufacturing firm, registered with the SEC, that was not dominant in its field of operations and had less than 250 to 1500 employees depending on its industry classification" [9].

Alves obtained a list of 200 business failures fiom Dun and Bradstreet covering 1971 to 1976. The final sample consisted of 41 failed firms. These failed firms were matched with nonfailed firms on the bases of industry membership and year of financial information provided. Alves did not match the firms on a measure of size because he felt that any characteristic important enough to be a matching

[2] There is more detailed discussion of the affects of multicolinearity included in Chapter 3 under "Independent Normally Distributed."

criterion should be included as an independent variable, such that, its importance could be empirically tested. Beaver believed that the firms should be matched on asset size, because even if two firms have the same ratio values the larger firm has a lower probability of failure [15].

The data analyzed included not only financial data, but also included owner/manager characteristics, business characteristics, and economic data. All data were collected for one and two years preceding failure.

Kolmogorov-Smirnov one-sample tests were used to test the normality of the individual variables. Most of the variables were extremely skewed with some outliers as far as ten standard deviations from the mean. To reduce the influence of these outliers on the discriminant function, all values that were more than three standard deviations from the mean were deleted. The mean for the deleted values was calculated and substituted for the variables. One of the assumptions of discriminant analysis is that the variables are multivariate normal. However, Alves used an univariate test to test the normality of each variable. He did not test for multivariate normality. Even after correcting for nonnormality Alves did not state that the variables were multivariate normal. Violation of this normality assumption may bias the tests of significance and estimated error rates. Lachenbruch, Sneeringer, and Revo concluded that the standard linear procedures of discriminant analysis may be quite sensitive to nonmultivariate normality [57].

Alves proposed four hypotheses. They were [9]:

1. Financial ratios can be combined in such a manner that their interactive information content can be used to predict a small manufacturer's tendency towards failure or nonfailure.

2. Nonfinancial information in conjunction with financial information can be combined to predict a small manufacturer's tendency towards failure.

3. Financial ratios which are transformed by industry average ratios can be combined in such a manner that their interactive information content can be used to predict a small manufacturer's tendency towards failure or nonfailure.

4. Financial ratios, transformed by industry averages, and nonfinancial information can be combined in such a manner that their interactive information content can be used to predict a small manufacturer's tendency towards failure or nonfailure.

Each of the four hypotheses was tested one and two years prior to failure. The discriminant functions to test the hypotheses were constructed using Biomedical Computer Programs which employ a stepwise procedure. The Lachenbruch-Mickey leaving-one-out or U method was used to validate the models.

The discriminant function for hypothesis one -- two years prior to failure consisted of: (1) collection period and (2) net worth to total assets. Collection period is defined as notes and accounts receivable divided by net sales per day. The accuracy rate for this function was only 62 percent. The function for one year prior to failure contained the variables: (1) net sales to inventory, (2) quick ratio, and (3) earnings before taxes to total assets. This function correctly predicted failure or nonfailure with 92.8 percent accuracy. Alves concluded that it is possible to predict a small manufacturer's tendency toward failure or nonfailure by combining financial ratios in a linear manner.

Included in the discriminant function for hypothesis two -- two years prior to failure were two financial variables, collection period and net worth to total assets; and two nonfinancial variables, management experience and diversification. This function correctly predicted failure or nonfailure with 75.6 percent accuracy. For one year prior to failure the function was identical to the function in the first hypothesis with the addition of firm age. This function correctly classified 88.1 percent of the firms.

Transformations were performed on the financial ratios to test hypotheses three and four. The transformations were: (1) dividing the firm ratio by the industry average ratio, (2) employing the deviation of the firm's ratio from the industry average, and (3) dividing the deviation from the industry average by the industry average.

For hypothesis three the most accurate function two years prior to failure included the collection period and fixed assets to net worth transformed by the industry average. This function correctly classified 65 percent of the firms, which is a three percent improvement over the function without the transformation. Employing the other two transformations produced 64.3 percent accuracy rates. The same transformation proved to be the most accurate one year prior to failure. This function included the independent variables: (1) net sales to inventory, (2) quick ratio, and (3) earnings before taxes to total assets. However, the accuracy rate for this model was only 85 percent, compared to 92.8 percent for the function in hypothesis one, that had not been transformed. Therefore, the use of these transformations does not improve the models accuracy when only financial data is considered. Hypothesis four took into consideration the use of nonfinancial data with the financial data.

The discriminant function for hypothesis four -- two years prior to failure contained two financial variables, transformed by industry average: (1) collection period, and (2) current debt to net worth. The function also contained three nonfinancial variables: (1) management experience, (2) diversification, and (3) number of employees. The function correctly classified 76.9 percent of the firms. This was a 1.3 percent improvement over the corresponding function for hypothesis two. The most accurate function for hypothesis four -- one year prior to failure had an accuracy rate of 92.9 percent, which is 0.1 percent more accurate than hypothesis one -- one year prior to failure. The variables included were: (1) net sales to inventory, (2) current debt to net worth, (3) the quick ratio, (4) cost of goods sold to inventory, (5) diversification, and (6) age of the firm. The financial variables were transformed by dividing the deviation from the industry average by the industry average.

Based on the results reported, the financial model one year prior to failure employing only financial data was the "best" model. This conclusion is drawn because only financial data are used; whereas, the model for hypothesis four -- one year prior to failure had a higher accuracy rate, but required a data transformation and nonfinancial data. This would require more time and effort of the user for an insignificant increase in the accuracy rate.

Alves' study was a decided improvement over Edmister's study. Edmister's six selection criteria reduced his sample to an extremely small size. Alves' sample consisted of 41 failed and nonfailed firms, compared to 21 for Edmister. Edmister did not attempt to validate his model. His sample was not large enough for a hold-out group nor did he choose to use the Lachenbruch-Mickey leaving-one-out technique. Alves compared discriminant models that contained only financial data and models that contained financial and nonfinancial data, whereas, Edmister only examined models that contained both financial and nonfinancial data.

The aforementioned studies imply a definite potential of ratios as predictors of financial strength. All the studies have examined only one aspect of financial stability -- failure. Business failure is at the end of the spectrum. There are many events that can precede failure, among these, is loan noncompliance.

Summary

This chapter first examines the contributions that small businesses make to the economy, specifically to the labor force, gross national product and income tax. Many of the problems faced by small businesses are discussed. The main problem encountered by a small business is the lack of adequate financing. This problem is compounded by the high cost of obtaining financing when it is available. Other problems faced by a small business include inflation and excessive government regulation.

Several indicators of failure are examined. These indicators are classified as either endogenous or exogenous. Finally, failure studies pertinent to this study are reviewed beginning with Beaver [15] in 1966 and continuing through Alves [9] in 1978.

CHAPTER III

METHODOLOGY

Data Acquisition

Data for the research were requested from Robert Morris Associates (RMA) member banks. RMA is a nation-wide association composed of commercial bank loan and credit officers, and 2135 commercial banks. The member banks represent 75-80 percent of the total assets, deposits, and loans of all U.S. commercial banks. RMA member banks were determined by consulting Robert Morris Associates Membership Roster, an annually published directory, which lists all RMA member banks. All member banks in Louisiana, and a random sample of member banks across the United States were contacted to obtain data. Each bank in Louisiana was initially contacted by telephone, then mailed an abstract of the research proposal and a cover letter assuring them of the anonymity of the data. The banks outside Louisiana received only the abstract and cover letter.

Each year RMA issues its Annual Statement Studies containing composite balance sheet, income statement, and ratios on over 300 different lines of business. The annual study is compiled from over 56,000 financial statements of borrowing customers, submitted to RMA by member banks [66].

The criteria for a firm to be submitted for the statement study are [66]:

1. Only one SIC code
2. A fiscal year ending between June 30 and March 31, and
3. Total assets less than five million dollars

The information requested from each bank was its RMA Data Submission Forms (an example of this form is contained in Appendix II). This is the form submitted to RMA for compilation of the Annual Statement Studies. On each form the bank indicated whether the firm was, or was not, in compliance with its loan agreement at the end of the firm's fiscal year. A total of 346 forms were received resulting in 51 matched pairs.

All the firms included in the sample have their fiscal years ending between June 30 and March 31, hence, the sample does not include any firms whose fiscal years end after March 31 and before June 30. This restriction was necessary because the RMA Data Submission Forms do not include firms whose fiscal years end during this time period.

The sample contains firms with four different legal forms of ownership:

1. Proprietorship
2. Partnership
3. Corporation
4. Sub Chapter S Corporation

Each firm's line of business is classified into one of four categories: (1) manufacturer, (2) wholesaler, (3) retailer, or (4) service.

Only financial data are available for analysis (i.e., quantitative data) and only year-end amounts. There is no qualitative data available. Because the RMA forms do not contain the entity's name, the firms cannot be contacted to collect additional data. Finally, the firms comprising the sample may or may not be audited, hence, the quality of information may vary from firm to firm.

Controlling for Extraneous Variables: Matching Procedures

The research will be quasi-experimental. The data will come from an environment which existed or events that occurred without the researcher's direct intervention.[1] When operating under a quasi-experimental setting maintaining control over extraneous variables can be difficult. Since the event of interest (loan noncompliance) has already occurred, the firms cannot be randomly assigned to groups. Therefore, another control technique must be employed. The control method selected for this study is a matched-pairs design. Each noncomplying firm will be matched with a complying firm on three characteristics: (1) by industry, employing two-digit standard industrial classification (SIC) codes; (2) year-end asset size in the year of noncompliance; and (3) year of financial information provided.

As early as 1923, the ratio literature suggested that industry factors must be incorporated in any complete ratio analysis [19]. The literature contends that "differences" exist among industries that prevent the direct comparison of firms from different industries. The evidence offered on behalf of industry differences

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[1] For a more thorough discussion of a quasi-experimental design see Abdel-Khalik and Ajinkya [1].

is the fact that ratio distributions differ among industries. For example, a 2:1 current ratio might be "good" in one industry, whereas, it would be extremely low in another [59]. Walter [85] reported that interindustry diversity has an important bearing upon technical solvency. Industry ratios of current liabilities to net cash flows vary from roughly one-fifth to one and one-fourth. Walter also reported that interindustry differences in profit margins are substantial. He reported that profit margins vary from 13 percent for chemical and allied products to 3 percent for apparel and finished textiles. For these reasons the complying and noncomplying firms will be matched using SIC codes.

SIC codes were chosen to match by industry for two reasons: (1) they are easily accessible, and (2) related research has employed SIC codes. Brown and Ball [19] determined that the two-digit SIC code is sufficient to segregate firms by industry. Hence, the two-digit SIC code is being used rather than the three or four digit.

Even though Alves felt that the firms should not be matched on a size measure, the more common belief is that some type of size measure is necessary [6, 29]. Other failure studies have matched the failed and nonfailed firms on an asset measurement basis. If firms are viewed as aggregates of assets and if asset returns are less than perfectly correlated with one another, statistical formulae suggest that the variability of total return to the firm will increase less than proportionately to the size of the firm [14]. The rate of return to the firm will become more stable as asset size increases. Empirical evidence indicates that the variability of the rate of return does behave in this manner [3, 4]. The implication is that larger firms are more financially stable, even if the values of their ratios are the same as those of smaller firms. Therefore, the ratios of firms from different asset size classes should not be directly compared without adjustment for size.

The financial statement data for the noncomplying and complying firms were matched according to year of noncompliance. This aids in reducing any peculiar industry effects (e.g., cycles, trends, and strikes) that might occur in one year, but not in another. By not matching on year, a firm on the downside of a cycle might be matched with a firm on the upside. This could create a discrepancy in the ratios that would affect their ability to predict loan noncompliance. Table 3-1 lists the noncomplying firms and their paired mates. The pairs are listed by year of noncompliance, SIC code, and asset size in the year of noncompliance. Mean asset size for the complying firms is $1,270,000 and $1,290,000 for the noncomplying firms. A t-test was performed to determine if the firms could have come from the same population. The probability of a larger t-value than the calculated value of -0.0652 was 0.94581, therefore, the null hypothesis was not rejected.

TABLE 3-1

MATCHED PAIRS

	Noncomplying		Complying	
Year End	SIC Code	Asset Size (thousands)	SIC Code	Asset Size (thousands)
1978				
March	4441	$ 957	4441	$1,013
June	5943	181	5944	220
July	2011	335	2011	232
	5064	699	5085	707
September	5084	332	5081	226
	5251	412	5271	546
October	6411	1,133	6435	1,161
	7312	5,390	7325	6,995
December	5085	1,445	5085	1,417
1979				
June	3599	313	3523	366
	5086	1,823	5093	1,889
	5261	444	5211	548
	5417	839	5423	845
	5733	160	5723	103
July	5417	748	5417	725
	5531	461	5531	479
September	5085	440	5064	352
	5251	393	5271	340
	5733	352	5741	338
October	5943	889	5942	873
	7394	1,335	7394	2,156
	8911	346	8911	369
November	5045	371	5085	372
	5812	138	5812	149
December	2086	1,277	2014	1,253
	2091	5,102	2091	4,673
	3551	6,115	3523	3,890
	4899	2,808	4833	2,817
	5511	675	5531	598
	5511	1,068	5511	1,086
1980				
January	2048	765	2011	759
June	2421	338	2431	467
	5261	872	5271	837

TABLE 3-1 (Continued)

Year End	Noncomplying SIC Code	Noncomplying Asset Size (thousands)	Complying SIC Code	Complying Asset Size (thousands)
	5733	135	5712	276
	5944	199	5944	118
September	4241	129	4244	145
October	5411	405	5417	481
	5661	103	5611	195
	7394	1,498	7394	1,483
December	2091	4,678	2091	4,358
	2851	575	2852	928
	3551	6,687	3523	4,430
	3585	696	3544	831
	3599	1,941	3599	1,939
	4273	1,972	4213	1,986
	5039	1,560	5039	1,740
	5082	4,685	5085	4,527
	5085	607	5065	680
	5181	1,263	5181	1,123
	5571	125	5531	177
	5912	141	5992	127

Variable Definitions

For the purposes of this study a small business is defined as: A business that is independently owned and operated and does not have net sales exceeding the SBA loan requirement for the business' four digit SIC code. If the SBA loan requirement is based on the number of employees a new standard is developed. The business is considered small, if its net sales do not exceed the average net sales of firms employing the number of employees established as the SBA standard.[2]

Loan noncompliance means that the terms of the original loan agreement were not met. The loan agreement need not have been formally altered for a firm to be in noncompliance with the original agreement. Other examples of loan noncompliance are: (1) missing an interest payment, (2) missing a principal payment, (3) late payments, and (4) failing to reduce and renew the loan upon maturity. The different types of noncompliance vary greatly in severity. A firm that has been late with a payment may not be as financially unstable as a firm that has missed a payment. Knowing why the firm was considered noncomplying would have been beneficial. However, the banks were not willing to disclose this information.

The dependent variable in each discriminant model is the complying/noncomplying status of each firm. The independent variables are divided into three classifications:

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[2] For calculation of the size standards see Appendix III.

1. Financial data of the complying/noncomplying firm
2. Financial data of the industry of which the complying/noncomplying firm is a member
3. Economic data

The financial data of each firm will be measured in ratio form. By using ratios, rather than absolute amounts, the problem of size differences between firms will be eliminated. For example, current assets of $100,000 and current liabilities of $50,000 will be interpreted the same as current assets of $500,000 and current liabilities of $250,000. In both cases the current ratio is 2 to 1. The financial data collected on each firm are listed in Table 3-2 and the financial ratios calculated are listed in Table 3-3. The majority of these ratios were selected because of their frequent appearance and success in prior bankruptcy and failure studies [5, 6, 15, 29, 32]. Some of the ratios involving liquid assets, current liabilities and current maturities are novel to this research. These ratios should aid in measuring the liquid assets available to make payments on short-term notes and maturing long-term debt.

The industry data were collected from the Robert Morris Associates (RMA) Annual Statement Studies [66]. The RMA industry data are segregated by asset size, SIC code, and year-end. Each financial ratio included in this study as an independent variable was transformed by the corresponding RMA average ratio. This allows the ratios of each firm to be compared to the industry average ratio.

The general condition of the economy has an effect on business failures [13, 17], and therefore, probably an effect on a firm's

TABLE 3-2

FINANCIAL INFORMATION COLLECTED

1. Cash and Equivalents
2. Accounts and Notes Receivable
3. Inventory
4. Other Current Assets
5. Total Assets
6. Notes Payable - Short-term
7. Current Portion of Long-term Debt
8. Accounts and Notes Payable (trade)
9. Accrued Expenses
10. All Other Current Liabilities
11. Net Worth
12. Net Sales
13. Earnings Before Taxes
14. Income Taxes (corporations only)
15. Depreciation, Depletion, and Amortization

TABLE 3-3

FINANCIAL RATIOS

I. Earnings before taxes to:
  (a) total liabilities
  (b) notes payable - short-term
  (c) current liabilities
  (d) current maturities

II. Debt to total assets
  (a) notes payable - short term
  (b) current maturities
  (c) current liabilities

III. Liquid assets to current maturities
  (a) cash and equivalents
  (b) quick assets
  (c) current assets

IV. Liquid assets to current liabilities
  (a) cash and equivalents
  (b) quick assets
  (c) current assets

V. Turnover ratios
  (a) sales to cash
  (b) sales to accounts receivable
  (c) sales to inventory
  (d) sales to quick assets
  (e) sales to current assets
  (f) sales to working capital
  (g) sales to net worth
  (h) collection period (A-R and N-R/(Net Sales/365))

IV. Debt to cash flow
  (a) total liabilities
  (b) current liabilities
  (c) current maturities

ability to comply with its loan agreements. During expansionary periods both business starts and failures increase. During downturns in the economy business starts decline, but business failures increase. Only during periods of a stable economy do business failures decrease. These conditions are due at least partially to credit rationing and capital availability. They indicate that economic factors have an important effect on business failures.[3]

In addition to the financial, industry, and economic variables examined, dummy variables are included to take into account the form of ownership and major line of business. These are potentially important variables because the form of ownership and line of business may contain qualitative information about the firm [14, 27].

Hypotheses

The major objective of this study is to develop a model to predict loan noncompliance for a sample of small business firms. The initial task will be to build a simple discriminant model based solely on financial ratios. Next, the financial ratios will be combined with the industry data to construct a more complex model that is hypothesized to better predict loan noncompliance. Finally, economic data will be included in an attempt to enhance the predictive ability

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[3] The economic measures employed are:
- Gross National Product
- Consumer Price Index (all products)
- Prime Interest Rate (at firms year-end and year average)
- M1 (currency and demand deposits)
- M2 (M1 plus time deposits at commercial banks, other than large certificates of deposit)

of the discriminant models. Therefore, the following null hypotheses are proposed.

Hypothesis I

> Combinations of financial ratios provide information concerning a small business' ability to comply with its loan agreements.

This initial hypothesis will allow comparisons between the loan noncompliance model and previous failure models. The purpose of this comparison is to determine if financial ratios are as useful in predicting loan noncompliance as they are in predicting small business failure. The results of this hypothesis will serve as a benchmark with which to compare the results related to the remaining hypotheses.

Hypothesis II

> Combinations of financial ratios and industry data are more effective at predicting a small business' ability to comply with its loan agreements than financial ratios alone.

This hypothesis attempts to assess the relationship between the characteristics of a specific firm and those of other firms in the same industry. A ratio by itself may appear not to provide any useful or new information, however, when compared to other firms in the industry an importance may be discovered. Therefore, by transforming a firm's financial ratios by industry averages some of the nonfinancial and/or other information important to assessing a small business' tendency towards loan noncompliance may be captured. For example, a current ratio of 2:1 may appear adequate until compared to the industry average of 3:1. Therefore, by transforming a firm's ratio by the industry average an important discriminating characteristic may appear. Both Alves [9] and Edmister [32] found that industry data enhanced the financial data's ability to predict small business failure.

<u>Hypothesis III</u>

> The inclusion of economic data, with the financial ratios and industry data, improve the discriminant model's ability to predict a small business' ability to comply with its loan agreements.

The results of testing this hypothesis will be compared to the results of the first two hypotheses. This will determine if the ability of financial ratios to predict small business loan noncompliance is enhanced by the addition of economic data.

<u>Hypothesis IV</u>

> The ratios involving current maturities are more effective, than other ratios, at predicting a small business' ability to comply with its loan agreements.

This hypothesis will be tested by ranking the variables in the discriminant model. The ratios consisting of current maturities should <u>a priori</u> be some of the highest ranked variables. The ranking procedure that will be employed is the partial F-values. The partial F-values are provided by <u>BMDP Biomedical Computer Programs</u> [18] when the discriminant stepwise procedure is selected. The variables are ranked by the absolute values of the significant F-values. The larger the absolute F-value, the greater the discriminating power.

Data Analysis

There are four major divisions to the data analysis section. The first division deals with descriptive characteristics of the sample (e.g., maximum and minimum values, mean, median, etc.) and will determine if any adjustments must be made to the data for outlying points. After making the necessary adjustments the data will be tested for normality to determine if parametric or nonparametric univariate tests must be employed.

The second major division concerns the univariate tests that are performed. The purpose of these tests is to determine if the complying and noncomplying firms come from the same population. For the variables that follow a normal distribution a parametric Student's t-test will be used. The nonnormal variables will be tested using the Kruskal-Wallis Median Test which is a nonparametric test.

The third division is development of the discriminant models. Included in this subdivision are: (1) model development, (2) the assumptions of discriminant analysis, and (3) biases that can occur when employing discriminant analysis.

The final division covers the validation technique that will be employed to determine the classification error rates. The method used in this study will be the Lachenbruch-Mickey Leaving-one-out technique (LM).[4] Included will be a discussion comparing the

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[4] This technique is also referred to as the U Method and Jackknife technique.

hold-out method, the resubstitution method, and the LM method. In Chapter 4, the results obtained from employing the resubstitution method and a hold-out sample of complying firms are compared to the results of the LM method.

Descriptive Statistics

Initially, the data will be analyzed to determine each variable's maximum and minimum values, range, variance, standard deviation, mean, median, skewness, and kurtosis. Since the possibility that the variable distributions may deviate from normality cannot be eliminated, the skewness and kurtosis measures are useful as an estimate in determining the degree of nonconformity. The kurtosis measures whether the peakedness of the distribution. Skewness measures the lack of symmetry of the curve.

After the initial analysis, Kolmogorov-Smirnov (KS) one sample tests will be performed to test for normality. The KS test was chosen because of: (1) the small sample size, and (2) it is the most powerful goodness-of-fit test. If the sample size was large enough the Chi-square goodness-of-fit test could have been used. However, both Siegel [74] and Ostle and Mensing [62] hold that the KS test is more powerful than the Chi-square test, especially for small samples. The Chi-square test would have compared the distribution of the variables to the theoretical distribution (i.e., a normal distribution in this study). Whereas, the KS test compares the cumulative frequency distribution of the sample $[S_N(X)]$ to the expected cumulative frequency distribution of the theoretical distribution $[F_0(X)]$. The KS test proceeds as follows [62]:

1. Specify the theoretical cumulative distribution expected under H_0.

2. Arrange the observed scores in a cumulative distribution, pairing each interval of $S_N(X)$ with the comparable interval of $F_0(S)$.

3. For each step on the cumulative distributions calculate $F_0(X) - S_N(X)$.

4. Calculate $D = \text{maximum} \left| F_0(X) - S_N(X) \right|$

5. Find the probability associated with the occurrence under H_0 of values as large as the observed value of D. If the probability is equal to or less than α, reject H_0.

The descriptive statistics were derived by PROC UNIVARIATE and the KS tests performed by PROC KSLTEST of the Statistical Analysis Systems (SAS) [70] software package. The results are reported in Chapter 4.

Testing for Between Group Differences

Student's T-Test

The next step in the analysis is to test for differences between groups with respect to each of the financial ratios. The null hypothesis is that the noncomplying and complying firms come from the same population. The test commonly employed is the parametric Student's t-test [7, 9]. However, being a parametric test, to be applicable, the data must meet certain conditions [74]:

1. The observations must be independent.

2. The observations must be drawn from normally distributed populations.

3. These populations must have the same variance, or have a known ratio of variance.

4. The variables must be at least measured in an interval scale, so that it is possible to use the operations of arithmetic on the data.

The t-test evaluates the question of whether the two groups have equal means. How the t-statistic is calculated depends on whether the samples have equal or unequal variances. For samples that have equal variances the t-statistic is [62]:

$$t = (\bar{X}_1 - \bar{X}_2)/[S_p^2(1/n_1+1/n_2)]^{\frac{1}{2}} \qquad \text{Eq. 3-1}$$

where, $\bar{X}_1$ = the mean of sample one

$\bar{X}_2$ = the mean of sample two, and

S_p^2 = the estimate of the common variance

$$S_p^2 = [(n_1-1)S_1^2+(n_2-1)S_2^2]/(n_1+n_2-2) \qquad \text{Eq. 3-2}$$

where, n_1 = the size of sample one

n_2 = the size of sample two

S_1^2 = the variance of sample one, and

S_2^2 = the variance of sample two

For samples that have unequal variances the t-statistic is calculated as follows:

$$t = (\bar{X}_1-\bar{X}_2)/(S_1^2/n_1+S_2^2/n_2)^{\frac{1}{2}} \qquad \text{Eq. 3-3}$$

The T-TEST procedure in <u>SAS</u> [71] will be used to perform the tests. This procedure test for the equality of variances using an F-test and provides the t-test results assuming equal and unequal variances.

One of the basic assumptions of a t-test is that the data follow a normal distribution; if the assumption is violated the results of the t-test are biased. For the variables that proved to be nonnormal, a nonparametric test will be used to test the hypothesis that the samples are from the same population.

Kruskal-Wallis Median Test

A nonparametric test, the Kruskal-Wallis (KW) median test, will be used to determine if the nonnormal variables are from populations that differ in central tendencies. The null hypothesis being tested is that the samples were drawn from populations with the same median.

In performing the KW test the median for the combined samples (i.e., complying and noncomplying firms) is determined. Then each sample is segregated into two groups--number of observations above the combined median and number of points below the combined median. A chi-square value is then used to determine the probability of the observed frequencies above and below the median.

The KW tests will be performed using SAS procedure NPAR1WAY [71]. The preceding two tests examine each variable individually to determine if the ratios of the complying and noncomplying firms come from similar populations. The next division discusses the assumptions of discriminant analysis and development of the discriminant models.

Discriminant Analysis

The purposes of discriminant analysis are to: (1) test for mean group differences and describe the overlaps among groups, and (2) construct classification schemes to optimally classify entities into groups.

The general two-group discriminant problem can be characterized as follows: On the basis of the measurement of several variables, an entity must be assigned to one of two groups. The assumption is made that the two groups are the only possible choices and that an assignment must be made. One approach to this classification problem is to form a linear combination of the variables to form a single number, then the entity is classified into one of the two groups. In this study, the entities being classified are small business firms. The variable measurements being used to classify the firms are financial ratios and nonfinancial information. The two groups to which the firms can be classified are: (1) firms that are in compliance with their loan agreements, and (2) firms that are not in compliance with their loan agreements.

Model Development

The mathematical objective of discriminant analysis is to weight and combine the independent variables in such a manner that the two groups are as statistically different as possible. The weights are obtained so as to maximize the ratio of the between-group variance to the within-group variance. The set of weights associated with the independent variables allows application of the function to other data, to determine the predictive ability of the discriminant function. The general form of the linear discriminant function with i independent variables is

$$Z = b_1X_1+b_2X_2+...+b_iX_i+c \qquad \text{Eq. 3-5}$$

where, x_i is the i^{th} independent variable

b_i is the discriminant weight associated with the i^{th} independent variable

c is the constant term

Z is the discriminant score

The weights or coefficients are estimated by

$$\bar{B} = S^{-1}(\bar{X}_1-\bar{X}_2) \qquad \text{Eq. 3-6}$$

where, $\bar{B}$ is the matrix of estimated coefficients b_i

S^{-1} is the pooled within sum of cross-product deviations matrix

$\bar{X}_1$ is the variable observation matrix of the noncomplying firms

$\bar{X}_2$ is the variable observation matrix of the complying firms

The constant is estimated by

$$C = \tfrac{1}{2}\,\bar{B}(\bar{X}_1+\bar{X}_2) \qquad \text{Eq. 3-7}$$

To construct the discriminant functions BMDP [18] program 7M "Stepwise Discriminant Analysis" will be utilized. A stepwise procedure selects only those variables that add the most to the separation of the groups. The stepwise procedure begins by selecting the variable that discriminates "best" between the groups. The next variable selected is the one that adds the most to the separation of the groups, i.e., the one with the highest F-to-enter. During the procedure, a variable that has previously entered the discriminant function may be removed if the information it contains is also contained in a combination of other variables. At the conclusion of the stepwise procedure either all the independent variables will be included in the discriminant function or the excluded variables do not contribute to the separation of the groups.

Because robustness of a discriminant function is affected by how well the data conform to the assumptions of linear discriminant analysis, a discussion of the assumptions and the possible effects caused by not conforming with them follows

Assumptions of Linear Discriminant Analysis

There are several assumptions central to linear discriminant analysis that must be considered [33, 48, 63]:

1. The populations from which the data are obtained have a multivariate normal (MVN) distribution with different means.

2. All populations have unknown but equal dispersion (variance - covariance) matrices.

3. Classification accuracies assume equal cost of misclassification, equal prior group probability, and known dispersion and covariance structures.

4. The variables are independently normally distributed.

5. The observations are grouped, and each observation in each group involves at least two variables.

6. Each population distribution is determined by the same variables.

7. The populations are mutually exhaustive and exclusive.

Generally these assumptions are simply held to be true. However, of major concern is whether the data are MVN and the dispersion matrices are equal.

Multivariate Normal

One approach used to determine if the data are MVN is testing each of the independent variables for univariate normality since the marginal distributions of the MVN distribution are univariate normal. This does not ensure multivariate normality, because all of the independent variables could be univariately normal, but when combined together they are not necessarily MVN. For example, a bell can represent a MVN distribution. If the bell is sliced in any direction a univariate normal distribution results, however, slices from several bells cannot necessarily be assembled to form a new bell.

The strategy applied most frequently is to assume that the distribution is MVN, or if it is not, assume that the discriminant analysis and classification procedures employed are robust to non-multivariate normality. Lachenbruch, Sneeringer, and Revo [57] investigated the robustness of both linear and quadratic procedures for a nonmultivariate normal distribution. They concluded that the standard linear procedures may be quite sensitive to nonmultivariate normality. However, the linear procedures did perform better than the quadratic. They found that the estimated overall classification error rates were not as affected as much as the individual group rates.

Dummy variables (being 0 or 1) by definition will not have a MVN distribution. Gilbert [40] examined the effect of dichomotous variables (e.g., dummy variables) on the linear discriminant function. She concluded that the linear discriminant function performed markedly better than the quadratic. Therefore, because dummy variables are used to represent each firm's legal form and major line of business, linear discriminant analysis should be used in this study, however, the final decision to use linear or quadratic discriminant analysis must be postponed until other factors are examined.

Equality of Dispersion Matrices

A second critical assumption of linear discriminant analysis is that the group dispersion matrices are equal across all groups.[5] Unequal dispersion matrices imply that quadratic discriminant rules may be appropriate. When a linear rule is used and the dispersions are unequal significant differences can occur that are directly related to the differences in the dispersions, the number of variables, and the separation among groups [41]. Agreement between the two procedures declines as the differences between the dispersions and the number of variables increases.

The factor of equality of dispersion matrices interacts with three other factors in influencing classification results: (1) MVN, (2) number and independence of predictor variables, and (3) sample size. For large samples the quadratic procedure performs better

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[5] For further discussion of the effect of unequal dispersions on linear discriminant functions see Ethel S. Gilbert, "The Effect of Unequal Variance-Covariance Matrices on Fisher's Linear Discriminant Function," Biometrics, XXV (September 1969).

when: (1) the differences between the dispersion matrices are large, (2) the number of variables is small relative to the sample size, and (3) the data are MVN. The quadratic procedure does not perform as well as the linear procedure for small samples that have a large number of variables with similar dispersions. The performance of the quadratic procedure decreases as the number of variables increases, however, as the dispersions become more dissimilar the quadratic rules dominate [33, 41, 57, 64].

Linear discriminant procedures will be employed in this study because of the: (1) dummy variables used to represent each firm's legal form and major line of business, (2) small sample size and large number of variables, and (3) similarity of the dispersion matrices.

A Priori Probability and Cost of Misclassification

Many authors [33, 34, 48, 64] are firm in their belief that the only *a priori* probability that can be used is the probability of group membership in the population. An incorrect *a priori* probability leads to incorrectly stating the null hypothesis and inaccurate classification results.

In the absence of knowledge of the population prior probabilities, the common practice is to estimate the prior probabilities from the sample. This is appropriate if the pooled data represent a random sample from the population. However, in matched-pairs studies [5, 9, 29, 32] equal priors have been used successfully. Joy and Tollefson [47] provided an indication of how Altman's [5] results might be tempered if the population priors had been estimated. They determined that if a prior probability of 0.01 of bankruptcy had been used, Altman's linear discriminant function would not have been able to perform significantly better than chance. If Altman had been using a random sample, then a prior probability different from 0.50 would have been appropriate. However, because he had matched-pairs, a prior probability of less than 0.50 would force less firms to be classified as bankrupt and more as nonbankrupt. Therefore, for the purposes of this study equal prior probabilities are used for the complying and noncomplying firms.

Anderson [10] points out that, "... a good classification procedure is one which minimizes ... the cost of misclassification." The reason behind measuring the cost of misclassification is that some types of misclassification may be more costly. Therefore, the objective is no longer to minimize the classification error rate, but, to minimize the misclassification costs.

As a practical matter, there have been relatively few attempts to incorporate the costs of misclassification into reported business research. The primary problem with incorporating these costs into the classification rules is the lack of appropriate estimates of the relative costs. The costs of misclassification do not interact with any other factors in influencing the classification results. Joy and Tollefson [48] did revise Altman's [5] results to include the cost of misclassification. They determined that Altman's model would be superior to proportional chance classification if and only if, the cost of misclassifying a bankrupt firm was 21 times as great as the cost of misclassifying a nonbankrupt. However, Joy and Tollefson did not use Altman's prior probabilities, but their own, as previously mentioned. Therefore, their results may be questionable.

To apply discriminant analysis both the population priors and the costs of misclassification should be incorporated. A technique for doing this will be examined in Chapter 5.

Independent Normally Distributed

This assumption states that the independent variables should be independent of each other, i.e., there should be no correlation between the independent variables. When employing financial ratios this is difficult, if not impossible, to achieve. Many ratios have common numerators or denominators and therefore, to an extent, measure similar items.

Altman and Eisenbeis [8] reported that multicollinearity is only a problem when it is so severe that the dispersion matrix cannot be inverted to calculate the discriminant coefficients. They argue that multicollinearity in discriminant analysis is not analogous to multicollinearity in regression analysis. In regression analysis multicollinearity affects the standard deviations of the coefficients, thereby, biasing the tests of significance of the coefficients. Altman and Eisenbeis support this belief with three points:

1. Multicollinearity does not affect the estimates of the coefficients.

2. In discriminant analysis the standard deviations of the coefficients are usually not calculated, and

3. There are no applicable tests for the significance of the individual coefficients.

Other authors have refuted this belief [25, 33, 48, 52, 64]. Cochran [24] concluded that: (1) any negative correlation is helpful, and (2) positive correlations have to be very large to be helpful. In a study employing continuous and dichomotous variables (as in this study) Krzanowski [52] found that the strength and direction of the correlation may increase the error rates in one population and reduce them in another. However, the overall classification rate is not effected. Finally, Scott [73] indicates that the ranking of variables appears to be influenced by the presence of correlation among the independent variables. Altman and Eisenbeis [8, p. 12, footnote 12] agree with this, though they still hold that there is no absolute test for the ranking of the discriminating variables.

While, theoretically, multicollinearity may not cause problems in discrimination, in applied research a thorough review of the literature indicates there is a definite relationship between the degree of correlation among the independent variables and the classification results. If the discriminating variables are not independent, assessing their discriminating power by ranking them according to their partial F-values is not valid [33], because the partial F-values do not take into consideration the correlation between the variables. Because the variables are going to be ranked in order to test hypothesis three the correlation between the variables must first be reduced. This is accomplished via factor analysis. The variables retained to construct the discriminant models will have a high absolute value factor loading.

If linear discriminant analysis is to be used to classify entities into one of n groups, then the final three assumptions must be satisfied. Obviously, if the data are not separated into discrete and identifiable groups, the observations could not be classified. Thus, the fifth and sixth assumptions are automatically satisfied if linear discriminant analysis is appropriate.

If each population distribution is not determined by the same variables and there are not at least two variables for each observation, determining a linear combination of the variables would be impossible. In other words, each group must be evaluated on at least two characteristics (e.g., two financial ratios). And the same characteristics must be used for each observation. If these seven assumptions are satisfied, then linear discriminant analysis is appropriate. If one of the assumptions is violated, quadratic discriminant analysis may be appropriate. If one of the last three assumptions is violated, discriminant procedures are not appropriate.

Significance Test and Validation Techniques

Once the discriminant functions are derived, their level of significance will be tested using Wilks' lambda [26, 33, 47]. This statistic test the hypothesis that the mean of the ratio vectors for each group are equal. Wilks' lambda converts to an F-statistic, which is then used to indicate the probability of a significant separation between the scores of noncomplying and complying firms.

However, with large samples the mean of the ratio vectors for each group could be virtually equal, and still statistically significant, if this is the case the discriminating ability of the discriminant function would be poor. Therefore, to provide additional support concerning the discriminant function's ability to correctly classify the firms the classification error rate will be calculated. In discriminant analysis the classification error rate is analogous to the r-square in regression. It reveals how well the discriminant function classified the firms, i.e., the percentage of firms correctly classified.

Several techniques are available to estimate the error rates of the discriminant models. Three popular methods were considered for use in this study, they were: (1) the hold-out method (HO), (2) the resubstitution method (R), and (3) the Lachenbruch-Mickey leaving-one-out method (LM). These methods have been extensively discussed in the literature [33, 34, 54, 55, 56, 64, 73] and applied in prior financial studies [5, 9, 32, 75]. Each of the three methods is discussed below with the reason(s) for applying it or not applying it in this study.

Hold-Out Method

If the initial samples are sufficiently large, a random subsample may be chosen from each group to estimate the discriminant function. If the groups are not of equal size, the random sample should be drawn in proportion to the total sample distribution. The remaining observations are then classified by the discriminant function to determine the classification error rates. This procedure can be repeated several times, each time using different random samples to construct the discriminant functions. The proportion misclassified is then averaged over the replications. Replicating the procedure provides a better estimate of the proportion misclassified and hence, the degree of bias [39].

There are several drawbacks to the HO method. First, in many financial applications large samples are not available. Hair, et al., [43] recommend, at minimum, one hundred observations in each sample before the HO method can be applied. Second, the discriminant function that is evaluated is not the one that will be used in practice. Third, the estimated error rates are based on the subsample and may differ significantly from those to be used in practice, which should be based on the total sample. Thus, the HO method may provide biased error rate estimates of the population. Finally, there are problems connected with the size of the hold-out sample. If it is large, a good estimate of the performance of the discriminant function will be obtained, but the discriminant function is likely to be poor. If the hold-out sample is small, the discriminant function will be better, but the evaluation of its performance will be highly variable [55].

A hold-out sample of complying and noncomplying will not be used in this study because of the large sample required. When applied to small samples the HO method provides a biased error rate estimate. If the sample had been sufficiently large the HO method would have been used to compare its error rates against other error rate estimates generated. However, the complying firms not used in the matched pairs sample constitute a hold-out group. These firms will be classified by the discriminant models and the error rate will be compared to the results for complying firms using the other validation methods.

Resubstitution Method

The R method is another technique sometimes used to estimate classification error rates. The R method is so named because the observations used to derive the discriminant function are then classified by the discriminant function to determine the error rates. This method provides overly optimistic estimates of the error rates, and the smaller the sample the more biased the error rates [55, 64].

Because the R method gives a much too optimistic estimation of the classification error rates, it generally is used only for comparative purposes. The R method was used for comparative purposes in this study. The main technique to be used to estimate the error rates is the LM method.

Lachenbruch-Mickey Method

The LM method yields almost unbiased estimates of the appropriate classification error rates. It provides a technique for estimating error rates for small samples, other than the R method. Some authors [54, 55] have found that the LM method is not sensitive to the normality assumption and will produce the least biased results when the data are nonnormal. Based upon their research Lachenbruch and Mickey [55] concluded that the HO method has no clear advantage over the LM method.

The LM method requires the calculation of n_1+n_2 discriminant functions. The method holds out one observation at a time, estimates the discriminant function based upon n_1+n_2-1 observations and classifies the held out observation. This procedure is repeated for all observations in the sample. The classification error rate is determined by totaling the number of misclassifications. With this method, no observation has any effect on the discriminant function classifying it.

In this study the LM method is used for calculating classification error rates. The main reason for using the LM method is that it is appropriate for nonnormal small samples. The data are nonnormal to an extent since dichomotous variables are included. The results of the LM method are compared to the results of the R method in Chapter 4.

Summary

The data for the research were gathered from Robert Morris Associates (RMA) member banks. The data requested were the RMA Data Submission Forms submitted to RMA by the banks. On each form the banks were requested to indicate whether the firm was, or was not, in compliance with its loan agreement at its year end.

From the RMA data Submission Forms twenty-four ratios were calculated for each firm. The ratios were initially analyzed to determine their distributional chacteristics (e.g., maximum and minimum value, standard deviation, range . . ., etc.). The set of twenty-four ratios was reduced to a smaller subset via factor analysis, before testing the hypotheses.

The four hypotheses set forth are:

1. Combinations of financial ratios provide information concerning a small business' ability to comply with its loan agreements.

2. The inclusion of industry data, with the financial ratios, will improve the discriminant model's ability to predict a small business' ability to comply with its loan agreements.

3. Combinations of financial ratios and economic data are more effective at predicting a small business' ability to comply with its loan agreements than financial ratios alone.

4. The ratios involving current maturities are more effective, than other ratios, at predicting a small business' ability to comply with its loan agreement.

The hypotheses will be tested via discriminant analysis. A discriminant function will constructed for the first three hypotheses. The results of hypothesis one, will be used as a benchmark to evaluate the results of the discriminant functions derived for hypotheses two and three. The fourth hypothesis will be tested by ranking the independent variables in the discriminant function. For hypothesis four the variables were ranked by the absolute value of the partial F-values calculated by the BMDP [18] stepwise discriminant procedure.

Wilkes' lambda will be used to test the significance of each discriminant function. To test the validity of each function the Lachenbruch-Mickey leaving-out-out method will be employed to determine the classification error rates. The results of the resubstitution method and a hold-out sample of complying firms will be compared to the results of the LM method.

CHAPTER IV

ANALYSIS

In this chapter the results of the data analysis and hypothesis testing are presented. To aid the flow of the material presented, the descriptive statistics for the original ratios are examined first, followed by the univariate tests, and then the same presentation is employed for the transformed data. Finally, the discriminant models developed to test the hypotheses are examined.

Descriptive Statistics - Original Ratios

Kolmogorov-Smirnov one-sample tests

Table 4-1 presents the D-values for the K-S tests on the original ratios. All but three of the D-values were significant at the 0.10 level. This means that the variables, generally, do not follow a normal distribution. The ratios with D-values that were not significant at the 0.10 level were:

1. Earnings before taxes to total liabilities
2. Earnings before taxes to current liabilities
3. Quick assets to current liabilities

Though there were some outlying points more than three standard deviations from the mean, only one ratio (net sales to accounts receivable) had as many as three outliers (see Table 4-2).

TABLE 4-1

KOLMOGOROV-SMIRNOV D-VALUES FOR COMPLYING AND NONCOMPLYING FIRMS[1]

Ratio	Complying	Noncomplying
Earnings Before Taxes to Total Liabilities	0.1619	0.0925[2]
Earnings Before Taxes to Notes Payable--Short-term	0.2998	0.3719
Earnings Before Taxes to Current Liabilities	0.1696	0.0778[2]
Earnings Before Taxes to Current Maturities	0.3798	0.2686
Debt to Notes Payable--Short-term	0.3284	0.3814
Debt to Current Maturities	0.2984	0.3036
Debt to Current Liabilities	0.3002	0.2290
Debt to Cash Flow	0.2971	0.2652
Net Sales to Cash	0.3678	0.2932
Net Sales to Accounts Receivable	0.4310	0.3748
Net Sales to Inventory	0.4375	0.4521
Net Sales to Quick Assets	0.3176	0.3923
Net Sales to Working Capital	0.3002	0.3186
Net Sales to Net Worth	0.2302	0.3868
Net Sales to Current Assets	0.1329	0.2959
Collection Period	0.2806	0.3230
Cash to Current Liabilities	0.1956	0.1935
Cash to Current Maturities	0.3596	0.2486
Quick Assets to Current Liabilities	0.1329	0.1088[3]
Quick Assets to Current Maturities	0.3023	0.2772
Current Assets to Current Maturities	0.3407	0.3324
Current Assets to Current Liabilities	0.1928	0.2859
Current Liabilities to Cash Flow	0.2983	0.1891
Current Maturities to Cash Flow	0.3720	0.1675

[1] All values are significant at $\alpha = 0.10$, unless indicated otherwise.

[2] Significant at $\alpha = 0.20$.

[3] Significant at $\alpha = 0.15$.

TABLE 4-2

SKEWNESS, KURTOSIS AND NUMBER OF OUTLIERS FOR THE COMPLYING AND NONCOMPLYING FIRMS

Ratio	Complying			Noncomplying		
	Skewness	Kurtosis	No. of Outliers	Skewness	Kurtosis	No. of Outliers
Earnings Before Taxes to Total Liabilities	1.3370	1.4664	0	0.0491	0.9006	0
Earnings Before Taxes to Notes Payable--Short-term	2.3896	5.2845	1	3.1368	11.5781	1
Earnings Before Taxes to Current Liabilities	1.3325	1.1316	1	0.0247	0.8383	0
Earnings Before Taxes to Current Maturities	4.3479	19.3018	2	3.0743	14.3291	1
Debt to Notes Payable--Short-term	3.0204	10.2871	1	2.3646	4.8666	1
Debt to Current Maturities	4.3861	22.5859	1	2.3658	4.4604	2
Debt to Current Liabilities	4.8773	28.7147	1	2.1596	6.0150	1
Debt to Cash Flow	3.4161	12.5557	2	-2.8564	22.0225	2
Net Sales to Cash	6.7072	46.4263	1	-1.9604	14.8109	1
Net Sales to Accounts Receivable	3.6417	12.1231	3	3.4786	11.6961	3
Net Sales to Inventory	6.5109	42.5773	1	5.5383	32.0744	1
Net Sales to Quick Assets	3.5566	14.2027	2	4.2948	18.5850	2
Net Sales to Working Capital	5.5463	35.3727	1	2.6698	12.8857	2
Net Sales to Net Worth	3.2810	12.0121	2	4.0636	17.0034	2
Net Sales to Current Assets	2.2469	7.9346	1	4.9387	28.4148	1
Collection Period	3.7950	17.7150	1	4.9167	27.4711	1
Cash to Current Liabilities	2.0103	4.8697	1	-0.0401	2.6450	0
Cash to Current Maturities	3.8689	15.3855	2	2.4244	6.7491	1
Quick Assets to Current Liabilities	1.4739	2.9071	1	0.6946	0.1864	0
Quick Assets to Current Maturities	4.1612	20.2019	1	4.3934	23.4558	1
Current Assets to Current Maturities	3.6493	12.9646	2	4.0966	18.0697	1
Current Assets to Current Liabilities	1.1556	0.4589	0	2.8660	8.9587	1
Current Liabilities to Cash Flow	3.9680	17.7668	1	-1.7845	7.3757	1
Current Maturities to Cash Flow	4.1144	18.0157	2	0.6349	3.5688	2

The measures of skewness and kurtosis suggest that the data are non-symmetrical and peaked. The skewness measure should have a value of zero if the distribution is a completely symmetric bell shaped curve. A positive value indicates that the points are clustered more to the left of the mean with most of the extreme values to the right. A negative value indicates clustering to the right of the mean. A normal distribution should have a kurtosis of zero. If the kurtosis is positive, then the distribution is more peaked than would be true for a normal distribution. A negative value means the curve is flatter than a normal curve. The kurtosis is calculated as follows:

$$\beta_2 = \frac{\dfrac{\Sigma(X_i-\mu)^4}{N}}{\dfrac{\Sigma(X_i-\mu)^2}{N}} - 3$$

where, β_2 is the measure of kurtosis

X_i is the i^{th} observation

μ is the population mean

As Table 4-2 shows all of the ratios for the complying firms had a positive skewness and kurtosis. The skewness measures ranged from 1.556 to 6.7072, whereas, the kurtosis measures were from 0.4589 to 46.4263. This indicates that most of the ratios values were less than the mean and the distribution was very peaked. For the non-complying firms four ratios (net sales to cash, debt to cash flow, cash to current liabilities, and current liabilities to cash flow) had a negative skewness. All the noncomplying firms' ratios had a positive kurtosis. The skewness and kurtosis measures ranged from -2.8564 to 5.5383 and 0.1864 to 32.0744, respectively.

Because discriminant analysis requires the data to be multivariate normal, an attempt was made to improve the normality of the individual variables. All the outlying points were summed, then the mean of the points was inserted in place of each outlying point. This was done for each ratio with more than one outlier. However, since the data were extremely skewed, this generally had the effect of replacing one outlying point with another. Because most ratios had only two outliers this decreased the outlying distance of one point, while increasing the distance of the other. This procedure did not significantly improve the normality of the distributions. If the data had been more normally distributed (i.e., with positive and negative outliers), substituting the mean of the outliers might have improved the distribution.

A procedure that is frequently employed to improve the normality of a distribution is a log transformation, however, because of the negative ratios much potentially valuable information would have been deleted. Therefore, this transformation was determined to be inappropriate for this study. The effect of the nonnormality on the discriminant models will be discussed later.

The mean, standard deviation, maximum value, median and minimum value are presented in Tables A4-1 and A4-2 in Appendix IV for the complying and noncomplying firms, respectively.

Univariate Tests For Differences Between Group Means-Original Ratios

Two tests were employed to determine if there was a statistically significant difference between the complying and noncomplying firms on an univariate basis. The tests were: (1) Student's t-test, and (2) Kruskal-Wallis median test. The null hypothesis tested was: There is no statistical difference in the central tendencies of the ratios of the complying and noncomplying firms. Because of the non-normality of the ratios the t-test results are biased. The potential of a Type II error is increased, that is, the t-test may indicate no difference when in fact there is a difference.

Table 4-3 recapitulates the results of the t-tests and the KW tests. Seven of the ratios were not statistically significant employing either test. Two were debt ratios, debt to notes payable--short-term and debt to current maturities. The remaining five ratios involved net sales. They were:

1. Net sales to cash
2. Net sales to accounts receivable
3. Net sales to quick assets
4. Net sales to net worth
5. Collection period[1]

The net sales ratios may not be statistically significant because the firms were classified as small because their net sales did not exceed an upper bound. Since the firms were matched according to 2-digit SIC codes the noncomplying firm and its mate had the same upper bound. The univariate tests were applied to the net sales of the complying and noncomplying firms and no significant difference was found. The remaining ratios were determined to be significantly different by at least one of the tests.

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[1] Collection period was defined as: accounts receivable/(net sales/365).

TABLE 4-3

RESULTS OF UNIVARIATE STATISTICAL TESTS--
ORIGINAL RATIOS

	Test	
	T-test	Kruskal-Wallis Median Test
Earnings Before Taxes to Total Liabilities	0.001	0.001
Earnings Before Taxes to Notes Payable--Short-term	0.094	0.058
Earnings Before Taxes to Current Liabilities	0.001	0.001
Earnings Before Taxes to Current Maturities	0.018	0.001
Debt to Notes Payable--Short-term	NS*	NS
Debt to Current Maturities	NS	NS
Debt to Current Liabilities	0.052	0.076
Debt to Cash Flow	0.052	NS
Net Sales to Cash	NS	NS
Net Sales to Accounts Receivable	NS	NS
Net Sales to Inventory	NS	0.051
Net Sales to Quick Assets	NS	NS
Net Sales to Working Capital	NS	0.001
Net Sales to Net Worth	NS	NS
Net Sales to Current Assets	0.022	NS
Collection Period	NS	NS
Cash to Current Liabilities	0.001	0.040
Cash to Current Maturities	0.026	0.007
Quick Assets to Current Liabilities	0.001	0.060
Quick Assets to Current Maturities	0.028	0.089
Current Assets to Current Maturities	NS	0.047
Current Assets to Current Liabilities	NS	0.043
Current Liabilities to Cash Flow	0.006	NS
Current Maturities to Cash Flow	0.032	NS

*Not significant at the 0.10 level.

Twenty-one of the 24 original ratios were transformed by dividing the firm's ratio by the industry average ratio for the firm's four digit SIC code. This was done to capture important information about the firm's relationship to the other firms in the industry. For example, a firm's current ratio may be extremely high or low in relation to other firms in the industry. By dividing the firm's ratio by the industry average ratio this information can now be utilized in developing the discriminant models. The data to transform the ratios were gathered from RMA Annual Statement Studies [66]. The three ratios involving cash flow were not transformed because RMA does not report the income tax information necessary to calculate the industry average cash flow.

Transformed Ratios

Table 4-4 presents the results of the two univariate tests performed on the transformed ratios. The detailed results of the student's t-tests, and the KW tests, as well as the KS tests, are presented in Appendix V. Eight of the 21 ratios were not significantly different employing either of the tests. They were:

1. Debt to notes payable--short-term
2. Debt to current maturities
3. Net sales to accounts receivable
4. Net sales to inventory
5. Net sales to quick assets
6. Net sales to net worth
7. Net sales to cash
8. Collection period

The remaining ratios were significantly different at the 0.10 level.

TABLE 4-4
RECAPITULATION OF UNIVARIATE STATISTICAL TESTS--
TRANSFORMED RATIOS

	P Value Results	
	T-test	Kruskal-Wallis Median Test
Earnings Before Taxes to Total Liabilities	0.050	0.001
Earnings Before Taxes to Notes Payable--Short-term	0.0252	0.015
Earnings Before Taxes to Current Liabilities	0.0247	0.001
Earnings Before Taxes to Current Maturities	0.0265	0.001
Debt to Notes Payable--Short-term	NS*	NS
Debt to Current Maturities	NS	NS
Debt to Current Liabilities	0.0332	0.030
Net Sales to Cash	NS	NS
Net Sales to Accounts Receivable	NS	NS
Net Sales to Inventory	NS	NS
Net Sales to Quick Assets	NS	NS
Net Sales to Working Capital	NS	0.001
Net Sales to Net Worth	NS	NS
Net Sales to Current Assets	NS	0.030
Collection Period	NS	NS
Cash to Current Liabilities	0.0297	0.003
Cash to Current Maturities	0.0813	NS
Quick Assets to Current Liabilities	0.0220	NS
Quick Assets to Current Maturities	0.0265	0.012
Current Assets to Maturities	0.0936	0.001
Current Assets to Current Liabilities	NS	0.005

*Not significant at the 0.10 level.

TABLE 4-5

P VALUE RESULTS OF UNIVARIATE STATISTICAL TESTS--
TRANSFORMED RATIOS AND
ORIGINAL RATIOS

Ratio	T-test		Kruskal-Wallis Median Test	
	Transformed	Original	Transformed	Original
Earnings Before Taxes to Total Liabilities	0.050	0.001	0.001	0.001
Earnings Before Taxes to Notes Payable--Short-term	0.025	0.039	0.005	0.006
Earnings Before Taxes to Current Liabilities	0.025	0.001	0.001	0.001
Earnings Before Taxes to Current Maturities	0.026	0.018	0.001	0.001
Debt to Notes Payable--Short-term	NS*	NS	NS	NS
Debt to Current Maturities	NS	NS	NS	NS
Debt to Current Liabilities	0.033	0.052	0.030	0.076
Debt to Cash Flow	N/A	0.052	N/A	NS
Net Sales to Cash	NS	NS	NS	NS
Net Sales to Accounts Receivable	NS	NS	NS	NS
Net Sales to Inventory	NS	NS	NS	0.051
Net Sales to Quick Assets	NS	NS	NS	NS
Net Sales to Working Capital	NS	NS	0.001	0.001
Net Sales to Net Worth	NS	NS	NS	NS
Net Sales to Current Assets	NS	0.022	0.030	NS
Collection Period	NS	NS	NS	NS
Cash to Current Liabilities	0.030	0.001	0.003	0.040
Cash to Current Maturities	0.081	0.026	NS	0.007
Quick Assets to Current Liabilities	0.022	0.001	NS	0.060
Quick Assets to Current Maturities	0.026	0.028	0.012	0.089
Current Assets to Current Liabilities	NS	NS	0.001	0.047
Current Assets to Current Maturities	0.094	NS	0.005	0.043
Current Liabilities to Cash Flow	N/A	0.006	N/A	NS
Current Maturities to Cash Flow	N/A	0.032	N/A	NS

* Not significant at the 0.10 level

Comparison of Univariate Results For Original and Transformed Ratios

Table 4-5 presents the results of the t-tests, and KW tests on both the original and transformed ratios. Seven ratios were significantly different at the 0.10 level or lower for both tests, in their original and transformed form. The seven ratios were:

1. Earnings before taxes to total liabilities
2. Earnings before taxes to notes payable--short-term
3. Earnings before taxes to current liabilities
4. Earnings before taxes to current maturities
5. Debt to current liabilities
6. Cash to current liabilities
7. Quick assets to current maturities

Cash to current maturities and quick assets to current liabilities were significantly different for both tests, except the KW test on the transformed data. Current assets to current maturities was significantly different for both tests, except the t-tests, in which case it was not significantly different in the original form.

There were 19 cases in which a ratio was significantly different in both its original and transformed form. In only five of these cases did the transformed variable have a lower significance level. In the other sixteen cases the transformed variable had the same or higher significance level.

Two ratios, current assets to current liabilities and net sales to working capital, were significantly different in both their transformed and original form when tested using the KW test. However, they were not found to be significantly different using the t-test. This could be attributed to the nonnormality of the ratios which increases the chance for a Type II error.

From examining Table 4-5 nine ratios independently appear to be poor indicators of a firms ability to comply with their loan agreements. Because they were not found to be statistically significant with the univariate tests. The ratios are:

1. Debt to notes payable--short-term
2. Debt to current maturities
3. Debt to cash flow
4. Net sales to cash
5. Net sales to accounts receivable
6. Net sales to inventory
7. Net sales to quick assets
8. Net sales to net worth
9. Collection period

This result implies that the amount of short-term notes payable or current maturities in relation to total debt was not an indicator of noncompliance. The amount of current liabilities to debt was a significant indicator of noncompliance. Therefore, when determining if a firm will be able to comply with its loan agreements all current liabilities should be considered, not just other loans or notes outstanding.

Sales has little or no relationship with compliance with loan agreements. However, a firm's earnings before taxes (EBT) was an important factor in distinguishing loan compliance or noncompliance. All the ratios involving EBT were significantly different.

The period of time required to collect accounts receivable (the collection period) was not a significantly different ratio; but cash flow was significantly different when combined with total debt, current liabilities, and current maturities.

Even though several ratios were significantly different on a univariate basis, the hypotheses set forth in Chapter III could only be tested on a multivariate basis. The next section will examine the results of testing these hypotheses.

Hypothesis Testing--Discriminant Analysis

As outlined in Chapter III, linear discriminant models were developed to test the first three hypotheses. Table 4-6 illustrates the data used to construct the discriminant models. The estimates of the models, the classification results, and the hypotheses conclusions are presented in this order.

Even though the variables were not univariate normal they were used as inputs to construct the discriminant models. A procedure recommended by Conover and Iman [25] was used to examine the effect of the nonmultivariate normality on the linear discriminant function. The procedure requires ranking the observations of each variable in ascending order, then, the ranks are employed to develop a discriminant model. They tested this procedure on nonnormal samples ranging from size eight to 2000. To test the effectiveness of the rank transformation they used a log transformation to normalize the nonnormal samples, then, the normalized data were used to construct a discriminant model. The results of the two transformations were then compared. In all cases the rank transformation performed better than the log normal transformation. Therefore, to determine if the nonnormality had an effect on the linear discriminant functions in this study the values for each ratio were ranked in ascending order and a discriminant model was constructed using the ranks. These results were compared to the results obtained using the nonnormal data (i.e., the ratio values). Since the results of the two models were similar

TABLE 4-6

MODEL COMPOSITION

Hypothesis Number	Data Included
I	Financial ratios
II	Financial ratios divided by industry average ratios
III	Financial ratios divided by industry average ratios, and economic data
IV	Current maturities--tested for each of the preceding hypothesis

the conclusion was drawn that the discriminant procedure was robust to the nonmultivariate normality.

Each discriminant model contains a constant which produces a cutting score equal to zero. The cutting score is the criterion against which each firm's discriminant score is judged to determine into which group (complying or noncomplying) the firm should be classified. Firms with a positive score are classified as complying and firms with a negative score are classified as noncomplying.

Two discriminant functions were derived for each hypothesis. The first function was derived from a subset of the original data, whereas, the second function was constructed employing the entire data set. The data set used to develop the first function was determined via factor analysis. PROC FACTOR from SAS [71] employing the principal axis method with a varimax rotation was used to produce an orthogonal solution, whereby, the factors by definition are independent [43]. Then one ratio was selected to represent each factor, thereby, producing a subset of independent predictor variables (i.e., financial ratios).[2] This procedure was used because it is practical and easily applied.

Hypothesis I

Model I - Reduced Data Set

The first hypothesis stated that, "combinations of financial ratios provide information concerning a small business' ability to comply with its loan agreements." The rotated factor pattern used to reduce the data set is presented in Table 4-7. The seven factors account for 88.6 percent of the variance. The ratios selected to represent the factors were:

1. Earnings before taxes to current liabilities
2. Net sales to accounts receivable
3. Debt to cash flow
4. Net sales to inventory
5. Debt to current liabilities
6. Cash to current liabilities
7. Net sales to working capital

The general rule in selecting the ratio to represent a factor is to select the ratio with the highest absolute value factor loading. However, for Factors 1 and 5 this was not done. Following the general rule, earnings before taxes to notes payable--short-term would have been chosen to represent Factor 1. Instead, earnings

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[2] An alternative approach is to use each observation's score on the factors as the input data to construct the discriminant function. This procedure was performed and the results were very similar to the results reported in Table 4-11.

TABLE 4-7

ROTATED FACTOR PATTERN FOR HYPOTHESIS I

Ratio	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
Earnings Before Taxes to Total Liabilities	0.95275*	-0.08311	-0.06074	-0.01906	-0.02984	0.15193	0.12845
Earnings Before Taxes to Notes Payable--Short-term	0.97805*	0.04002	0.14361	-0.04671	0.16939	0.08728	-0.05813
Earnings Before Taxes to Current Liabilities	0.95530*	-0.10036	-0.05913	-0.01528	0.03919	0.15027	0.08384
Earnings Before Taxes to Current Maturities	0.93723*	-0.09740	-0.01189	-0.06359	0.10742	0.22499	0.14421
Debt to Notes Payable--Short-term	0.25567	-0.04135	-0.12673	0.06744	0.87002*	0.8666	0.14305
Debt to Current Maturities	0.19905	-0.04501	-0.22888	-0.14884	0.81126*	0.32602	0.10132
Debt to Current Liabilities	-0.13515	-0.05099	-0.17010	-0.01223	0.77825*	-0.06538	-0.20468
Debt to Cash Flow	-0.01314	-0.03549	0.96704*	-0.08059	0.01488	-0.02462	-0.04557
Net Sales to Cash	-0.04989	0.11229	-0.10715	-0.07648	0.05198	-0.45974	0.67068*
Net Sales to Accounts Receivable	-0.05317	0.98802*	0.02798	0.04974	-0.01268	-0.03184	0.02189
Net Sales to Inventory	-0.01090	-0.04296	-0.02331	-.98378*	-0.01405	0.10509	-0.02681
Net Sales to Quick Assets	-0.03349	0.90446*	-0.03653	0.00581	-0.07200	-0.21853	0.13144
Net Sales to Working Capital	0.18644	0.02871	0.06095	0.01341	-0.03402	0.11435	0.70607*
Net Sales to Net Worth	-0.03706	0.36845	0.48914*	0.22680	-0.11099	-0.10275	0.45266
Net Sales to Current Assets	-0.06209	0.58425	-0.05549	0.73746*	0.01650	-0.16872	0.10898
Collection Period	0.05317	-0.98802*	-0.02798	-0.04974	0.01268	0.03184	-0.02189
Cash to Current Liabilities	0.15529	-0.10838	-0.03359	0.03002	-0.03321	0.91274*	-0.14612
Cash to Current Maturities	0.26683	-0.11300	-0.04900	-0.06328	0.19630	0.89874*	0.02290
Quick Assets to Current Liabilities	0.26404	-0.56939*	-0.13055	0.01780	0.20815	0.56221	0.32509
Quick Assets to Current Maturities	0.36790	-0.38921	-0.14927	-0.10542	0.36537	0.58157*	0.37861
Current Assets to Current Liabilities	0.41539	-0.01382	-0.08303	-0.51394*	0.19779	0.33898	0.47367
Current Assets to Current Maturities	0.45964	-0.06407	-0.09484	-0.39970	0.42273	0.46404*	0.40451
Current Liabilities to Cash Flow	0.03101	0.00284	0.94281*	-0.05318	-0.20298	0.02623	0.07039
Current Maturities to Cash Flow	-0.02367	0.02814	0.87463*	0.08249	-0.34761	-0.12926	-0.07944

* Significant factor loading

before taxes to current liabilities was chosen, because it was significantly different at lower levels in the KW test. For Factor 5, debt to notes payable--short-term had the highest absolute value factor loading. However, it was not found to be significantly different by the nonparametric test. Therefore, debt to current liabilities was chosen to represent Factor 5.

These seven ratios were combined with the dummy variables representing legal form and product line to produce the following discriminant function:

$$Z = 2.01981X_2 + 2.13674X_{11} + 0.01388X_{25} + 2.24603X_{26} - 0.75888$$

where, X_2 = Dummy variable for proprietorship
X_{11} = Earnings before taxes to current liabilities
X_{25} = Debt to cash flow
X_{26} = Cash to current liabilities

This function had a Wilks' lambda of 0.68519, which when converted to a F-statistic is significant at the 0.001 level.

Table 4-8 presents the classification results using the resubstitution and jackknife methods. The resubstitution method reflects the application of the model to the data that were used to derive it. The jackknife method is the Lachenbruch-Mickey leaving-one-out method.

Based on the 73.5 percent classification accuracy of the model, using the jackknife method, the first hypothesis would not be rejected because the model performed significantly better than the

TABLE 4-8

CLASSIFICATION MATRIX FOR THE REDUCED DATA SET--
ORIGINAL RATIOS

Actual Classification of Firms	Percent Correct	Number of Firms Classified Into Group	
		Comply	Noncomply
Resubstitution			
Complying	66.7	34	17
Noncomplying	82.4	9	42
Total	74.5	43	59
Jackknife			
Complying	66.7	34	17
Noncomplying	80.4	10	41
Total	73.5	44	58

proportional chance model.[3] The Z-statistic was significant at the 0.001 level.[4] A holdout sample of 204 complying firms was employed to further test the model. Fifty-one percent (104 firms) of the holdout sample was correctly classified. Upon examining the results of the holdout sample the decision to reject or not reject the first hypothesis was postponed until the results of the discriminant function derived from the entire data set were examined.

Model II - Entire Data Set

The second discriminant function for the first hypothesis was derived from the entire data set (i.e., examining all 24 ratios). Because BMDP [18] employs a stepwise procedure, it includes a safeguard to prevent highly correlated variables from entering the discriminant function. No variable is entered into the function

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[3] Under the proportional chance model, firms are randomly assigned to groups with probabiliites equal to group frequencies. The expected fraction of correct classifications under this scheme is:

$$\left(\frac{50}{100}\right)^2 + \left(\frac{50}{100}\right)^2 = 0.50$$

For detailed discussions of chance models see: Hair, et al [43], Joy and Tollefson [48], and Morrison [61].

[4] The test statistic used is [8]:

$$Z = \frac{\bar{Y} - \pi}{\frac{1 - \pi}{n..}} \qquad \text{Eq. 4-1}$$

where, $\bar{Y}$ is the proportion of observations correctly classified by the function

π is the probability of classification by chance

n.. is the number of firms in the sample whose squared multiple correlation with already entered variables exceeds 0.20 or whose entry would cause the squared multiple correlation of an already entered variable with the other variables to exceed 0.20. Setting this standard does provide somewhat of a safeguard against multicollinearity, but it is not as stringent as reducing the data set via factor analysis.

The discriminant function derived from the entire data set was:

$$Z = 4.07928X_9 + 1.99067X_{26} + 0.04534X_{31} - 0.91541$$

where, X_9 = Earnings before taxes to total liabilities
X_{26} = Cash to current liabilities
X_{31} = Current liabilities to cash flow

The Wilks' lambda for this function was 0.64386, which converted to an F-statistic of 18.069 that is significant at the 0.001 level. The classification results are presented in Table 4-9. Of the 204 firms in the holdout sample, this model correctly classified 127 of the firms (62.2%).

This function was more accurate than the function derived from the reduced data set. The change mainly occurred in the classifying of the complying firms. The first model correctly classified 66.7 percent of the original complying firms and only 51 percent of the holdout sample. Whereas, the second model correctly classified 74.5 percent of the original complying firms and 62.2 percent of the holdout sample.

Based on the results of the second discriminant function the first hypothesis was not rejected. A firm's financial ratios, when

TABLE 4-9

CLASSIFICATION MATRIX FOR THE ENTIRE DATA SET--
ORIGINAL RATIOS

Actual Classification of Firms	Percent Correct	Number of Firms Classified Into Group	
		Comply	Noncomply
Resubstitution			
Complying	74.5	38	13
Noncomplying	80.4	10	41
Total	77.5	48	54
Jackknife			
Complying	74.5	38	13
Noncomplying	78.4	11	40
Total	76.5	49	53

combined in a linear manner, do provide an indication of the firm's ability to comply with its loan agreements.

Hypothesis II

Model I - Reduced Data Set

The second hypothesis posited that, "combinations of financial ratios and industry data are more effective at predicting a small business' ability to comply with its loan agreements than financial ratios alone."

The first discriminant model was derived from a reduced data set. The rotated factor patterns utilized to reduce the data set are illustrated in Table 4-10. The six factors accounted for 87 percent

TABLE 4-10

ROTATED FACTOR PATTERN FOR HYPOTHESIS II

Ratio	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Earnings Before Taxes to Total Liabilites	0.96200*	-0.00647	-0.07539	0.02980	0.06687	0.15641
Earnings Before Taxes to Notes Payable--Short-Term	0.95143*	0.16803	0.14722	-0.09716	-0.07903	0.11452
Earnings Before Taxes to Current Liabilities	0.96555*	0.01163	-0.01010	0.04350	0.05491	0.15094
Earnings Before Taxes to Current Maturities	0.95514*	-0.01602	0.06232	-0.03510	0.12863	0.19458
Debt to Notes Payable--Short-Term	0.24192	0.10919	0.85468*	0.13545	0.07176	0.21382
Debt to Current Maturities	0.12539	-0.05204	0.82499*	-0.12105	0.00482	0.39658
Debt to Current Liabilities	-0.22396	0.07644	0.84401*	-0.05866	-0.10002	-0.01245
Net Sales to Accounts Receivable	0.08601	0.98069*	0.07361	0.03915	0.07637	0.00284
Net Sales to Inventory	-0.00264	-0.05476	-0.04825	0.96261*	0.07655	0.12255
Net Sales to Working Capital	0.15008	0.13528	0.01124	0.04671	0.59355*	0.24385
Net Sales to Quick Assets	0.01454	0.86245*	-0.00585	0.01406	0.28198	-0.21138
Net Sales to Net Worth	0.08053	0.32529	-0.14817	0.29184	0.55001*	-0.18078
Net Sales to Cash	-0.05014	0.07846	0.03780	-0.00928	0.82172*	-0.26456
Net Sales to Current Assets	-0.10226	0.61492	0.10319	0.66076*	0.19849	-0.19561
Collection Period	-0.08601	-0.98069*	-0.07361	-0.03915	-0.07637	-0.00284
Cash to Current Liabilities	0.11062	0.00351	0.03486	0.05801	-0.30522	0.90369*
Cash to Current Maturities	0.19679	-0.03221	0.22673	0.00237	-0.16190	0.90628*
Quick Assets to Current Liabilities	0.20747	-0.55531	0.18841	0.19648	0.21680	0.64066*
Quick Assets to Current Maturities	0.33544	-0.43174	0.33638	0.04197	0.24936	0.67727*
Current Assets to Current Maturities	0.42940	-0.17160	0.40706	-0.28819	0.28730	0.61890*
Current Assets to Current Liabilities	0.42290	-0.13697	0.25046	-0.36497	0.33423	0.53676*

* Significant factor loadings

of the total variance. The ratios selected to represent the factors were:

1. Earnings before taxes to total liabilities
2. Net sales to accounts receivable
3. Debt to current liabilities
4. Net sales to inventory
5. Net sales to working capital
6. Cash to current liabilities

For Factors 3 and 5 the ratio with the highest absolute value factor loading was not chosen to represent the factor. If the ratio with the highest absolute value factor loading had been chosen, debt to notes payable--short-term and net sales to cash would have been selected to represent Factors 3 and 5, respectively. These ratios were not selected because they were not found to be significantly different by the nonparametric test.

The discriminant function derived from the reduced data set was:

$$Z = -0.56700X_{15} - 0.00846X_{18} + 0.06604X_{19} + 0.25517X_{23} + 0.52924$$

where, X_{15} = Debt to current liabilities
X_{18} = Net sales to inventory
X_{19} = Net sales to working capital
X_{23} = Cash to current liabilities

This model had a Wilks' lambda of 0.86132, which converts to an approximate F-statistic of 3.904, that is significant at the 0.001 level.

The classification results employing the resubstitution and jackknife methods are shown in Table 4-11. These results do not support the second hypothesis because the discriminant function

TABLE 4-11

CLASSIFICATION MATRIX FOR THE REDUCED DATA SET--TRANSFORMED RATIOS

Actual Classification of Firms	Percent Correct	Number of Firms Classified Into Group	
		Comply	Noncomply
Resubstitution			
Complying	80.4	41	10
Noncomplying	58.8	21	30
Total	69.6	62	40
Jackknife			
Complying	78.4	40	11
Noncomplying	56.9	22	29
Total	67.6	62	40

derived from the reduced data set--original ratios had higher classification accuracy rates. However, when the discriminant function was applied to the holdout sample of complying firms, it correctly classified 62.1 percent of the firms versus 51 percent for the discriminant function derived from the reduced data set--original ratios. Therefore, by comparison of the classification accuracies hypothesis two is rejected.

Model II - Entire Data Set

The discriminant function derived from the entire data set was:

$$Z = 2.62863X_2 + 0.10479X_{10} + 0.02776X_{12} - 0.46178X_{15} + 0.46185X_{24} - 0.18209$$

where, X_2 = Dummy variable for proprietorship
X_{10} = Earnings before taxes to notes payable--short-term
X_{12} = Earnings before taxes to current maturities
X_{15} = Debt to current liabilities
X_{24} = Quick assets to current liabilities

Wilks' lambda for this model was 0.801777, which, when converted to an F-statistics is significant at the 0.001 level. The classification matrix for this model is presented in Table 4-12.

TABLE 4-12

CLASSIFICATION MATRIX FOR THE ENTIRE DATA SET--TRANSFORMED RATIOS

Actual Classification of Firms	Percent Correct	Number of Firms Classified Into Group	
		Comply	Noncomply
Resubstitution			
Complying	54.9	28	23
Noncomplying	78.4	11	40
Total	66.7	39	63
Jackknife			
Complying	51.0	26	25
Noncomplying	78.4	11	40
Total	64.7	37	65

Again, as with the reduced model, the results of the resubstitution and jackknife method do not support hypothesis two. This model accurately classified 62.1 percent of the hold out sample, the same as the reduced model. This is 0.1 percent less than the discriminant model derived from the original ratios.

Therefore, hypothesis two is rejected. Financial ratios transformed by industry averages are not more effective at predicting small business loan noncompliance than financial ratios alone.

Hypothesis III

Hypothesis three was, "the inclusion of economic data, with the financial ratios and industry data, improve the discriminant model's ability to predict a small business' ability to comply with its loan agreements." This hypothesis was not supported by either the original ratios or the transformed ratios, for either the full or reduced data sets.

The main reason for not finding support for this hypothesis is due to the method used to control for extraneous variables. Because the firms were matched by year-end, the economic variables were practically the same for each firm. When the univariate tests were performed, no economic variable had a significance level lower than 0.75. Therefore, the fact that hypothesis three was rejected, was not totally unexpected.

Hypothesis IV

This hypothesis maintained that the ratios involving current maturities would be more effective than other ratios at predicting loan noncompliance. Based on the discriminant functions developed for the first two hypotheses, the ratios involving current maturities were not the most effective at predicting a firm's ability to comply with its loan agreements.

None of the ratios involving current maturities were included in the discriminant model derived from the entire data set for the original data. Even though the ratios were found to be significantly different by the univariate tests, in combinations with other ratios the current maturities ratios did not aid in discriminating between complying and noncomplying firms. Only one ratio, earnings before taxes to current maturities, for the transformed data, was included in a discriminant model.

By ranking the partial F-values generated by BMDP [18], an indication of the relative importance of the individual variables can be obtained. The partial F-value measures the additional contribution of a variable above the contributions of those variables already in the equation.

By ranking the partial F-values of the original data set, four of the ratios involving current maturities ranked in the top ten. For the transformed data four of the five ratios involving current maturities ranked in the top ten. This implies that the current maturities ratios can discriminate between the complying and noncomplying firms, however, they are not the best discriminators. The ratios were not entered into the discriminant function because of their high correlation with the variables already in the function.

Three of the ratios from the original data, earnings before taxes to current maturities, quick assets to current maturities, and current assets to current maturities, were highly correlated with earnings before taxes to total liabilities. Cash to current maturities was significantly correlated with cash to current liabilities and the remaining two current maturities ratios were correlated with current liabilities to cash flow.

Of the four current maturities ratios of the transformed data not included in the discriminant function, three were significantly correlated with quick assets to current liabilities. They were: (1) cash to current maturities, (2) quick assets to current maturities, and (3) current assets to current maturities. The fourth ratio, debt to current maturities, was correlated with debt to current liabilities.

The ratios involving current maturities may be effective at predicting loan noncompliance, but hypothesis four most be rejected because the ratios were not the "most" effective predictors of noncompliance. Though the ratios for current maturities did have high partial F-values, the ratios involving current liabilities had higher F-values. Therefore, the current liability ratios were considered to be more effective predictors of loan noncompliance. This implies that a business is concerned with meeting current obligations other than current maturities of notes. More precisely, a business is making payments to all creditors; not just payments on their notes.

Summary

None of the ratios included in the analysis had a high probability of being normally distributed. Only two ratios, earnings before taxes to total liabilities and earnings before taxes to current liabilities for the noncomplying firms, had as much as a twenty percent probability of being normally distributed. This nonnormality was caused by the extreme skewness and kurtosis of the data. Therefore, the t-tests that were performed were supported by a nonparametric test, the Kruskal-Wallis median test.

Seven ratios, in their original and transformed form, were determined to be statistically significant at the 0.10 level by both tests. Six ratios were not found to be significant at the 0.10 level in either their original or transformed state by either test. These six ratios involved either net sales or total debt.

Two discriminant functions were developed to test each of the first three hypotheses. The first function was derived from a subset of the entire data set by reducing the entire data set via factor analysis. This was done to aid in controlling for multicollinearity. The second function was derived from the entire data set.

Classification results were obtained by using three validation techniques. They were: (1) the resubstitution method, (2) the jackknife or Lachenbruch-Mickey leaving-one-out method, and (3) a holdout sample of complying firms. Based on the results of these validation methods the first hypothesis was not rejected and the second was rejected.

The inclusion of economic data in the models did not aid in discriminating between the complying and noncomplying. Therefore, the third hypothesis was rejected.

Though the ratios involving current maturities were statistically significant in the univariate tests, they did not prove as significant when used in a linear combination with the other ratios. Only one current maturities ratio entered into a discriminant model. By ranking the partial F-values the current maturities ratios ranked high, but, because of their correlation with other variables in the function they did not enter into the function. Therefore, little support was found for the fourth hypothesis.

Chapter five will compare: (1) the discriminant models, (2) univariate results to variables in the discriminant functions, (3) current results with previous failure studies, and (4) general conclusions and recommendations.

CHAPTER V

CONCLUSIONS

As the evidence presented in Chapter 4 indicated, it was possible to differentiate between a small business' tendency towards loan compliance or noncompliance by employing financial information. In this chapter several subjects are discussed that relate to the results of the hypothesis testing and other findings not directly related to evaluation of the hypotheses.

First, the models are summarized with particular attention to the classification accuracy of the models and the variables that recur from model to model. This includes a comparison of the overall classification accuracies of the models and the classification accuracy for complying and noncomplying firms. Next, the most accurate discriminating model is compared to previous bankruptcy or failure models. Finally, comments concerning the application of the model, model weaknesses, and areas for further study are addressed.

Comparison of Models

The four models developed to test the hypotheses are presented in Table 5-1 with their overall classification accuracy results. Each model contained at least three variables, with one model containing five variables. The number of possible variables

TABLE 5-1

COMPARISON OF DISCRIMINANT MODELS

Hypothesis	Model	Classification Accuracy			Variable Definition
		Resubstitution	Jackknife	Holdout	
1 - Reduced	$Z = 2.01981X_2 + 2.13674X_{11} + 0.01388X_{25} + 2.24603X_{26} - 0.75888$	74.5	73.5	51.0	X_2 = dummy variable for proprietorship X_9 = earnings before taxes to total liabilities X_{10} = earnings before taxes to notes payable--short-term X_{11} = earnings before taxes to current liabilities X_{12} = earnings before taxes to current maturities X_{15} = debt to current liabilities X_{18} = net sales to inventory X_{19} = net sales to working capital X_{24} = quick assets to current liabilities X_{25} = debt to cash flow X_{26} = cash to current liabilities X_{31} = current liabilities to cash flow
1 - Full	$Z = 4.07928X_9 + 1.99067X_{26} + 0.04534X_{31} - 0.91541$	77.5	76.5	62.2	
2 - Reduced	$Z = -0.567X_{15} - 0.00846X_{18} + 0.06604X_{19} + 0.25517X_{26} + 0.52924$	69.6	67.6	62.1	
2 - Full ...	$Z = 2.62863X_2 + 0.10479X_{10} + 0.02776X_{12} - 0.46718X_{15} + 0.46185X_{24} - 0.18209$	66.7	64.7	62.1	

ranged from 13 for the reduced-transformed model to 31 for the full-original model.

One item revealed in Table 5-2 was that only three variables were included in more than one model. The variables were: (1) the dummy variable for proprietorships, (2) debt to current liabilities, and (3) cash to current liabilities. Cash to current liabilities was the only variable to be included in three models. Of the variables included in the discriminant models only one, net sales to inventory, was not able to differentiate between the groups on an univariate basis.

The sign of the discriminant coefficient for ten of the twelve predictor variables was positive. This implies that a firm with a positive ratio tended to comply with its loan agreements, while a firm with a negative ratio leaned towards noncompliance. The ten ratios with positive coefficients were:

1. Dummy variable for proprietorship
2. Earnings before taxes to notes payable--short-term
3. Earnings before taxes to current maturities
4. Earnings before taxes to current liabilities
5. Earnings before taxes to total liabilities
6. Quick assets to current liabilities
7. Cash to current liabilities
8. Debt to cash flow
9. Current liabilities to cash flow
10. Net sales to working capital

The inclusion of the dummy variable representing proprietorships as a predictor variable indicates that the legal form of a business might affect the business' ability to meet its loan obligations. Since the discriminant coefficient is positive a proprietorship is more likely (than a partnership or corporation) to be

TABLE 5-2

VARIABLES INCLUDED IN THE DISCRIMINANT MODELS

Variable No.	Variable Name	1-Reduced	1-Full	2-Reduced	2-Full
2	Dummy variable for proprietorships	*			*
9	Earnings before taxes to total liabilities		*		
10	Earnings before taxes to notes payable-short--term				*
11	Earnings before taxes to current liabilities	*			
12	Earnings before taxes to current maturities				*
15	Debt to current liabilities			*	*
18	Net sales to inventory			*[1]	
19	Net sales to working capital			*	
24	Quick assets to current liabilities				*
25	Debt to cash flow	*			
26	Cash to current liabilities	*	*	*	
31	Current liabilities to cash flow		*		

[1] Did not statistically differentiate between groups on an univariate basis for the transformed ratios.

classified as complying. One reason that the proprietorship legal form is important could be because the proprietor will pay the maturing obligations from personal funds to protect the business' credit rating.

Earnings before taxes to notes payable--short-term measures the coverage, before taxes, of a component of current liabilities--short-term notes payable. That is, the ratio measures the adequacy of earnings to pay the short-term notes.

Earnings before taxes to current maturities differs from earnings before taxes to notes payable--short-term in that the former ratio includes current maturities of long-term debt in addition to short-term notes. This implies that a firm must be concerned with the coverage of all maturing debt and not just short-term notes. A firm must comply with short-term and long-term loan agreements.

The inclusion of earnings before taxes to current liabilities as a predictor variable indicates that a firm must not only be concerned with short-term notes and current maturities of long-term obligations but, also other current obligations. For example, a firm needs to cover its accounts payable and accruals from prior periods.

The earnings before taxes to total liabilities ratio measures the coverage of all liabilities (current and noncurrent) before income taxes. The positive discriminant coefficients of the above variables supports the theoretical rationale that the higher the profitability of a firm the healthier the firm.

The quick asset to current liabilities ratio focuses on immediate liquidity. Excluded from the ratio are deferred charges and inventory which are items that may not be readily converted into cash. The cash to current liabilities ratio provides a more acute measure of the assets available to meet current debt than either the current or quick ratio. This measure reflects a firm's liquidity position without the consideration of accounts receivable (which may or may not be coverted to cash), deferred charges (which are seldom converted to cash), and inventory (the least liquid current asset).

Debt to cash flow measures the net cash flow available to pay all liabilities, regardless of whether the liability is currently maturing or not. The positive discriminant coefficient supports the theoretical assumption that a firm with a cash flow sufficient to cover its debt is a credit-worthy firm. Current liabilities to cash flow[1] measures whether the cash flow generated by the business will be sufficient to meet all current liabilities, not only current maturities of debt. This indicates that small business firms are concerned with paying all current liabilities, not just their maturing loans.

A priori debt to cash flow and current liabilities to cash flow would have been expected to have had a negative coefficient. This would have indicated the more debt or current liabilites to cash flow the greater the tendency towards loan noncompliance. However, because the discriminant coefficient has a positive value a firm with a high ratio would be classified as complying even though it might

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[1] Cash flow was defined as earnings before taxes less income taxes, plus depreciation, depletion and amortization.

have little or no cash to pay its debt. An explanation for these ratios having a positive coefficient is that many of the noncomplying firms had a negative value for these ratios. Thus, when a firm's negative ratio was combined with the positive discriminant coefficient the discriminant score moved towards zero.

Net sales to working capital provides information about the number of times working capital is earned (i.e., working capital turnover). A priori this predictor variable would be expected to have a positive discriminant coefficient because each time working capital turns over sales have been sufficient to pay current debt.

Two predictor variables, debt to current liabilities and net sales to inventory, had negative discriminant coefficients. This means the larger these ratios the greater the tendency towards loan noncompliance. By definition these ratios cannot be negative (because neither the numerator nor the denominator can assume a negative value). The noncomplying firms tended to have higher values for these ratios than the complying firms. This aids in explaining why these two predictor variables had negative discriminant coefficients. Table 5-3 shows the mean and median for these two ratios.

Classification Accuracy

On the whole, the discriminant models developed did differentiate between the complying and noncomplying firms. Three measures of classification accuracy were employed. They were: (1) the resubstitution method, (2) the jackknife method, and (3) a

TABLE 5-3

MEAN AND MEDIAN OF PREDICTOR VARIABLES WITH NEGATIVE DISCRIMINANT COEFFICIENTS

	Complying Firms	Noncomplying Firms
Debt to Current Liabilities		
Mean	1.736	2.333
Median	1.271	1.827
Net Sales to Inventory		
Mean	43.791	79.420
Median	7.372	9.122

holdout sample of complying firms. The resubstitution method accuracy rate is determined by classifying the firms used to construct the discriminant model. Many authors have reported these results as part of their justification that their models are useful [5, 9, 29, 32]. The jackknife method refers to the Lachenbruch-Mickey leaving-one-out approach. While not as robust a technique as a true holdout sample, it has been shown to be reliable [9, 33, 34, 54, 55]. Finally, a holdout sample of complying firms was used to test the accuracy of the models.

As illustrated in Table 5-4, the overall classification accuracy rate for the resubstitution method ranged from 66.7 percent (full-transformed model) to 77.5 percent (full-original model). For the jackknife method the accuracy rate ranged from 64.7 percent to 76.5 percent with the same models having the high and low. The accuracy rate for the holdout sample of complying firms was from a low of 51 percent for the reduced-original model to 62.2 percent for

TABLE 5-4

COMPARISON OF CLASSIFICATION ACCURACY
FOR ALL MODELS
(Percent)

	Method					
	Resubstitution			Jackknife		
Hypothesis (Model)	Overall	Complying	Non-complying	Overall	Complying	Non-complying
1-Reduced	74.5	66.7	82.4	73.5	66.7	80.4
1-Full	77.5	74.5	80.4	76.5	74.5	78.4
2-Reduced	69.6	80.4	58.8	67.6	78.4	56.9
2-Full	66.7	54.9	78.4	64.7	51.0	78.4

the full-original model. The accuracy rate for the full-original model differed only slightly from the rates for the full- and reduced-transformed models, whose accuracy rates were both 62.1 percent. Hair, et al. [43], suggest that the classification accuracy should be at least 25 percent greater than by chance for the model to be considered significant. Therefore, an accuracy rate greater than 62.5 percent is considered significant since the chance accuracy rate is 50 percent (see footnote 3, Chapter IV). Thus, all four models were significant compared to a random chance model using the resubstitution and jackknife validation methods. However, based on the holdout sample of complying firms none of the models were significant. This might be because of a limitation inherent in the data, that is, the firms in the sample could have been in compliance or noncompliance until the end of the year at which time they were reclassified. Thus, the firm would be exhibiting characteristics of the opposite classification. This would have lead to misspecification of the discriminant model.

Table 5-4 indicates that the models were more accurate at predicting loan noncompliance. Only one model, reduced-transformed, more accurately classified the complying firms. The accuracy rate for complying firms, employing the resubstitution method, ranged from a low of 54.9 percent to a high of 80.4 percent for the full transformed and reduced transformed models, respectively. Using the jackknife validation method the accuracy rates for the complying firms ranged from 51.0 percent to 78.4 percent, with the same models having the high and low as with the resubstitution method.

For the noncomplying firms, using the resubstitution method, a low of 58.8 percent of the firms were correctly classified by the reduced-transformed model. A high of 82.4 percent of the noncomplying firms were correctly classified by the reduced-original model. Employing the jackknife method the same models recorded the high and low. The low accuracy rate was 56.9 percent and the high was 80.4 percent.

Most Accurate Overall Model

The most accurate overall model was the one developed for hypothesis one utilizing all the variables. The discriminant function was

$$Z = 4.07928X_9 + 1.99067X_{26} + 0.04534X_{31} - 0.91541$$

where, X_9 = earnings before taxes to total liabilities
X_{26} = cash to current liabilities
X_{31} = current liabilities to cash flow

A priori the earnings before taxes to current liabilities and the cash to current liabilities ratios would be expected to be higher for complying firms and, the current liabilities to cash flow ratio to be less. Table 5-5 shows that this belief is correct for the

TABLE 5-5

MEAN AND MEDIAN VALUES OF THE RATIOS INCLUDED IN THE MOST ACCURATE DISCRIMINANT MODEL

	Mean		Median	
	Complying	Non-complying	Complying	Non-complying
Earnings before taxes to total liabilities	0.21615	0.00389	0.17000	0.00792
Cash to current liabilities	0.21887	0.06934	0.15367	0.05109
Current liabilities to cash flow	7.56374	0.96796	3.19831	2.22275

earnings before taxes to current liabilities and the cash to current liabilities ratios, however, the mean and median values of the current liabilities to cash flow ratio is greater for the complying firms. The reason for this is that many of the noncomplying firms had a negative cash flow and, therefore, a negative current liabilities to cash flow ratio. The skewness of the ratio for the complying and noncomplying firms is 3.96798 and -1.78448, respectively. This indicates that the ratios of the noncomplying firms are clustered to the right of the mean and the extreme points lie to the left of the mean. Furthermore, this aids in explaining why the ratio had a positive discriminant coefficient rather than the expected negative coefficient.

Comparison With Prior Failure Models

Table 5-6 highlights the comparative overall classification accuracy produced by the discriminant models in the prior business failure studies of Altman [5], Deakin [29], Edmister [32], and Alves [9] to the current study on loan noncompliance.

The current model, 1-Full, does not compare too favorably with the results of the other models, especially employing the resubstitution method. Using the jackknife validation technique it compares somewhat more favorably. The current model was not expected to have as good an overall classification rate as the previous models for several reasons.

Altman and Deakin examined large business failures, which generally, have more management experience; the lack of management experience has been cited as a leading cause of failure [9, 13, 22, 31, 45]. Secondly, they examined business failure rather than loan noncompliance. Beaver [15] demonstrated that business failure is such a drastic event, that its coming is reflected in the financial ratios five years in advance; whereas, loan noncompliance is not as severe as failure and, therefore, may not be as easily detected by examining financial ratios.

TABLE 5-6

OVERALL CLASSIFICATION ACCURACY COMPARISON
WITH PRIOR BUSINESS FAILURE MODELS

Model	Resubstitution Method	Validation Technique
Altman	95	84[1]
Deakin	97	79.5[1]
Edmister	93	N/A[2]
Alves	90.5	90.5[3]
1-Full	77.5	76.5[3]

[1] The holdout approach was used to validate the model.

[2] Edmister did not attempt to validate his model. He noted that the sample size of 42 firms was not large enough [32]. He apparently did not consider the Lachenbruch-Mickey leaving-one-out technique.

[3] The validation results were based on the Lachenbruch-Mickey leaving-one-out technique.

Edmister and Alves examined small business failures. However, they employed not only financial ratios but trends, averages, and qualitative information. By employing this additional information the accuracy of their models should have been better than just using financial information.

An interesting fact was uncovered by comparing the ratios included in this study's best model (1-Full), to Altman's model and Alves' model, employing only financial information. The ratios that differentiated between failed and nonfailed firms were quite different from the ratios that differentiated between complying and noncomplying firms. The majority of the ratios in Altman's and Alves' models involved an asset measure, whereas, the ratios for loan compliance (noncompliance) all involved a debt measure. Table 5-7 illustrates the ratios in the discriminant models.

General Conclusions

The basic conclusions drawn from this research are:

1. On an univariate basis liquidity ratios are better differentators between complying and noncomplying firms.

2. Univariately, turnover ratios are generally unable to differentiate between complying and noncomplying firms.

3. Transforming an individual firm's ratio by the industry average, does not improve the differentiating ability of the ratio.

4. Multivariately, financial ratios are successful in differentiating between complying and noncomplying firms.

5. Transformation of the firm's ratios by the industry average does not improve the classification accuracy of the discriminant models.

6. The inclusion of economic data does not aid in classifying a firm as either complying or noncomplying.

7. The most accurate discriminant model contained three predictor variables: (a) Earnings before taxes to total liabilities, (b) cash to current liabilities, and (c) current liabilities to cash flow.

The models developed in this project proved to be successful in differentiating between complying and noncomplying firms. The most accurate model, the 1-Full model, combined earnings before taxes to total liabilities, cash to current liabilities and current liabilities to cash flow. The classification error rates were greater than the error rates for the previous business failure studies; this was expected. Loan noncompliance could be a very minor

TABLE 5-7

COMPARISON OF RATIOS INCLUDED IN NONCOMPLIANCE DISCRIMINANT MODEL WITH RATIOS INCLUDED IN BUSINESS FAILURE DISCRIMINANT MODELS

Model	Ratios
Altman	Working capital to total assets Retained earnings to total assets Earnings before interest and taxes to total assets Market value of equity to book value of total debt Sales to total assets
Alves	Net sales to inventory Quick ratio Earnings before taxes to total assets
1-Full	Earnings before taxes to total liabilities Cash to current liabilities Current liabilities to cash flow

problem, it could range from a few late payments to the point where the lender has to foreclose on pledged assets. Business failure or bankruptcy is a much more legally defined event. When a firm is bankrupt some form of legal preceedings have commenced.

The model developed to predict loan noncompliance was not expected to be 100 percent accurate at classifying firms as complying or noncomplying. To apply the discriminant function to another firm or group of firms, they would need to meet the same definitional requirements as those used to construct the model. However, the purpose of developing the discriminant model was not necessarily to develop a model to apply to other firms. The purpose of developing the model was twofold: (1) to demonstrate that financial ratios are able to indicate a firm's tendency towards loan compliance or noncompliance and therefore, are useful as a loan screening device; and (2) to provide guidance concerning what specific ratios or class(es) of ratios are useful in differentiating between complying and noncomplying firms.

A significant fact is that the transformation of the firm's ratio by the industry average ratio did not improve the classification rate. This implies that the industry average does not need to be considered when assessing an individual firm's ability to comply with its loan agreements.

One group of financial ratios that did not differentiate between the complying and noncomplying firms either on a univariate or multivariate basis were the turnover ratios (net sales ratios). There are two explanations for this. First, because of the leads and lags between revenue recognition and cash receipts, the amount of cash generated by a company during a short period of time will equal its reported sales for that period only by chance. Therefore, the net sales for a period provide no information concerning the cash to be generated to meet current debt. Second, most of the turnover ratios were net sales to an asset measure; apparently the turnover of assets has no effect on a firm's ability to comply with its loan agreements.

The economic information did not have an effect on any discriminant model. There are two explanations for this that do not preclude the potential importance of the economic information. First, each of the eight variables had only twelve possible values per year (one for each of the twelve months). Therefore, with so few possible observation points the distribution was far from normal. Second, since the firms were matched by year, the complying and noncomplying firms tended to have the same economic variable values.

Possibly, more specific economic data would prove to be beneficial. For example, the economic data could be gathered for specific industries, rather than general data. Also, instead of using the prime interest rate, a firm's incremental borrowing rate could be employed. By employing more firm specific information more observation points would be available and there would be a greater variance between the information for a matched pair.

Comments

When presented with a discriminant model that is claimed to be predictive in nature, one must question its applicability to other firms. Besides the problem of definitional characteristics there are other factors that affect the models applicability.

First, the models were developed based on equal size samples of complying and noncomplying firms, therefore, the prior probability of group membership was 50 percent. In actual application the prior probabilities are not 50 percent. Ideally, the samples employed should have been in proportion to their actual occurrence in the sample population being examined.

Another problem with the samples concerns when the firms were classified as complying or noncomplying. Because the firms were classified as of the end of their fiscal year the possibility exist that a firm could have been noncomplying or complying the entire year, until the last day. This firm would probably exhibit characteristics that would lead to misclassification.

Finally, the data used to construct the discriminant models not multivariate normal. The effect of this problem was assessed by employing a rank transformation to approximate normality [25]. The results of this transformation supported the results of the nonmultivariate normal data. However, the lack of multivariate normality is a limitation.

Altman and Eisenbeis [8] suggest that error rate estimates can be adjusted to take into account unequal prior probabilities. If the objective is to minimize total expected error rates, classification accuracy can be estimated using the following equation.

$$R = q_1(n_{11}/n_{1.}) + q_2(n_{22}/n_{2.}) \qquad \text{Eq. 5-1}$$

where, R is the estimated classification accuracy
q_1 is the prior probability of being assigned to the noncomplying group
q_2 is the prior probability of being assigned to the complying group
n_{11} is the number of noncomplying firms correctly classified
$n_{1.}$ is the total sample size of noncomplying firms
n_{22} is the number of complying firms correctly classified, and
$n_{2.}$ is the total sample size of complying firms

Another fact that should be considered is the cost of misclassification. Including the cost of misclassification changes the objective from minimization of classification error to minimization of misclassification costs. The user must now, however, provide estimates of both prior probabilities and misclassification costs, which may be difficult. The cost of misclassification can be incorporated in equation 5-1 as follows:

$$C = q_1(n_{11}/n_{1.})C_{12} + q_2(n_{22}/n_{2.})C_{21} \qquad \text{Eq. 5-2}$$

where, C_{12} is the cost of classifying a noncomplying firm as a complying firm, and
C_{21} is the cost of classifying a complying firm as a noncomplying firm

Potential users of any predictive or screening model should be aware of the models inherent weaknesses. For example, in the models developed for this study a variety of shortcomings might exist. First, is the possibility that the samples selected do not sufficiently represent the overall population characteristics. This is especially a problem with the complying firms because they suffer from self-selection bias, that is, they were selected because of characteristics they had in common with the noncomplying firms. This representation problem is encountered by all sample derived models or estimates. The use of a holdout sample to validate a model can reduce the problem, but not eliminate it.

Another problem that exist is definitional in nature, that is, that noncompliance was defined in a very broad sense. There are varying degrees of noncompliance. Obviously, a firm that is two or three days late with a payment is not in as serious of financial distress as a firm that has missed two payments. Also, what is considered noncompliance by one lending institution may not be considered noncompliance by another. Possibly, models can be developed based on the degree of noncompliance. By stratifying the firms according to how they were in noncompliance, then, either construct models for each strata or employ dummy variables to represent the strata of the degree of noncompliance. The problem of varying definitions of noncompliance between lending institutions could be solved by providing a more strict definition of noncompliance. For example, instead of considering a firm in noncompliance for "late payments" state specific time periods, such as, "payments one week late," "two weeks late," etc. Then dummy variables could be used to represent the time periods. The same procedure could be employed for other types of noncompliance.

A major problem could be that the information needed to differentiate between complying and noncomplying firms is not included in the financial statements; especially year-end financial statements. Many authors [9, 13, 22, 28, 31, 45] have asserted that the management of a firm is important in determining whether a firm succeeds or fails, the same could hold for whether a firm complies with its loan agreements. By including measures regarding the qualitative characteristics of the firm, the accuracy of the discriminant models might be improved.

Suggestions for Further Research

Any research that is basically grounded in empirical evaluation of generally unsupported theory raises many questions to be investigated. This study was no exception. The two major areas are better specification of the discriminant model and evaluation of coefficient stability and variable relationship stability.

Improved specification of the model to reflect nonfinancial information is likely to be difficult. The majority of the institutions supplying data for this study refused to supply information concerning why the firm was considered to be in noncompliance. They also replied that they did not have ready access to qualitative information about the firms. However, an improved sample of complying and noncomplying firms could be obtained by classifying the firms based on their loan status for substantially all the year. In other words, if a firm was in noncompliance for eleven months and then in compliance the twelfth month, the firm would still be classified as noncomplying.

Coefficient stability and variable relationship stability could be evaluated by employing inter-temporal testing [9, 48]. This would provide an indication as to whether the discriminant model is stable over time.

Future studies could determine what financial information loan officers consider when making a "loan-no loan" decision. Then based upon this information discriminant models would be constructed to determine loan compliance or noncompliance. The next step would be to test the applicability of the model as a screening tool. To do this two groups of users (e.g., commercial loan officers) would be required. A control group would receive only the financial ratios, while the test group received the financial ratios and the model prediction of the discriminant model. *A priori* the group receiving both the financial ratios and the model prediction should perform better.

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APPENDIX I

SMALL BUSINESS PROBLEMS

Small Business Problems

During the 1970s four regulatory agencies affecting small businesses were created: (1) the Environmental Protection Agency, (2) the Occupational Safety and Health Administration, (3) the Consumer Products Safety Commission, and (4) the Federal Mining Safety and Health. Compliance with government regulations is very costly to small businesses. Faced with the option of complying and going bankrupt, or not complying, and facing fines and/or penalties, many small businessmen choose not to comply. The constant threat of being caught, demoralizes many businessmen and leads to other problems. Fortunately, the government is beginning to realize that the regulations enacted to control large corporations often are serious problems for small businesses [76].

Another problem encountered by small businesses in the 1970s and into the 1980s, was record high inflation rates. The problem began with the Arab oil embargo in 1973, which caused prices to increase in all areas as illustrated in Table A1-1. Table A1-2 shows continued increases in the unadjusted Consumer Price Index, for all items, into 1980. When annualized, the percentage of change has fluctuated since June 1980.

Price increases affect businesses in two ways: (1) if a firm is unable to pass the price increase along, their profit margin is reduced; and (2) the capital investment required to maintain fixed

TABLE A1-1

AVERAGE CONSUMER PRICES INDEXES 1973-1979
(1967 = 100)

	1973	1974	1975	1976	1977	1978	1979
All Items	133.1	147.7	161.2	170.5	181.5	195.3	217.7
Food, drink	139.5	158.7	172.1	177.4	188.0	206.2	228.7
Housing	133.7	148.8	164.5	174.6	186.5	202.6	227.5
Apparel, upkeep	126.8	136.2	142.3	147.6	154.2	159.5	166.4
Transportation	123.8	137.7	150.6	165.5	177.2	185.8	212.8
Medical Care	137.7	150.5	168.6	184.7	202.4	219.4	240.1
Entertainment	130.0	139.8	152.2	159.8	167.7	176.2	187.7
Other	132.5	142.0	153.9	162.7	172.2	183.2	196.3

Source: Bureau of Labor Statistics, U.S. Labor Department

assets and inventories increases. Small businesses are more affected by these two factors than large businesses. They are generally unable to pass on price increases because they operate in highly competitive markets, whereas, large businesses operate in less competitive markets and have no problems in passing on price increases [76]. The excess cash required to carry more expensive inventories and fixed assets can be raised either internally from cash generated by operations, or externally from new equity or debt. However, since inflation has reduced the firm's profit, little or no cash can be generated internally and the chance of borrowing is greatly reduced. Many small businessmen are unwilling to sell equity in their business, therefore, the chances of receiving externally generated cash are low.

TABLE A1-2

MONTHLY CONSUMER PRICES INDEXES FOR 1980 AND 1981
(1967 = 100)

	CPI	% Change From Preceding Month	% Change Annualized
1980			
January	233.3	1.4	18.2
February	236.5	1.4	18.2
March	239.9	1.4	18.2
April	242.6	1.1	14.0
May	245.1	1.0	12.7
June	247.8	1.1	14.0
July	248.0	0.1	1.2
August	249.6	0.6	7.4
September	251.9	0.9	11.4
October	254.1	0.9	11.4
November	256.4	0.9	11.4
December	258.7	0.9	11.4
1981			
January	260.7	0.8	10.0
February	263.5	1.1	14.0
March	265.2	0.6	7.4
April	266.8	0.6	7.4
May	269.0	0.8	10.0
June	271.3	0.8	10.0
July	274.4	1.1	14.0
August	276.5	0.7	8.7
September	279.3	1.0	12.7
October	279.9	0.2	2.4

Source: Consumer Price Index, Bureau of Labor Statistics, U.S. Labor Department.

Perhaps the most pressing problem faced by small businesses is acquiring adequate financing [3, 11, 12, 36, 76]. On the average, small businesses are riskier borrowers. This is attributed to the fact that the uncertainty of payment is greater, because small businesses experience higher failure rates and generally have higher debt to equity and current debt to total debt ratios [20, 36, 76].

While large firms are capable of borrowing at or near the prime interest rate, small business frequently must pay in excess of the prime rate [47, 76]. Table A1-3 shows the average interest rates charged by small banks and all banks on large and small short-term loans. The rates on small loans parallel those on large loans and the prime. The higher capital cost frequently charged small businesses may be explained by [12]:

1. Recognition of lower failure rates in large business and higher stability of sales and profits due to a large number of customers or due to the tendency of large firms to offer products and services whose sales are less than perfectly correlated with each other over time.

2. A capital structure reflecting a small firms lack of access to the range of alternative capital sources available to large businesses.

3. Higher administrative cost in small loans versus large loans.

Another factor limiting a small business' access to funds is that only a small portion of the eligible banks are SBA lenders. Of the 10,000 eligible banks only 2,000 have as many as ten loans and only 700 have as many as 25 [76]. This means that a large portion of the small business community may not be aware of the many SBA programs they are eligible to participate in or have access to SBA

TABLE A1-3

BANK LOAN INTEREST RATES

	% Interest Charged on Small Size Loans (Thousands of Dollars)		% Interest Charged on Large Size Loans (Thousands of Dollars)		Average Prime Rate
	$50-99	$100-499	$500-999	Over $1000	
Average 1980					
All Banks	13.0	12.5	12.0	10.9	11.12
Small Banks	13.1	12.6	12.1	11.4	
February 1980					
All Banks	15.9	16.2	16.3	15.5	15.63
Small Banks	15.7	16.1	16.4	16.0	
November 1979					
All Banks	15.9	15.4	16.0	16.2	15.55
Small Banks	15.7	15.0	15.8	16.3	
August 1979					
All Banks	12.5	12.4	12.6	12.2	11.91
Small Banks	12.3	12.2	12.5	12.4	
February 1979					
All Banks	12.8	12.6	12.6	12.0	11.75
Small Banks	12.8	12.4	12.6	12.3	
November 1978					
All Banks	11.4	11.5	11.2	11.4	10.94
Small Banks	11.3	11.4	10.9	11.4	

Source: Federal Reserve Board, Statistical Release E.2 and Federal Reserve Bulletin, various issues.

funds because their bank chooses not to participate, or participates in a minimum way.

Banks may be willing to provide funds for working capital, but they are often unwilling to provide funds necessary for capital expansion. Therefore, the growth of a small business is habitually financed through reinvestment or retention of earnings [20]. This means the owner may have to forego a salary in order to expand the business. Many times, the owner and/or the owner's family are the major sources of investment funds.

Managerial Characteristics of Small Businesses

Traditionally, small businesses have had a very centralized management with a minimal number of support personnel. This places the owner-manager in complete control, enabling (or requiring) him to make all the decisions. Not only the normal day-to-day decisions, but also decisions that may affect the business for years and determine its eventual success or failure. Problems may arise because the owner-manager may be limited in experience. A decision that confronts the manager of a large business frequently may only confront a small businessman once or twice the entire time he is in business. Unfortunately, when making these decisions the small businessman may not make efficient use of his professional support personnel, i.e., attorneys, accountants, and bankers. Therefore, even though he has sufficient time to make the decision he makes an improper decision.

Many small businessmen are disappointed to learn that operating their business is not a "9-to-5" job. They must arrive in time to prepare for the customers and they can not leave until all things are taken care of at closing. They find themselves not only being the chief executive officer, but the personnel manager, payroll clerk, bookkeeper, production supervisor, and secretary.

The time the owner-manager devotes to his business detracts not only from the time he could spend with his family, but also his recreation time. This can create problems at home and at the business and problems at home, compound problems at work [31].

In small businesses owners and employees generally work side-by-side. This lets the employee learn more about the total operation of the business, versus a large corporation where the employee usually concentrates on a specialized job. This can create a closer-knit work group, depending on how well relations are between the employees and employer.

In conclusion, the owner-manager must fill many different functions. He will not only fill the top executive positions, but may also be the janitor. He must be prepared to work long hours for low pay. He may have to support the business financially. To succeed in business the owner-manager must be willing to make many sacrifices.

APPENDIX II

RMA DATA SUBMISSION FORM

rma STATEMENT STUDIES DATA SUBMISSION FORM

(1) Bank Name ....
Address ....
City .... State .... Zip ....

(6) Firm's Fiscal Year End:
Month .... Day ....

(7) RMA CHAPTER #

(8) RMA MEMBER #

(9) SERIAL #

(2) Company Name (actual or coded) ....

(3) LEGAL FORM (Check one)
☐ Corporation ☐ Proprietorship ☐ Partnership
☐ Other (Specify — Including Subchapter S Corp.) ....

(10) FISCAL YEAR CODE
(Check one)
6/30-9/30 ☐ 1
10/1-3/31 ☐ 2

(4) LINE OF BUSINESS (Check one)
☐ Manufacturer ☐ Wholesaler ☐ Retailer
☐ Service ☐ Other ....

(5) Describe Primary Product or Service Rendered: ....

(11) RMA INDUSTRY #

(12) S.I.C. #

USE RED FIGURES TO INDICATE LOSSES, CREDITS, ETC. — NOT PARENTHESES

ASSETS (IN THOUSANDS)	June 30, 1976 to March 31, 1977	June 30, 1977 to March 31, 1978	June 30, 1978 to March 31, 1979	June 30, 1979 to March 31, 1980	June 30, 1980 to March 31, 1981
(13) Cash & Equivalents					
(14) Accounts & Notes Receivable — Trade (net)					
(15) Inventory					
(16) All Other Current					
(17) Fixed Assets (net)					
(18) Intangibles					
(19) All Other Non-Current					
(20) TOTAL ASSETS					
LIABILITIES (IN THOUSANDS)					
(21) Notes Payable — Short Term					
(22) Current Maturities — L/T/D					
(23) Accounts & Notes Payable Trade					
(24) Accrued Expenses					
(25) All Other Current					
(26) Long Term Debt					
(27) All Other Non-Current					
(28) Net Worth					
(29) TOTAL LIABILITIES & NET WORTH					
INCOME DATA (IN THOUSANDS)					
(30) Net Sales					
(31) Gross Profit					
(32) Operating Profit					
(33) Earnings Before Taxes					
(34) Income Taxes — Corporations Only					

**Please itemize the following specific annual expenses which are included in the above Income Data (lines (30) to (34)).
Be certain to provide only those expenses incurred during the past year.
Do not leave blank — If zero, so indicate. If unavailable, use N/A.**

(IN THOUSANDS)					
(35) Depreciation/Depletion/Amortization Expense					
(36) Lease and Rental Expense					
(37) Interest Expense					
(38) Officers' Compensation (including drawings of partners & proprietors)					

(39) Explanation of Unusual Items: ....

Return statements as they are completed to ROBERT MORRIS ASSOCIATES, Credit Division, 1432 Philadelphia National Bank Building, Philadelphia, Pa., 19107. Phone 215/563-0287.

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The following list is a line-by-line guide delineating the items included on the RMA Data Submission Form.

ASSETS

Line	Item
13	Bonds Cash-in bank Cash-on hand Municipal Bonds Securities-readily marketable U.S. Government Securities
14	Accounts Receivable - customers (net) Bill Receivable Notes Receivable - trade Trade Acceptance
15	Advances for merchandise Inventory Merchandise - advances on - finished goods - in-transit - on consignment - raw materials - work in process Real Estate held for resale
16	Deposits with factor
17[1]	Buildings Delivery Equipment Emergency Plan Facilities Equipment Fixed Assets Fixtures Furniture Improvements Land Leaseholds Improvements Machinery Mineral Land Mines Motor Vehicles Packaging and Shipping Items

ASSETS (Continued)

Line	Item
	Plant and Property Quarries Real Estate - not held for re-sale Ships Timber (standing or uncut) Tools
18[1]	Brands - Trade Catalogues Contracts Copyrights Designs Development Expense Dies Drawings Financing Expense Formulas Franchises Goodwill Leaseholds Licenses Lasts Magazine Titles Mailing Lists Models Organization Expense Patents Patterns Processes Research & Development Expense Rights Subscription Lists Tracings Trade Marks & Trade Names Unamortize Mortgage or Bond Expense
19	Accounts Receivable - Affiliates & Subsidiaries - Directors, Employees, Officers - Partners - Miscellaneous

ASSETS (Continued)

Line	Item
	Advances
	- for travel
	- to Affiliates & Subsidiaries
	- to Employees
	Cash
	- in Sinking Fund
	- restricted
	Cash Surrender Value, Life Insurance (net of loans)
	Deferred Charges
	Deposits with
	- Mutual Insurance Co.
	- Workmen's Compensation Committee
	Foreign Assets - Restricted
	Interest Income, accrued
	Investments in Subsidiaries & Affiliates
	Merchandise - suppliers (misc. office)
	Mortgage Receivable
	Municipal Bonds in Default
	Prepaid Items
	- insurance
	- interest
	- rent
	- royalties
	- supplies
	- taxes
	Securities - non-readily marketable
	Sinking Fund
	Tax Refund Receivable

LIABILITIES AND NET WORTH

Line	Item
21	Floor Planning
	Loans Payable
	Notes Payable to Banks (short-term & demand)
22[2]	Bonds
	Debentures
	Mortgages Payable
23	Accounts Payable
	- for merchandise
	- for services
	- to factor
	Bills and Notes Payable - Trade

LIABILITIES AND NET WORTH (Continued)

Line	Item
	Notes Payable - Trade Trade Acceptances Payable
24	Accruals - commissions - interest - miscellaneous - payroll & related taxes - rent - salaries - taxes Income taxes - state and federal
25	Accounts Payable - to directors, employees, & officers - to partners - to related concerns - miscellaneous Advances from - customers - officers & stockholders Conditional Bill of Sale Contracts Payable Customer Deposits and Credit Balances Deposits from - customers - employees - officers Dividends Payable Notes Payable to - individuals (unsubordinated) - officers, partners, and directors - stockholders Renegotiation Reserve
26[3]	Bonds Debentures Mortgages Payable
27	Deferred Credits or Income Subordinated Debt Unearned Income
28	Capital Stock Minority Interest Net Worth (of proprietorship or partnership)

LIABILITIES AND NET WORTH (Continued)

Line	Item
	Stockholders' Equity - additional paid-in capital - capital stock - deficit retained earnings - donated surplus - retained earnings - treasury stock

---

[1] All items on lines 17 or 18 are shown net of accumulated depreciation, depletion, or amortization.

[2] The amounts reported on line 22 are the portion maturing within one year.

[3] The amounts reported on line 26 are the portion maturing after one year.

APPENDIX III

CALCULATION OF SIZE STANDARDS

TABLE A3-1

CALCULATION OF SIZE STANDARD

SIC No.	SBA Std.	No. Firms	Sales (millions)	Avg. Std. (millions)
2001	500	79	$6731.6	$ 85.21
2026	500	4	1898.9	474.73
2048	250	27	622	23.03
2051	250	351	3059.2	8.72
2086	250	208	3009.9	14.47
2091	500	7	166.4	23.77
2298	250	19	98.9	5.21
2421	250	322	3410.0	10.59
2431	250	108	935.6	8.66
2752	250	307	2208.1	7.19
2821	750	18	2264.9	125.83
2851	250	29	1300.1	44.83
2869	1000	30	4178.7	139.29
3273	250	70	698.4	9.98
3317	1000	18	900.3	50.02
3325	500	73	1350.9	18.50
3361	250	96	644.0	6.71
3362	250	44	130.6	2.97
3398	750	8	367.1	45.89
3429	250	98	715.4	7.30
3471	250	64	311.6	4.87
3494	500	90	1585.3	17.61
3499	500	20	273.3	13.67
3551	250	5	186.5	37.30
3585	750	3	77.9	25.97
3599	250	158	898.4	5.69
3639	500	4	115.6	28.90
3823	500	22	356.8	16.22

APPENDIX IV

DESCRIPTIVE STATISTICS OF COMPLYING AND NONCOMPLYING FIRMS

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TABLE A4-1

DESCRIPTIVE STATISTICS OF COMPLYING FIRMS--
ORIGINAL RATIOS

	Mean	Standard Deviation	Maximum Value	Median	Minimum Value
Earnings Before Taxes to Total Liabilities	0.2162	0.2154	0.8582	0.1700	-0.0091
Earnings Before Taxes to Notes Payable - Short-term	2.5041	4.4616	16.7500	0.5376	-0.0116
Earnings Before Taxes to Current Liabilities	0.3420	0.3512	1.4118	0.2594	-0.0174
Earnings Before Taxes to Current Maturities	4.0719	10.9658	60.5417	0.9592	-0.0291
Debt to Notes Payable - Short-term	18.0546	33.0069	149.0000	4.1720	1.1628
Debt to Current Maturities	11.5594	19.7446	124.4580	5.5927	1.1148
Debt to Current Liabilities	1.7357	1.4048	10.3333	1.2713	1.0000
Debt to Cash Flow	9.9484	15.0086	80.7000	4.6613	1.1686
Net Sales to Cash	147.7050	504.0090	3580.0000	49.4598	-103.0000
Net Sales to Accounts Receivable	29.4436	70.5149	319.4000	9.5489	0.9809
Net Sales to Inventory	43.7908	207.5060	1369.8000	7.3715	1.3537
Net Sales to Quick Assets	14.1015	20.6824	117.4800	8.1575	0.7739
Net Sales to Working Capital	19.0654	51.7093	351.2380	7.0769	-32.6470
Net Sales to Net Worth	10.7338	13.1976	73.2143	6.3351	0.7448
Net Sales to Current Assets	3.9747	2.2274	14.0495	3.3428	0.7739
Collection Period	51.6994	59.9949	372.1100	38.2325	1.1428
Cash to Current Liabilities	0.2189	0.2524	1.1968	0.1537	-0.1136
Cash to Current Maturities	1.8055	4.3486	22.5454	0.4884	-0.1470
Quick Assets to Current Liabilities	0.9386	0.7223	3.5203	0.7491	0.0154
Quick Assets to Current Maturities	7.4801	14.4151	87.3182	2.3366	0.0159
Current Assets to Current Maturities	17.2520	37.3199	185.3180	6.0402	0.5929
Current Assets to Current Liabilities	1.8364	1.0191	4.6486	1.4462	0.5634
Current Liabilities to Cash Flow	7.5637	13.1016	77.0000	3.1983	0.6296
Current Maturities to Cash Flow	4.8973	12.4760	70.1000	0.7148	0.0267

TABLE A4-2

DESCRIPTIVE STATISTICS OF NONCOMPLYING FIRMS--
ORIGINAL RATIOS

	Mean	Standard Deviation	Maximum Value	Median	Minimum Value
Earnings Before Taxes to Total Liabilities	0.0039	0.1545	0.4052	0.0079	-0.4217
Earnings Before Taxes to Notes Payable - Short-term	0.6193	3.6555	15.6667	0.1045	-5.1600
Earnings Before Taxes to Current Liabilities	-0.0208	0.3242	0.8545	0.0192	-0.8333
Earnings Before Taxes to Current Maturities	0.2078	1.9239	10.0000	0.0550	-2.9394
Debt to Notes Payable - Short-term	9.0547	11.6450	47.6667	5.6250	1.1791
Debt to Current Maturities	9.0612	11.9455	47.6667	4.7452	1.1286
Debt to Current Liabilities	2.3331	1.6525	9.4444	1.8267	1.0000
Debt to Cash Flow	-0.1727	33.2627	113.6670	4.3929	-186.1150
Net Sales to Cash	83.7608	335.8620	957.0000	49.6250	-1564.0000
Net Sales to Accounts Receivable	49.0945	113.0470	541.6667	11.4743	0.4177
Net Sales to Inventory	79.4197	314.2640	1930.0000	9.1224	1.8934
Net Sales to Quick Assets	35.3395	99.6650	521.3333	9.8820	-62.5000
Net Sales to Working Capital	5.9528	90.1517	417.7500	-1.0152	-217.4120
Net Sales to Net Worth	37.0870	116.3990	631.3333	5.9895	-67.7547
Net Sales to Current Assets	9.8393	17.6385	117.1670	4.0563	0.3831
Collection Period	65.1214	134.8180	873.8350	31.8347	0.6738
Cash to Current Liabilities	0.0694	0.1484	0.5000	0.0511	-0.3536
Cash to Current Maturities	0.3596	0.7507	3.3333	0.1156	-0.7250
Quick Assets to Current Liabilities	2.6323	4.8917	30.8333	0.9680	-0.6500
Quick Assets to Current Maturities	0.5452	0.4396	1.7201	0.4447	-0.3171
Current Assets to Current Maturities	7.6687	17.5812	101.1670	1.9353	0.0500
Current Assets to Current Liabilities	1.4272	1.6728	8.8333	0.9318	0.0052
Current Liabilities to Cash Flow	9.9680	10.6766	27.3333	2.2228	-44.6923
Current Maturities to Cash Flow	0.8468	3.9066	13.3333	0.9461	-8.5385

APPENDIX V

UNIVARIATE TESTS RESULTS

Univariate Tests For Differences Between Group Means - Original Ratios

T-tests Results

A t-test was performed on each variable, even though the majority of the variables did not satisfy the normality assumption of the t-test. Because of the nonnormality of the ratios the t-test results are biased. The potential of a Type II error is increased, that is, the likelihood of accepting a false null hypothesis is increased. In other words, the t-test may indicate no difference when in fact there is a difference. However, the t-test is a parametric test and, therefore, more powerful than the KW test, when its basic assumptions are satisfied. The results of the t-tests are reported in Table A5-1.

Of the 24 ratios, five were significantly different at the 0.01 level. The ratios were:

1. Earnings before taxes to total liabilities
2. Earnings before taxes to current liabilities
3. Cash to current liabilities
4. Quick assets to current liabilities
5. Current liabilities to cash flow

Five additional ratios were significantly different at the 0.05 level. They were:

1. Earnings before taxes to current maturities
2. Cash to current maturities
3. Quick assets to current maturities
4. Net sales to current assets
5. Current maturities to cash flow

Three more ratios were significantly different at the 0.10 level. The additional ratios were:

TABLE A5-1

T-TESTS ON ORIGINAL FINANCIAL RATIOS OF COMPLYING AND NONCOMPLYING FIRMS

Ratio	T-Value	Significance Level
Earnings Before Taxes to Total Liabilities	5.7185	0.0001
Earnings Before Taxes to Notes Payable--Short-term	1.7062	0.0939
Earnings Before Taxes to Current Liabilities	5.4212	0.0001
Earnings Before Taxes to Current Maturities	2.4543	0.0175
Debt to Notes Payable--Short-term	1.2956	0.2053
Debt to Current Maturities	0.7655	0.4462
Debt to Current Liabilities	-1.9670	0.0520
Debt to Cash Flow	1.9807	0.0516
Net Sales to Cash	0.7314	0.4665
Net Sales to Accounts Receivable	-1.0369	0.3028
Net Sales to Inventory	-0.6101	0.5438
Net Sales to Quick Assets	-1.4760	0.1459
Net Sales to Working Capital	0.9010	0.3703
Net Sales to Net Worth	-1.6065	0.1143
Net Sales to Current Assets	-2.3557	0.0223
Collection Period	-0.6410	0.5237
Cash to Current Liabilities	3.5470	0.0007
Cash to Current Maturities	2.2889	0.0262
Quick Assets to Current Liabilities	3.3141	0.0014
Quick Assets to Current Maturities	2.2493	0.0282
Current Assets to Current Maturities	1.6426	0.1050
Current Assets to Current Liabilities	1.4920	0.1395
Current Liabilities to Cash Flow	2.7870	0.0064
Current Maturities to Cash Flow	2.1908	0.0325

1. Earnings before taxes to notes payable--short-term
2. Debt to current liabilities
3. Debt to cash flow

One interesting feature revealed by the t-tests was that seven of the eight ratios involving net sales were not significant. Of the other four nonsignificant ratios, two were debt ratios and two were current asset ratios (one of which was the current ratio).

Because the hypothesis that the ratios come from a normal distribution was rejected, the results of the t-tests were suspect. To compensate for the nonnormality of the data a nonparametric test was used to test that the samples came from populations with the same central tendencies.

Kruskal-Wallis Median Tests

The results of the KW tests are shown in Table A5-2. Using the KW test the null hypothesis was rejected at the 0.01 level of significance for five of the ratios. The significantly different ratios were:

1. Earnings before taxes to total liabilities
2. Earnings before taxes to current liabilities
3. Earnings before taxes to current maturities
4. Cash to current maturities
5. Net sales to working capital

At the 0.05 significance level three additional ratios were significantly different. Those ratios were: (1) cash to current liabilities, (2) current assets to current maturities, and (3) current assets to current liabilities. Then, at the 0.10 level five more ratios were significantly different. The ratios were:

1. Earnings before taxes to notes payable-short-term
2. Debt to current liabilities

TABLE A5-2

KRUSKAL-WALLIS MEDIAN TEST

Ratio	Number of Points Above the Median		Expected Above the Median Under H_0		Significance Level
	Complying	Noncomplying	Complying	Noncomplying	
Earnings Before Taxes to Total Liabilities	34	17	25.5	25.5	0.001
Earnings Before Taxes to Notes Payable--Short-term	25	29	12.5	14.5	0.058
Earnings Before Taxes to Current Liabilities	35	16	25.5	25.5	0.001
Earnings Before Taxes to Current Maturities	34	16	25.0	25.0	0.001
Debt to Notes Payable--Short-term	12	15	12.5	14.5	0.787
Debt to Current Maturities	27	23	25.0	25.0	0.426
Debt to Current Liabilities	21	30	25.5	25.5	0.076
Debt to Cash Flow	26	25	25.5	25.5	0.844
Net Sales to Cash	25	22	25.0	22.0	1.000
Net Sales to Accounts Receivable	22	27	24.0	25.0	0.421
Net Sales to Inventory	17	25	21.5	20.5	0.051
Net Sales to Quick Assets	24	26	25.5	25.0	0.621
Net Sales to Working Capital	35	16	25.5	25.5	0.001
Net Sales to Net Worth	26	25	25.5	25.5	0.844
Net Sales to Current Assets	22	29	25.5	25.5	0.168
Collection Period	26	23	24.0	25.0	0.421
Cash to Current Liabilities	30	17	25.0	22.0	0.040
Cash to Current Maturities	31	15	24.5	21.5	0.007
Quick Assets to Current Liabilities	30	20	25.5	25.0	0.060
Quick Assets to Current Maturities	29	20	25.0	24.5	0.089
Current Assets to Current Maturities	30	20	25.0	25.0	0.047
Current Assets to Current Liabilities	33	18	25.5	25.5	0.003
Current Liabilities to Cash Flow	29	22	25.5	25.5	0.168
Current Maturities to Cash Flow	24	26	25.0	25.0	0.691

3. Quick assets to current maturities
4. Net sales to inventory
5. Quick assets to current liabilities

Descriptive Statistics--Transformed Ratios

The D-statistics for the KS tests performed on the transformed ratios are presented in Table A5-3. All of the D-values are significant at the 0.01 level. This implies that the transformed ratios are not normally distributed. The degree of skewness and kurtosis is the main reason the ratios are not normally distributed. To reduce the effect of any outlying points, the same adjustment was made to the transformed ratios as was made to the original ratios. Again, the adjustment had no significant affect on the KS tests. All the D-values were still significant at the 0.01 level. Table A5-4 presents the number of outlying points along with the measures of skewness and kurtosis. The mean, standard deviation, maximum and minimum values, and the median of the transformed ratios are presented in Tables A5-5 and A5-6.

Univariate Tests For Differences Between Group Means--Transformed Ratios

T-Tests Results

Even though none of the transformed ratios appeared to be normally distributed a t-test was performed on each ratio. The t-tests were performed for two reasons: (1) Because the t-test is a powerful parametric test, and (2) for comparison to the results obtained with the original ratios.

TABLE A5-3

KOLMOGOROV-SMIRNOV D-VALUES FOR COMPLYING AND NONCOMPLYING FIRMS--TRANSFORMED RATIOS

Ratio	Complying	Noncomplying
Earnings Before Taxes to Total Liabilities	0.3485	0.3201
Earnings Before Taxes to Notes Payable--Short-Term	0.3594	0.3265
Earnings Before Taxes to Current Liabilities	0.3578	0.2354
Earnings Before Taxes to Current Maturities	0.3499	0.2516
Debt to Notes Payable--Short-Term	0.3282	0.2937
Debt to Current Maturities	0.3177	0.3328
Debt to Current Liabilities	0.2080	0.2032
Net Sales to Accounts Receivable	0.3184	0.4161
Net Sales to Inventory	0.3147	0.4533
Net Sales to Working Capital	0.2983	0.2873
Net Sales to Quick Assets	0.2693	0.3621
Net Sales to Net Worth	0.3030	0.3292
Net Sales to Cash	0.3650	0.2252
Net Sales to Current Assets	0.3044	0.3552
Collection Period	0.4119	0.3159
Cash to Current Liabilities	0.2912	0.2107
Cash to Current Maturities	0.3477	0.3683
Quick Assets to Current Liabilities	0.2107	0.2047
Quick Assets to Current Maturities	0.2773	0.2768
Current Assets to Current Maturities	0.3145	0.3591
Current Assets to Current Liabilities	0.1811	0.2838

TABLE A5-4

SKEWNESS, KURTOSIS AND NUMBER OF OUTLIERS
FOR THE COMPLYING AND NONCOMPLYING FIRMS--
TRANSFORMED RATIOS

Ratio	Complying			Noncomplying		
	Skewness	Kurtosis	No. of Outliers	Skewness	Kurtosis	No. of Outliers
Earnings Before Taxes to Total Liabilities	4.2807	19.1545	2	5.6621	37.3260	1
Earnings Before Taxes to Notes Payable--Short-Term	1.8900	2.0294	0	2.0956	6.7231	1
Earnings Before Taxes to Current Liabilities	4.6532	25.0741	1	3.9360	23.7208	1
Earnings Before Taxes to Current Maturities	3.5512	15.8468	1	2.3429	9.9924	2
Debt to Notes Payable--Short-Term	2.6322	7.4144	1	1.9319	2.4008	0
Debt to Current Maturities	5.2647	31.5791	1	2.9055	8.6753	1
Debt to Current Liabilities	3.3458	14.0618	1	2.7767	10.5634	1
Net Sales to Accounts Receivable	2.9920	8.8252	2	5.7849	35.2822	1
Net Sales to Inventory	3.3964	12.1103	2	5.3870	30.4765	1
Net Sales to Working Capital	3.7106	16.5997	1	0.1441	7.6929	3
Net Sales to Quick Assets	3.4875	14.5162	1	4.9642	30.7128	1
Net Sales to Net Worth	4.0826	19.2372	1	3.3758	13.6762	1
Net Sales to Cash	4.9716	26.9161	1	-0.6897	7.3403	1
Net Sales to Current Assets	6.2494	42.3131	1	5.9880	38.8966	1
Collection Period	3.1830	9.4088	2	4.7567	25.9614	1
Cash to Current Liabilities	5.3393	32.9566	1	0.9692	1.2782	0
Cash to Current Maturities	3.7129	14.2172	2	5.0074	27.7176	1
Quick Assets to Current Liabilities	3.0515	10.5291	2	1.6925	3.0847	1
Quick Assets to Current Maturities	2.9590	9.1261	2	2.5383	6.2404	1
Current Assets to Current Maturities	3.7339	14.2176	2	3.2258	10.0612	2
Current Assets to Current Liabilities	1.3594	1.5963	1	2.9433	9.2851	1

TABLE A5-5

DESCRIPTIVE STATISTICS OF COMPLYING FIRMS--
TRANSFORMED RATIOS

	Mean	Standard Deviation	Maximum Value	Median	Minimum Value
Earnings Before Taxes to Total Liabilities	2.8797	8.1586	41.9204	0.9101	-0.1020
Earnings Before Taxes to Notes Payable - Short-term	3.7965	6.8029	21.4582	0.7307	-0.0204
Earnings Before Taxes to Current Liabilities	2.9405	8.4370	52.1139	1.0004	-10.8039
Earnings Before Taxes to Current Maturities	7.5361	22.7356	125.2960	1.1913	-36.6561
Debt to Notes Payable - Short-term	3.2756	5.4335	23.3402	1.0106	0.0959
Debt to Current Maturities	2.8656	5.6507	37.9812	1.3600	0.1860
Debt to Current Liabilities	1.1746	0.7383	4.9521	0.9195	0.5327
Net Sales to Accounts Receivable	1.8713	2.5314	12.2381	1.2378	0.0363
Net Sales to Inventory	2.2844	3.5074	18.2514	1.0590	0.0504
Net Sales to Working Capital	1.7461	3.7302	21.5518	0.7116	-2.1515
Net Sales to Quick Assets	1.7034	2.1627	12.7693	1.0589	0.0444
Net Sales to Net Worth	2.0667	3.2900	20.1634	1.1656	0.0898
Net Sales to Cash	6.3747	18.5308	116.0770	1.3035	-2.6526
Net Sales to Current Assets	1.4150	2.1926	16.1081	1.0536	0.0731
Collection Period	2.8712	6.2284	27.5431	0.8079	0.0817
Cash to Current Liabilities	1.7391	3.5086	23.7887	0.8820	-0.8514
Cash to Current Maturities	3.5985	6.0002	29.2527	1.1961	0.0523
Quick Assets to Current Liabilities	1.5990	1.6952	8.6100	1.1365	0.0704
Quick Assets to Current Maturities	3.5985	6.0002	29.2527	1.1961	0.0523
Current Assets to Current Maturities	3.6557	7.2523	38.3076	1.4731	0.1359
Current Assets to Current Liabilities	1.2880	0.7199	3.5731	1.0408	0.3352

TABLE A5-6

DESCRIPTIVE STATISTICS OF NONCOMPLYING FIRMS--
TRANSFORMED RATIOS

	Mean	Standard Deviation	Maximum Value	Median	Minimum Value
Earnings Before Taxes to Total Liabilities	0.4047	3.4646	22.9389	0.1139	-4.4487
Earnings Before Taxes to Notes Payable - Short-term	0.2913	3.3578	12.3768	0.0721	-5.6657
Earnings Before Taxes to Current Liabilities	0.0630	2.9076	17.0727	0.1587	-5.2860
Earnings Before Taxes to Current Maturities	0.0904	3.8429	17.5932	0.0863	-6.9819
Debt to Notes Payable - Short-term	1.5928	2.0931	7.0550	0.6673	0.1675
Debt to Current Maturities	2.4010	3.6987	18.7430	1.0064	0.2636
Debt to Current Liabilities	1.6101	1.2312	7.6178	1.1211	0.4792
Net Sales to Accounts Receivable	4.9717	17.8321	117.6540	1.0120	0.0368
Net Sales to Inventory	17.4620	71.8771	437.8660	1.3074	0.1112
Net Sales to Working Capital	-0.3352	8.1255	28.5340	-0.0419	-27.9941
Net Sales to Quick Assets	3.4946	10.4215	67.7579	1.3308	-16.6352
Net Sales to Net Worth	4.3533	11.2809	60.7066	1.1129	-14.7648
Net Sales to Cash	3.2160	7.8973	23.6584	1.3766	-29.7039
Net Sales to Current Assets	3.3445	8.7257	60.6299	1.4432	0.1046
Collection Period	2.1210	4.2606	27.2069	0.9882	0.0085
Cash to Current Liabilities	0.5784	1.0600	3.2493	0.2914	-1.5692
Cash to Current Maturities	1.4310	4.4593	27.3315	0.3023	-1.1051
Quick Assets to Current Liabilities	0.9324	0.8796	3.9852	0.6859	-0.2588
Quick Assets to Current Maturities	1.5174	2.4306	10.9477	0.5878	-0.1822
Current Assets to Current Maturities	1.7180	3.5212	16.0840	0.4998	0.0220
Current Assets to Current Liabilities	0.9707	1.1794	6.2696	0.5961	0.0045

None of the transformed ratios were significantly different at the 0.01 level. However, eight of the ratios were significantly different at the 0.05 level. The ratios were:

1. Earnings before taxes to total liabilities
2. Earnings before taxes to notes payable--short-term
3. Earnings before taxes to current liabilities
4. Earnings before taxes to current maturities
5. Debt to current liabilities
6. Cash to current liabilities
7. Quick assets to current liabilities
8. Quick assets to current maturities

Three additional ratios, earnings before taxes to total liabilities; cash to current maturities; and current assets to current maturities, were significantly different at 0.10. One ratio, net sales to current assets, was significantly different at 0.10 before the transformation, but not afterwards.

The eight ratios involving net sales and two of the debt ratios were not significantly different. The current ratio was not significantly different, yet the acid test ratio was significantly different. This implies that for short-term credit or currently maturing debt, quick assets are more important than current assets. This is further supported by the fact that the quick asset to current maturities ratio was significantly different. Complete results of the t-tests are presented in Table A5-7.

Kruskal-Wallis Median Tests

Employing the KW test the null hypothesis was rejected for seven ratios at the 0.01 level. They were:

TABLE A5-7

T-TESTS ON TRANSFORMED FINANCIAL RATIOS
OF COMPLYING AND NONCOMPLYING FIRMS

Ratio	T-value	Significance Level
Earnings Before Taxes to Total Liabilities	1.9941	0.0502
Earnings Before Taxes to Notes Payable--Short-Term	2.3421	0.0252
Earnings Before Taxes to Current Liabilities	2.3028	0.0247
Earnings Before Taxes to Current Maturities	2.2833	0.0265
Debt to Notes Payable--Short-Term	1.4581	0.1552
Debt to Current Maturities	0.4867	0.6278
Debt to Current Liabilities	-2.1664	0.0332
Net Sales to Accounts Receivable	-1.2047	0.2340
Net Sales to Inventory	-1.3669	0.1791
Net Sales to Working Capital	1.6625	0.1009
Net Sales to Quick Assets	-1.1905	0.2392
Net Sales to Net Worth	-1.3896	0.1699
Net Sales to Cash	1.0995	0.2754
Net Sales to Current Assets	-1.5316	0.1312
Collection Period	0.6910	0.4915
Cash to Current Liabilities	2.2289	0.0297
Cash to Current Maturities	1.7695	0.0813
Quick Assets to Current Liabilities	2.3381	0.0220
Quick Assets to Current Maturities	2.2699	0.0265
Current Assets to Current Maturities	1.6996	0.0936
Current Assets to Current Liabilities	1.6402	0.1048

1. Earnings before taxes to total liabilities
2. Earnings before taxes to current liabilities
3. Earnings before taxes to current maturities
4. Net sales to working capital
5. Cash to current liabilities
6. Current assets to current maturities
7. Current assets to current liabilities

The additional ratios significantly different at the 0.05 level were:

1. Earnings before taxes to notes payable--short-term
2. Debt to current liabilities
3. Quick asset to current maturities
4. Net sales to current assets

The results of the KW tests are presented in Table A5-8.

Eight of the 21 ratios were not significantly employing either test. They were·

1. Debt to notes payable-short-term
2. Debt to current maturities
3. Net sales to accounts receivable
4. Net sales to inventory
5. Net sales to quick assets
6. Net sales to net worth
7. Net sales to cash
8. Collection period

TABLE A5-8

KRUSKAL-WALLIS MEDIAN TEST--
TRANSFORMED RATIO

Ratio	Number of Points Above the Median		Number of Points Expected Above the Median Under H_o		Significance Level
	Complying	Noncomplying	Complying	Noncomplying	
Earnings Before Taxes to Total Liabilities	34	17	25.5	25.5	0.001
Earnings Before Taxes to Notes Payable--Short-Term	17	10	12.5	14.5	0.015
Earnings Before Taxes to Current Liabilities	34	17	25.5	25.5	0.001
Earnings Before Taxes to Current Maturities	34	16	25.0	25.0	0.001
Debt to Notes Payable--Short-Term	13	14	12.5	14.5	0.787
Debt to Current Maturities	29	21	25.0	25.0	0.111
Debt to Current Liabilities	20	31	25.5	25.5	0.030
Net Sales to Accounts Receivable	26	22	24.0	24.5	0.364
Net Sales to Inventory	19	23	21.5	21.0	0.332
Net Sales to Working Capital	34	17	25.5	25.5	0.001
Net Sales to Quick Assets	23	27	25.5	25.5	0.373
Net Sales to Net Worth	26	25	25.5	25.5	0.844
Net Sales to Cash	24	23	25.0	22.5	0.763
Net Sales to Current Assets	20	31	25.5	25.5	0.030
Collection Period	21	27	24.0	24.5	0.266
Cash to Current Liabilities	32	15	25.0	22.5	0.003
Cash to Current Maturities	28	18	24.5	22.0	0.120
Quick Assets to Current Liabilities	28	22	25.5	25.0	0.276
Quick Assets to Current Maturities	31	18	25.0	24.5	0.012
Current Assets to Current Maturities	32	18	25.0	25.0	0.005
Current Assets to Current Liabilities	34	17	25.5	25.5	0.001

VITA

Charles Thomas Moores was born in Little Rock, Arkansas on October 22, 1954. He attended public elementary schools and graduated from Little Rock Central High School in Little Rock in May 1973. In September 1973 he enrolled at the University of Arkansas at Little Rock. He received a Bachelor of Science in Accounting in May 1977.

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EXAMINATION AND THESIS REPORT

Candidate: Charles Thomas Moores

Major Field: Accounting

Title of Thesis: The Prediction of Small Business Instability--Loan Noncompliance: A Discriminant Analysis Approach

Approved:

Major Professor and Chairman

Dean of the Graduate School

EXAMINING COMMITTEE:

Date of Examination:

September 24, 1982