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AN EMPIRICAL INVESTIGATION INTO DEVELOPING A FAILURE PREDICTION MODEL FOR FARMING ENTERPRISES: THE FIFTH FARM CREDIT DISTRICT

by

Daryl Vincent Burckel

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AN EMPIRICAL INVESTIGATION INTO DEVELOPING
A FAILURE PREDICTION MODEL FOR
FARMING ENTERPRISES: THE FIFTH
FARM CREDIT DISTRICT

BY

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Dedication

To my wife, Mary, whose loving support, friendship, encouragement and patience made this educational endeavor possible.

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This research would not have been possible without the cooperation of Mr. Don Oates and Mr. Ron Roy at the Federal Intermediate Credit Bank in Jackson, Mississippi. Your insightful comments in the formative stages of the project and your cooperation in securing the data are very much appreciated.

ABSTRACT

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Title of Dissertation: An Empirical Investigation into Developing a Failure Prediction Model for Farming Enterprises: The Fifth Farm Credit District

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This study was an inquiry into developing a failure prediction model for farming enterprises in the Fifth Farm Credit District. Financial statement elements and transformations of these elements were the variables considered in the model building process using the discriminant analysis statistical technique.

The Federal Intermediate Credit Bank was searched to identify farms within the commercial farm category ($50,000-500,000 value of farm production) with adequate balance sheet and income statement information. This sample was further broken down to include only those farms with their latest financial statement

date between the years 1981 and March 1986. Farms considered failures for the study were those that were foreclosed, bankrupt, unable to obtain additional borrowings from the Federal Intermediate Credit Bank or whose loans were classified as bad debts and written-off by the bank.

Discriminant functions were derived for each of the three years prior to failure. Each model was validated by a holdout sample in the year the model was derived and the long range accuracy of the model was assessed by classifying the samples from prior periods. A final model was developed by using the change in financial statement ratios for three years prior to failure and one year prior to failure.

The model one year prior to failure, composed of the working capital to total asset and net farm income to net worth ratios, classified 66.42%, 70.65% and 76.67% of the farms accurately one, two and three years prior to failure, respectively. The two year model variables were the level of current assets and intermediate liabilities while the three year model consisted only of the intermediate liability variable. The change-in-ratio model identified the depreciation-to-value-of-farm-production ratio as the best discriminator between failed and non-failed farms.

The findings suggest that traditional financial statement ratios and financial statement elements alone may not be able to accurately distinguish between failed and non-failed farms. Additional factors such as qualitative data and data not disclosed in the financial statements may prove to be good discriminating variables and enhance predictive purposes.

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CHAPTER I

THE RESEARCH PROBLEM

The agricultural sector of the U.S. economy is in turmoil. Today's farmer is facing an economic crisis that may be the most severe in the nation's history. Another banner harvest is again making people aware of the financial problems on the farm. These financial problems are being felt not only by the farmer but equally so by the creditor. The resulting shakeout in the agricultural sector will have a drastic effect on the Farm Credit System and the farmers it services. Therefore, this complex situation has elicited the following research into developing a model using financial statement elements and ratios to predict potential farm failure.

Agricultural Background

There have been three distinct economic phases in the United States farming sector over the past 25 to 30 years. A moderate accumulation of new farm wealth created by capitalized earnings, starting in the late 1950s, was the beginning of the first phase. Part of the earnings came from government programs aimed mainly at production control, as farmers adopted output increasing technologies.[1] This was a time period of generally favorable world markets and farm policies coupled with the use of modern farm machinery, hybrid seeds, fertilizers, pesticides, and irrigation equipment. The result of this integrated environment was manifest in the productivity of land being tripled on a per acre basis.

The second phase came in the 1970s when there was free market gold and the American economy was pursuing an expansionary monetary policy and an uneven fiscal policy.[2] First, OPEC drastically affected farming with three-fold increases in energy prices. This increased production cost was accompanied by rising incomes for those countries that sold the inputs. The result was the creation of an enormous demand for U.S. crop exports. In turn, this increased crop prices to three to four times their previous levels. Government policy encouraged additional plantings, while lenders

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[1]P.J. Blokland, "A Perspective on the Current Agricultural Financial Crisis," Farm Management News and Views, (May, 1985).

[2]Ibid.

and extension personnel strongly recommended expansion.[3] Consequently, in the better crop areas land prices increased five hundred percent, and demand for farm machinery accelerated. The earnings multiple, defined as the price-earnings ratio, rose from 25:1 to 50:1, since farmers were now paying a high price for land relative to the income return it generated.

All of these events occurred while inflation increased from 4% to 20%. Real rates of interest became negative, making it more advantageous to borrow, and farm debt increased from $60 billion to $170 billion.[4]

The third phase is manifest in the current agricultural situation. Preservation of new wealth accumulated in the 1970s required continuing growth in earnings. Earnings growth, in turn, could only be sustained by more sales, higher prices or government programs, which were never accomplished. The grain embargo of the late 1970s severely cut export sales, which left farmers holding huge amounts of inventory. The embargo encouraged countries such as Brazil, Argentina and Australia to increase contribution to world grain markets and they rapidly filled the demand

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[3]Ibid.

[4]Ibid.

vacated by the United States. Today the strong dollar, coupled with decreased exports, has put the American farmer in a very precarious situation. Thus, the early 1980s have shown that the present U.S. farm supply-demand relationship cannot sustain the earnings growth of the 1970s.

Farm Sector Status

From 1950 to 1979 land prices soared twelvefold as income from farm assets increased. The associated capital gain was more than a half trillion dollars in the 1970s alone and the average commercial[5] farmer experienced capital gains of about $500,000.[6] These transitory earnings in capital gains were incidental to farming operations, and were more than three times farm income for the 1970s. However, from the early 1950s to the late 1970s, annual farm income (after interest expense) fell, on the average, between $15 billion and $20 billion in 1984 dollars.[7] This plunge corresponds closely to the increase in interest expense farmers paid on loans.

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[5]The average commercial farmer has gross sales between $50,000 and $500,000.

[6]Lawrence Shepard, paper presented at the Western Economic Association Meeting, Anaheim, California, August, 1985.

[7]Ibid.

In the early 1950s the average annual interest expense was only 17% (at $2.4 billion), of the average net income from assets, or $14 billion. However, as increasingly large proportions of returns to farm assets were needed in order to service debt, the percentage average interest expense of average net income from assets rose to over 50%. Thus, between the period 1975-79 average interest expense had risen to $13 billion while average net income from assets was $23 billion. The interest expense of farmers in constant dollars rose by 60% between the period 1975-79 and the period 1980-84, leveling off at $21 billion per year, as opposed to income from assets that averaged only $19 billion. "The agricultural sector could not physically service its debt without resorting to additional borrowing or massive transfers from other sectors of the economy."[8]

Table 1-1 shows the national farm situation in the 1980s in terms of real returns to assets and equity. The income returns to assets, which indicate profitability, show income after removing an imputed labor charge for family labor and management to capital invested in production assets. The real capital gains,

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[8]Ibid.

or price appreciation, figures portray the wealth adjustment on farms. These are real returns to farm land after adjusting for inflation and land improvements.

The income returns in Table 1-1 are lower than at any time since the 1950s, when this series of statistics was started. There have only been seven negative years in real capital gains in the entire series (four of which are included here) and the negative total returns are unique.

TABLE 1-1 INCOME AND CAPITAL GAIN RETURNS FOR THE FARMING SECTOR 1980 - 1983

	Return as % of Equity Value		
Year	Income	Real Capital Gains[1]	Total
1980	1.3	-0.6	0.7
1981	2.1	-9.2	-7.1
1982	1.3	-7.0	-6.5
1983	0.5	-3.1	-2.6

Source:

U.S. Department of Agriculture, Economic Research Service, Economic Indicators of the Farm Sector: Income and Balance Sheet Statistics, ECIF 2-2 (September 1984).

[1]The change in the real value of physical farm assets (after subtraction of real net investment) plus the change in the real value of currency, demand deposits and farm assets.

Troubled Farms

Intuitively, a crisis exists in the U.S. farm sector. Without special policies 200,000 of the total 2.2 million farmers either may voluntarily sell out or be forced out in the next five years.[9] Approximately 80% of all farms are financially strong, but the number of farms experiencing financial difficulties continues to be abnormally large. Of the total number of farms in the U.S., 18% have a debt load exceeding 40% of the value of assets. Farms within this category are considered to be susceptible to financial problems. Within this group about 67% were distressed, i.e. unable to cover their production expenses, family living costs and debt principle payments out of current farm and nonfarm income. These farms hold about 45% of total farm operator debt. Figure 1 is a representation of the farm financial condition of all farms by region as of January 1, 1985.[10]

While some farmers of all sizes have been experiencing financial stress, these problems have been most pronounced for family size commercial farms. The

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[9]United States Department of Agriculture. "A Summary Report of the Financial Condition of Family - Size Commercial Farms." Agriculture Information Bulletin No. 492, Economic Research Service, (January, 1985).

[10]Profit Management, Doane's Agricultural Report, Vol. 48, 32-5, August 9, 1985.

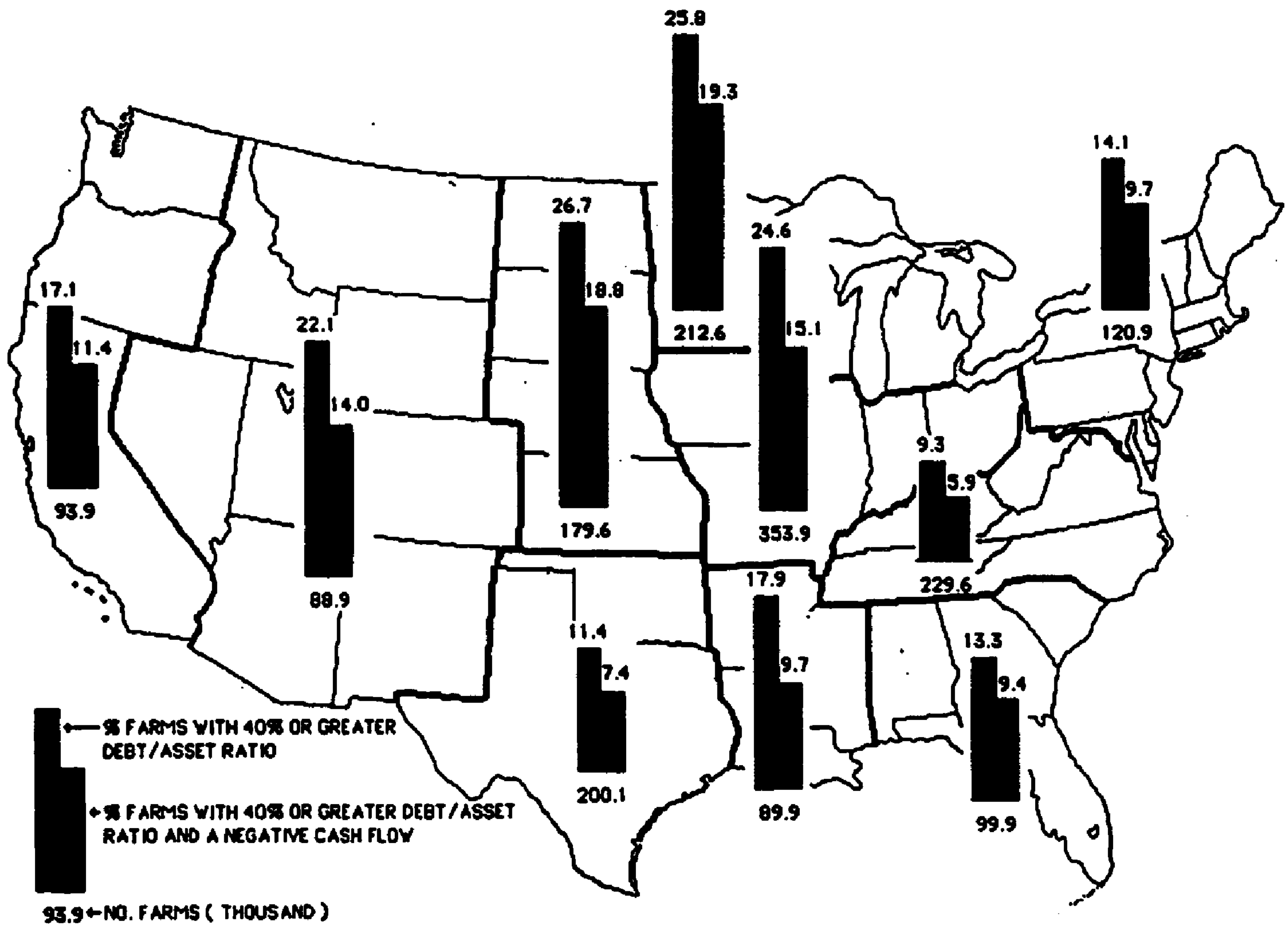

FIGURE 1: FARM FINANCIAL CONDITION BY REGIONS (JANUARY 1, 1985)

vast majority of these farms have gross sales between $50,000 and $500,000. There are an estimated 679,000 farms in this category; they account for 31 percent of all farms and 51 percent of all sales of agricultural products. Those farms with sales over $500,000 are by no means exempt from financial difficulties, but often earn a higher-than-average rate of return on their assets. They make up a little over one percent of U.S. farms, supply about one-third of U.S. farm output and earn three-fifths of the net farm income. Their earnings are impressive despite carrying 20 percent of all farm debt. The farms with under $50,000 of gross sales are not in financial difficulty today. They generally are not profitable but the farm operators are earning sufficient money in off-farm jobs to supply the cash requirements of their farming enterprises. These small farming concerns constitute about 12 percent of U.S. farm output.

The seriousness of the current financial condition for family-size commercial farms is documented in detail in The Current Financial Condition of Farmers and Farm Lenders.[11] Of the 679,000 such units, as

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[11]United States Department of Agriculture. "The Current Financial Condition of Farmers and Farm Lenders." Agriculture Information Bulletin No. 490, Economic Research Service, (January, 1985).

shown in Table 1-2, the USDA reported that:

* 43,000 or 6.3% have a debt/asset ratio over 100% and owe 9.3% of all farm debt.(technically insolvent)

* 50,000 or 7.4% of the farms have debt/asset ratios of 70-100% and owe 11.1% of all farm debt.(extreme financial problems)

* 136,000 or 20% have debt/asset ratios of 40-69% and owe 25.9% of all farm debt.(serious financial problems)

* 450,000 or 66.3% have debt/asset ratios under 40% and owe 17.9% of all farm debt.(no apparent financial problems)

TABLE 1-2 Number and Proportion of Family Size Commercial Farms, January 1985

Family-Size Farms	% of F-S Farms	% share of all Farm Debt	Debt/Asset Ratio
43,000	6.3	9.3	100
50,000	7.4	11.1	70-100
136,000	20.0	25.9	40-70
450,000	66.3	17.9	under 40
679,000	100.	64.2	

Source:

<u>Agriculture Information Bulletin No. 492</u>, Economic Research Service, (Jan 1985).

These family-size farms are responsible for 64% of all farm debt. As stated earlier, family-size farms represent just under one-third of all farms. Of the

679,000, slightly over one-third have some type of financial problem.(Figure 2)[12] The farms that are currently insolvent or approaching insolvency face the greatest danger of being forced out of business. Of the total 229,000 farms under financial stress, 93,000 (or 40%) of these farms are insolvent or face extreme financial stress. The other 136,000 (or 60%) are faced with less serious financial stress.

While these farms have the most extreme financial problems, not all face immediate bankruptcy or foreclosure. Nevertheless, debt adjustment programs that reduce principal or interest or lengthen payments are not likely to be sufficient to help those that are in financial difficulty to survive. Thus, their continued operation may depend upon their lenders' willingness and ability to carry the borrowers.

Farm Creditors Dilemma

Farm lenders are already feeling the pressures of poor farm loan performance. The debt owed on all family-sized commercial farms is almost two-thirds of all farm debt. Of this two-thirds, an amount just over 66% of the debt is in the hands of farmers facing some

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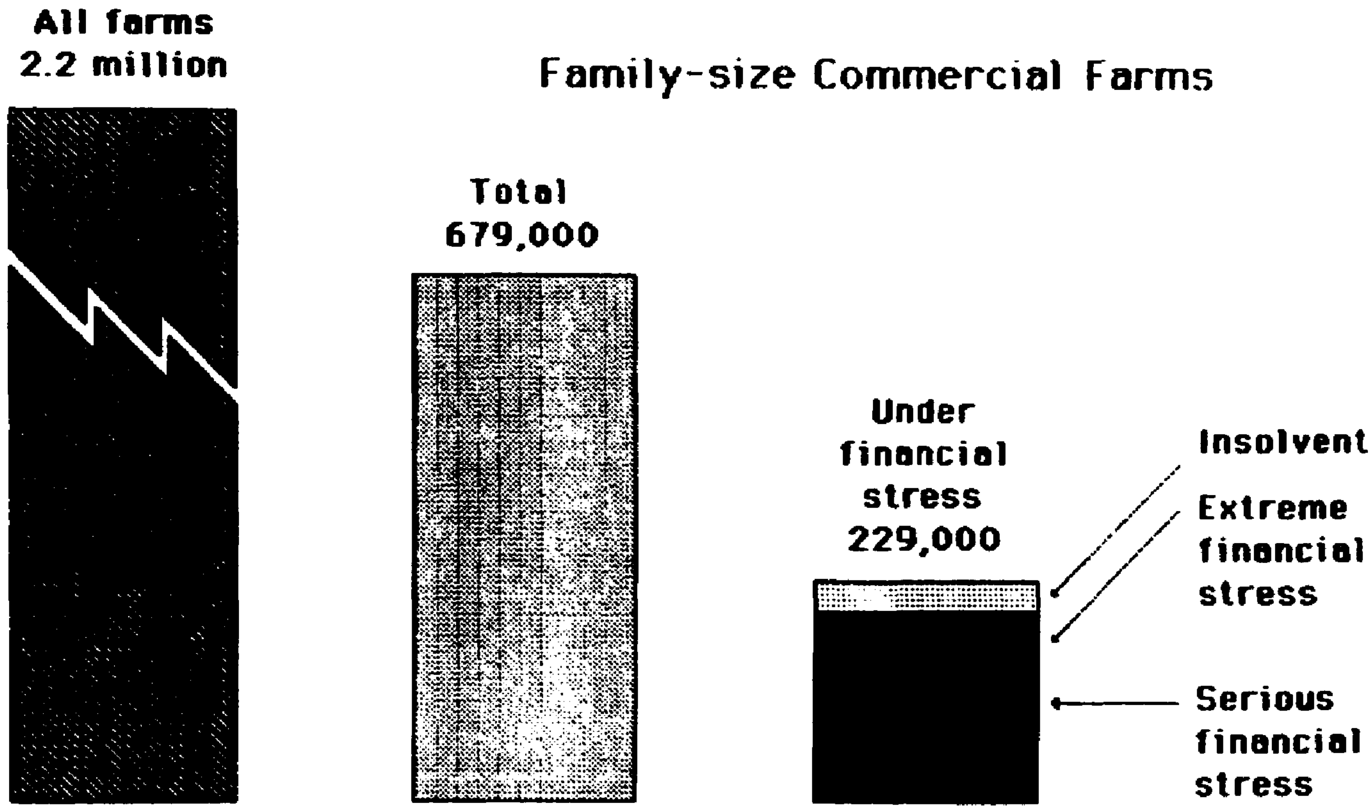
[12] Agriculture Information Bulletin No. 492, Economic Research Service, (January, 1985).

Figure 2

Number of Family-Size Commercial Farms Under Financial Stress, January 1985



degree of financial stress, as shown in Figure 3.[13] To compound the problem for lenders, loan delinquencies and charge-offs are up substantially, coinciding with an increase from 106 to 288 in problem agricultural banks over the past eighteen months prior to January 1985.

Bank failures in the agricultural sector are running at approximately 10 times the average annual rate of the 1970s, as seen in Table 1-3.

TABLE 1-3 AGRICULTURAL BANK FAILURES

YEAR	BANK FAILURES
1984	79
1981-83	100
1970-79	83

Source:

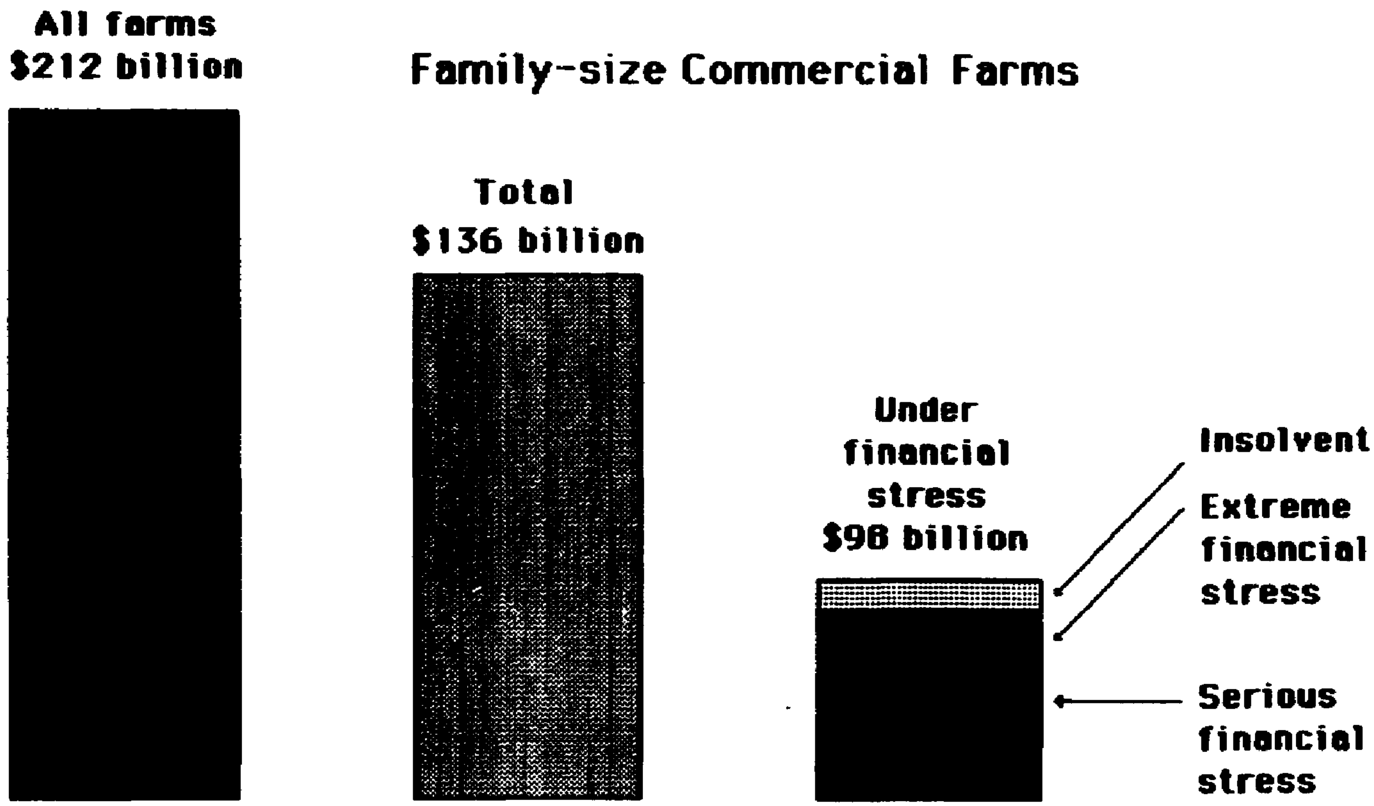
Agriculture Information Bulletin No. 492, Economic Research Service, (Jan 1985).

The 79 failed banks represent less than 2% of the 4,077 agricultural banks in the United States. Not only do the problems of these agricultural banks pose serious repercussions for local farmers and rural communities,

[13] Ibid.

Figure 3

Farm Debt Owed in January 1985



but the entire Federal Farm Credit System was in danger of collapsing. However, this situation has been alleviated since the new Farm Bill assures that the government will stand behind the securities of the Farm Credit System. This will help to reduce the riskiness of new issues and keep the interest rates down for farmers.

The Farm Credit System is a complex network of 12 regional banks, each of which consists of a land bank for farm real estate loans; an intermediate credit bank that makes short-term operating loans, mostly through production credit associations; and a bank for farm cooperatives.[14] Other holders of farm debt include commercial banks, the Farmers Home Administration (the U.S. Agriculture Department's direct lending arm), finance companies, insurers and an array of federal agencies such as the Commodity Credit Corporation. Table 1-4 shows the distribution of total farm debt by lender.

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[14] John Penson, Danny Klinefelter and David Lins, Farm Investment and Financial Analysis, (Englewood Cliffs, N.J.: Prentice Hall, 1982) p. 203.

TABLE 1-4 DISTRIBUTION OF TOTAL FARM DEBT

LENDER	TYPE OF DEBT Real Estate	Non-Real Estate	TOTAL %	TOTAL $
Commercial Banks	4.8	19.1	23.9	51
Farm Credit System	22.8	9.0	31.8	67
Federal Land Bank	22.8	NA	22.8	48
Prod. Credit Assoc	NA	8.6	8.6	18
Fed. Intr. Cr. Bank[1]	NA	.4	.4	1
Farmers Home Admin	4.7	7.2	11.9	25
Life Insurance Co.	5.8	NA	5.8	12
Individuals & Other[2]	14.1	8.5	22.6	48
Commodity Credit Corp.	NA	4.0	4.0	9
TOTALS	52.2	47.8	100	$212 BILL

Source:

Agriculture Information Bulletin No. 492, Economic Research Service, (Jan 1985).

[1]Financial Institutions other than PCA's that obtain funds from the FICB's.

[2]Includes Small Business Administration

The preceding table is depicted in the following pie chart (Figure 4) which shows the relative size of the distribution of all farm debt. The bar chart (Figure 5) reveals the magnitude of the type of debt held by the different investors and the exposure of investors due to declining real estate values. The Farm

Figure 4 TOTAL FARM DEBT

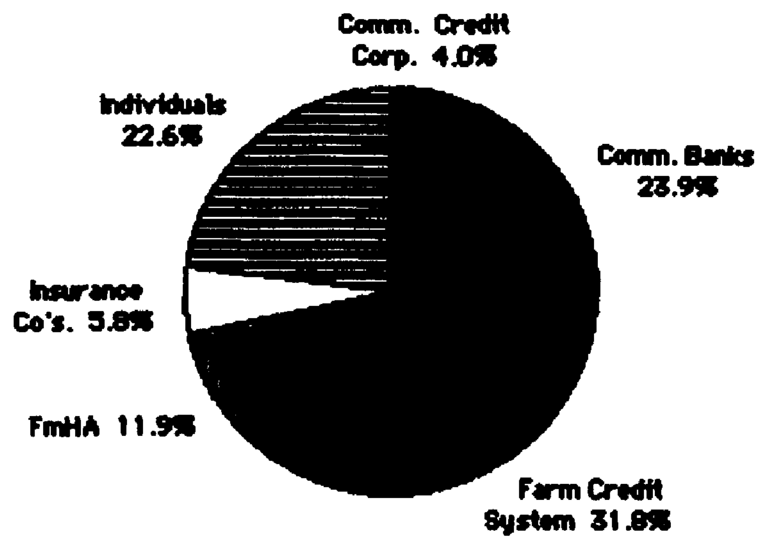
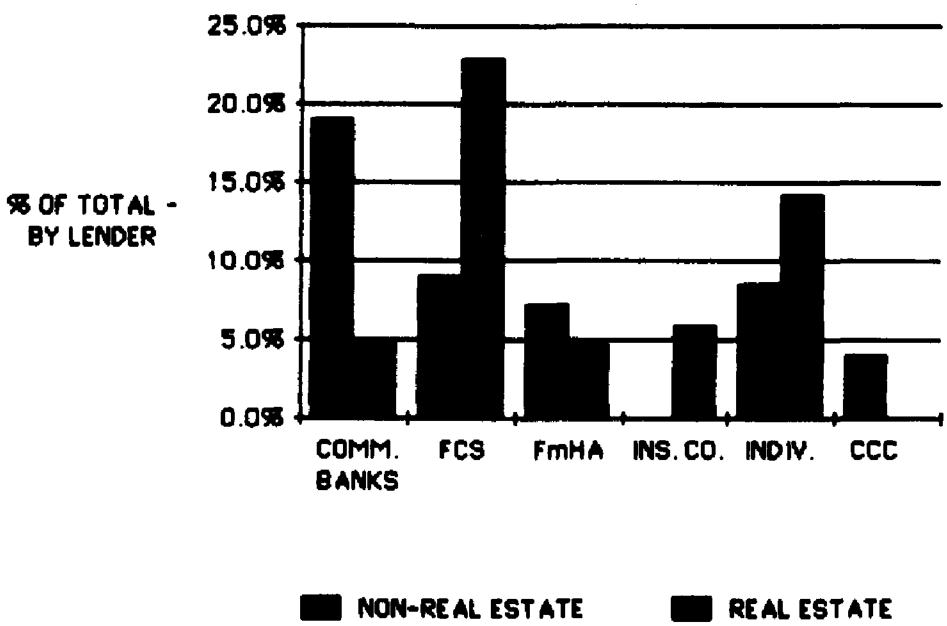


Figure 5 TYPE OF FARM DEBT
JAN. 1985 - DISTRIBUTION BY LENDER



COMM. BANKS - COMMERCIAL BANKS
FCS - FARM CREDIT SYSTEM
FmHA - FARMERS HOME ADMINISTRATION
INS. CO. - INSURANCE COMPANIES
INDIV. - INDIVIDUALS
CCC - COMMODITY CREDIT CORPORATION

Credit System, which holds $74 billion in loans, (of which $67 billion is owed by farmers and ranchers), will incur a loss for calendar year 1985 due to mounting loan losses. The General Accounting Office projected that the Farm Credit System will have a loss of $2.6 billion for the twelve months ending June 30, 1986.[15] A public accounting firm is currently auditing the System and promptly turned up $6 billion of current but poorly collateralized loans.[16] This situation is not expected to improve in the near future. Fundamental farm economics continue to deteriorate at accelerated rates. Land values continue to erode and commodity prices are being driven down with the loss of export markets due to the high value of the dollar and expanding foreign competition. The declines in land value have eroded as much as half of the collateral backing up loans made at a time of inflated land prices during the 1970s and early 1980s. Beyond that, the Farm Credit System is implementing a tighter credit policy and a currently approved court regulation allows the Farmers Home Administration to initiate foreclosure on delinquent loans, ending a two year moratorium on

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[15]"Farm Credit System Loss of $2.6 Billion Seen by GAO for year ending June 30, 1986," Wall Street Journal, 7 October 1985.

[16]"Farm Credit System Relies on Accounting that Hides Bad Loans," Wall Street Journal, 7 October 1985.

such foreclosures. These potential foreclosures could force more land into the already glutted land market.

Statement of the Problem

For decades, the criteria by which an agricultural enterprise has been judged were rate of growth and rate of increase in market share. This perception views the size of the enterprise as the determining factor in the judgment of success. Growth allows for the building of a larger capital base that will return a higher income in future years. Thus, these criteria stipulate that the larger a farm becomes, both in physical size and in growth rate, the more successful the farm. Yet it appears that the total emphasis on success (as measured by growth) has excluded completely the thought of failure (inability to continue operations) and the disastrous consequences that accompany it.[17] The current farm situation is a combination of poor management decisions, by both farmer and creditor, and external economic factors over which they have no control. However, the uncontrollable external factors are usually not the cause of failure. The most cited cause of failure is management oriented.

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[17]John Argenti, Corporate Collapse - The Causes and Symptoms, (New York, N.Y.: John Wiley and Sons, 1976) p. 2.

Before proceeding, a clarification must be made for the terms "failure" and "success" for this research. Failure will be defined as the inability of a farm to continue its normal activities for the forthcoming year and success, to the contrary, is the ability of a farm to continue its normal activities into the next year.

It is not logical for a manager whose business entity succeeds to accept full credit for such success, yet, in turn, when the entity fails, for the same manager to place all blame on external factors. The avoidance of failure has always been as much a part of the manager's task as the achievement of success. This task has always been significant, and will be more so in the future, as the penalties for failure become increasingly more severe.

With the aforementioned task in mind, how can a manager or creditor determine in which direction an enterprise is going? Unfortunately it is already too late for many farmers to ponder direction, since liquidation is the next step the business of many must take. But what about those concerns that are not in any present significant financial stress? A financial management tool for farmers and creditors must be developed to identify those factors that are indicators of an enterprise's future financial position. This research will not seek to identify all economic factors that have an effect on farm financial health, but only those that are endogenous to the financial statements. Thus the formal statement of the problem is expressed as follows:

Can financial elements or ratios, either singularly or in combination, that are relevant financial indicators, be developed into a model to predict future farm financial health?

Justification

The justification for this study is found on several fronts. Primary justification is the lack of research in the agricultural accounting area. There are many studies dealing with ratios as predictors of bankruptcy, for example Altman's[18] study, but there have been very few applications to the farming sector of the United States economy. It is felt that this study would not only benefit the agricultural sector but also add to the body of accounting knowledge by analyzing the predictive ability of accounting data for this sector of the economy.

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[18] Edward I. Altman, Corporate Bankruptcy in America, (Toronto, Canada: D.C. Heath and Company, 1971).

The second line of justification deals directly with the farmer. Agricultural producers continually face production, marketing and financial management decisions affecting the success or failure of their enterprises. In the past hard work and mastery of production techniques resulted in farming success. However, in today's economy, financial management skills and effective marketing strategies are needed to ensure success for the farmer. Perhaps, in the future, financial management skills will determine the difference between those farms that will continue and those that will face liquidation.

Farmers must begin to think of their businesses in terms of assets, liabilities, owner's equity, net income and cash flow, as well as yield per acre, pounds of grain, horsepower rating and fertilizer rates. Low profit margins, uncertain prices, large capital investment and intensive use of credit all emphasize the need for greater concern with financial management. Thus, this study is justified in its value to the farmer because of its potential predictive ability of the farm enterprise as a going concern. By analyzing his current financial situation and incorporating the model's prediction of the future operations of the farm, the farm manager can decide on whether or not to continue his current operation or the need to make major operational changes.

Creditors, perhaps more than the farmer, will find the study a source of valuable information. As suppliers of credit to farming enterprises, banks have a vested interest in these businesses. Decisions must be made concerning new and continuing lending activities to farmers. Therefore it is essential that the lender have a knowledge of the current financial position of the farm and the ability to forsee where it will be in the future.

Farm experts feel many banks have compounded their potential losses by their decisions to continue financing many essentially insolvent farmers in the spring of 1985 in hopes that a farm economy turnaround would bail them out in the fall. Only 5% of all farmers were denied planting loans in 1985, despite many farm economists' beliefs that 10% to 15% were not credit worthy. But now with 1985 farm income projected to drop to about $27 billion from last year's $34.5 billion, even some farmers who were previously not in financial stress will likely deteriorate to a critical financial position. George Norde, president of the First National Bank of Paullina, Iowa, said "If you stuck with farmers who were questionable, you can just forget about them paying back their loans."[19] A farm bank consultant based in Kansas, W. H. Shirley, echoed the previous quote when he said "This fall we're going to see bad farm loans rising through the roof and the number of essentially insolvent institutions is going to rise right with it."[20] Thus, farm lending institutions will gain valuable insight into the probability of the continued existence of their investments afforded by this research into the predictability of future farm success.

Objectives of the Research

There are two primary objectives of this research study:

(1) To identify those financial statement ratios and financial statement elements that would be used in a model to predict failure for the Alabama, Louisiana and Mississippi agricultural sector and

(2) To develop and empirically test a model that predicts future farm financial health by using those identified ratios and elements for the agricultural sector of Alabama, Louisiana and Mississippi.

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[19] "Commercial Agriculture Banks' Woes from Falling Farm Economy Intensify," Wall Street Journal, 5 September 1985.

[20] Ibid.

Remainder of the Study

Chapter II provides an overview of past research performed in the financial distress area. Chapter III addresses the research methodology while Chapter IV gives the analysis of the research results. Chapter V concludes the dissertation by suggesting directions for further research.

CHAPTER II

LITERATURE REVIEW

Predicting financial distress has been a recurring research topic over the past fifty years. There have been many contributors to the literature with varying methodologies and results. Studies in financial distress have concentrated mainly on industrial manufacturers, banks and retailers due to readily accessible financial statement data. The nonavailability of multi-year financial statement data for agricultural enterprises has been a deterrent to model formulation in efforts to predict failure for this sector of the economy. Thus studies in this area are limited.

The intent of this chapter is to present the efforts made to design models to predict failure. The voluminous research in the distress area has necessitated the selection of a few studies to be presented herein. Objectives, methodology, and results of these studies are reviewed to familiarize the reader with past research. Many other studies are given a brief explanation while others will only be cited in the footnotes. The contents of this chapter are divided into early studies, multivariate analysis, specific firm failure, the impact of specific factors on failure prediction, studies improving past models' predictive ability and failure studies in the farming sector.

Early Studies

Shortly after the end of the nineteenth century the first efforts were made to design models to predict failure.[21] The primary objective of these efforts was to compare the financial ratios of failed firms to non-failed firms in order to detect systematic differences for failure prediction. The examination of characteristics of distressed firms is possible by empirically testing ratios.

Fitzpatrick[22] was one of the first to study the corporate distress phenomenon. Other researchers such

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[21] B. Lev, Financial Statement Analysis: A New Approach, (Englewood Cliffs, New Jersey: Prentice Hall, 1974) p. 133.

[22] P.J. Fitzpatrick, "A Comparison of Ratios of Successful Industrial Enterprises with those of Failed Firms," Certified Public Accountant, (October, November and December, 1932).

as Mervin[23] and Seiden[24], found as Fitzpatrick, that particular ratios of unsuccessful firms deteriorated as the year of failure approached. Winakor and Smith[25] produced evidence that unsuccessful or bankrupt firms had ratios that were frequently below the mean value used for comparison and showed substantial deterioration as the date of bankruptcy drew near.[26] Although these research studies were weak by design, they did establish the presence of a systematic difference between the ratios of bankrupt and non-bankrupt firms.

One of the most cited analyses to distress prediction was performed by Beaver[1966].[27] This seminal work examined 30 financial ratios of a paired sample of

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[23]C.L. Mervin, "Financing Small Corporations in Five Manufacturing Industries," 1926-1936 (New York: National Bureau of Economic Research, 1942).

[24]M.H. Seiden, "Trade Credit: A Quantitative and Qualitative Analysis," Tested Knowledge of Business Cycles, 42nd Annual Report (National Bureau of Economic Research, 1962).

[25]C.H. Winakor, and R.F. Smith, "Changes in Financial Structure of Unsuccessful Industrial Companies," Bulletin No. 51 (Urbana: University of Illinois Press, Bureau of Economic Research, 1935).

[26]For additional studies see Saulnier, Halcrow and Jacoby(1958), and Moore and Atkinson(1961).

[27]W. Beaver, "Financial Ratios as Predictors of Failure," in Empirical Research in Accounting: 1966, Supplement to the Journal of Accounting Research, IV (71-111).

79 failed and 79 non-failed firms from 1954-1964. A univariate model was employed that utilizes a single accounting-based variable to distinguish failed firms from their non-failed counterparts. Beaver conducted three major empirical experiments: (1) comparison of mean values, (2) dichotomous classification, and (3) analysis of likelihood ratios.

Of the 30 ratios that Beaver examined, the data indicate that three ratios best predict financial failure: cash flow/total assets, net income/total debt, and cash flow/total debt. He found that the cash flow to debt ratio performed best as a signal of impending financial failure. Table 2-1 contains some of Beaver's results, which show the percentage of misclassifications from a holdout sample and the original sample.

TABLE 2-1 FRACTION OF SAMPLE MISCLASSIFIED

Years Before Sample Failure	RATIOS Cash Flow / Tot. Assets	Net Income / Tot. Debt	Cash Flow / Tot. Debt	Size
1	.10[1] (.10)	.15 (.08)	.13 (.10)	158
2	.20 (.17)	.20 (.16)	.21 (.18)	153
3	.24 (.20)	.22 (.20)	.23 (.21)	150
4	.28 (.26)	.26 (.26)	.24 (.24)	128
5	.28 (.25)	.32 (.26)	.22 (.22)	117

Source:
Beaver (1966, table A-4)

[1]The first fraction measures misclassification for the holdout sample; the fraction in parentheses measures misclassification for the original sample.

Even five years before failing, only 22% of the firms in either the holdout or the original samples are misclassified by the cash flow to debt ratio. Thus using the paired sample design, Beaver demonstrated the predictive power of financial ratios (accounting data) for individual firm failure. In a later study Beaver[28] observed that changes in market prices of stocks were also good indicators of potential financial distress.

Multivariate Analysis

Altman[1968][29] extended Beaver's univariate analysis to allow for multiple predictors of failure (Beaver considered the effects of using one ratio at a time). Multiple discriminant analysis was employed in an attempt to develop a linear function of a number of explanatory variables to classify or predict the value of a qualitative variable. The initial matched sample was composed of sixty-six corporations with thirty-three bankrupt and thirty-three nonbankrupt firms. The bankrupt group were manufacturers that filed a bankruptcy petition under Chapter X of the National Bankruptcy Act during the period 1946-1965. The non-bankrupt group consisted of a paired sample of manufacturing firms chosen on a stratified random basis. Asset size of all firms in the study ranged between $1-$25 million.

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[28] W. Beaver, "Market Prices, Financial Ratios and the Prediction of Failure," Journal of Accounting Research, (Autumn, 1968) pp. 179-192.

[29] E.I. Altman, "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy," Journal of Finance, (September, 1968) pp. 589-609.

Due to the large number of significant variables, as indicated in past studies, twenty-two potentially significant ratios were compiled for evaluation. They were classified into five standard ratio categories, including liquidity, profitability, leverage, solvency and activity ratios. Altman felt the ratios, when analyzed within a multivariate framework, would take on a greater statistical significance than the common technique of sequential ratio comparison. Five variables of the twenty-two analyzed one period before bankruptcy were eventually selected to be included in his final discriminant function. Those five variables were:

X1 Working Capital to Total Assets (liquidity)

X2 Retained Earnings to Total Assets (age of firm and cumulative profitability)

X3 Earnings before Interest and Taxes to Total Assets (profitability)

X4 Market Value of Equity to Book Value of Debt (financial structure)

X5 Sales to Total Assets (capital turnover rate)

These ratios were used to develop the following predictive equation:

$$Z = .012(X1) + .014(X2) + .033(X3) + .006(X4) + .999(X5)$$

The original 33 firms sampled were examined to determine the overall effectiveness of the discriminant model for a five year time period. The model classified 95 percent of the original 33 bankrupt firm sample correctly one year before bankruptcy and only 72 percent the second year before bankruptcy. The results of the five year examination are in Table 2-2.

TABLE 2-2 FIVE YEAR PREDICTIVE ACCURACY OF MDA MODEL

Years Prior to Bankruptcy		Hits	Misses	% Correct
1st	n=33	31	2	95%
2nd	n=32	23	9	72%
3rd	n=29	14	15	48%
4th	n=28	8	20	29%
5th	n=25	9	16	36%

Source:
Altman, E.I., Corporate Bankruptcy in America, (Lexington, Massachusetts; Heath Lexington Books, 1971), p.73.

The reduced sample in years two through five is due to the fact that several of the firms were in existence for less than five years.

The findings suggest that the bankruptcy prediction model is an accurate forecaster of failure up to two years prior to bankruptcy and that accuracy diminishes substantially as the lead time increases. Altman[30] felt the most important conclusions of the trend analysis were:

> (1) that all the observed ratios show a deteriorating trend as bankruptcy approaches and (2) the most serious changes in the majority of these ratios occurred between the third and second years prior to bankruptcy.

Simultaneous research using multiple discriminant analysis for failure prediction was performed by Daniel[1968].[31] The objective of the research was to use conventional financial statement information which is generally available to investors to evaluate the financial standing of an enterprise with regard to a tendency toward failure by quantitatively classifying firms on the basis of financial statement variables. Prediction of failure rather than the explanation of the causes was the major emphasis. Daniel employed simple correlation, factor analysis and stepwise regression to select financial statement data and ratios which best correlated with failure and non-failure as the dependent variable.

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[30] Ibid.

[31] Troy E. Daniel, "Discriminant Analysis for the Prediction of Business Failures," (Unpublished PhD. dissertation, University of Alabama, 1968).

A random sample of 30 publicly held industrial corporations was used for the derivation of the discriminant function. Firm failure was defined as bankruptcy: liquidation or merger following periods of unprofitable operations: substantial losses for three or more years or normal earnings in one year and substantial losses in two years: or a deficit in retained earnings for three or more years. Non-failure was defined as continuing in business and also providing a return greater than that available on essentially riskless investments.

Forty-six potentially significant variables were compiled for evaluation to be used in the discriminant function. Thirteen financial statement classifications and thirty-three generally accepted ratios were tested by the three aforementioned statistical methods. Stepwise regression yielded ten variables at the .005 level of significance, that provided the most significant difference between the two groups. Those variables included in the discriminant function were:

X1 Net Profit after Taxes
X2 Long Term Liabilities
X3 Investments/Sales
X4 Sales/Fixed Assets
X5 Net Working Capital/Total Assets
X6 Long Term Liabilities/Total Liabilities
X7 Net Profit after Taxes/Net Working capital
X8 Long Term Liabilities/Net Working Capital
X9 Investments/Current Assets
X10 Net Working Capital/Net Worth

These ratios yielded the following discriminant function:

$$Z = 1.82917(X1) - .04798(X2) + .4849(X3) - .00849(X4) + .27217(X5) - .02593(X6) + .47031(X7) + .0099(X8) - .07182(X9) + .15787(X10)$$

A validation sample of fifty randomly selected non-failure firms and fifty firms selected by the failure criteria were examined to determine the overall effectiveness of the discriminant model. The results are shown in Table 2-3.

TABLE 2-3 ACTUAL AND PREDICTED RESULTS

		Actual Outcome			
		Failed	Borderline	Non-failed	Total
Predicted Outcome	Failed	45	20	0	65
	Non-failed	4	9	22	35
	Total	49	29	22	100

Source:
Daniel (Unpublished PhD. dissertation, 1968) p. 133

In the analysis of the results a firm was considered a failure if it met the previously mentioned criterion and a non-failure if the firm provided a return greater than the riskfree rate. Firms that did not clearly belong to either group were considered borderline cases. Only four firms which were predicted to be non-failing were found to be failures. Daniel concluded after an analysis of the misclassified firms that some of the difficulty in classification stems from the differences in rates at which companies move toward failure. Thus the results of the research confirm that meaningful conclusions can be drawn on the basis of "Z" values calculated with the discriminant function.

Meyer and Pifer[32] improved previous research by introducing financial data from more than one period prior to failure into the model. They regressed each financial ratio on time and determined the time trend, coefficient of variation, and shift away from the trend in the period prior to failure. These data were then used along with other financial statement data as independent variables in a linear probability model. This method considered the financial decay process of bankruptcy in deriving the model coefficients. Even though this model has produced very good results, the associated computational burden will only be justified by a substantial increase in predictive ability.

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[32]Paul A. Meyer, and Howard W. Pifer, "Prediction of Bank Failures," Journal of Finance, (September, 1970) pp. 853-868.

A March 1972 study by Deakin[33] proposed an alternative business failure model to the ones developed by either Beaver or Altman. He liked Beaver's empirical results for their predictive accuracy and Altman's multivariate approach for its intuitive appeal. Deakin wanted to capture the best of both prior studies by employing the 14 ratios Beaver used and to search for the best linear combination of the ratios with the greatest predictive ability. Thirty-two firms that failed between 1964 and 1970 were matched with non-failed firms on the basis of industry, asset size, and year of financial data.

A replication of Beaver's dichotomous classification test generated similar results. Using discriminant analysis, Deakin hoped to improve upon the univariate classification results by linearly combining the 14 variables for each of the five years prior to failure. Deakin did not use paired samples to derive the discriminant function but used a sample of 32 failed firms and a random sample of 32 non-failed firms drawn from Moody's Industrial Manual for the years 1962-1966. To test the model Deakin classified the

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[33]E.B. Deakin, "A Discriminant Analysis of Predictors of Business Failure," Journal of Accounting Research, (March, 1972) pp. 176-179.

original sample of 64 firms and a holdout sample consisting of 11 failed firms and 23 non-failed firms selected at random from Moody's Industrial Manual.

The total misclassification rate on the original sample for the first three years prior were all less than 5%. Deakin's results which emphasize accuracies based on specific models built for each year prior to failure were taken from relatively small samples. In the fourth and fifth year the groups were less distinct and the error rates were, according to Deakin, "probably too high for decision making purposes."

Specific Firm Failure

As research progressed many studies focused upon particular types of business failure. In September of 1972 Edmister[34] set forth to develop and test a number of methods of analyzing financial ratios to predict the failure of a small business. A business with a loan from the Small Business Administration (SBA) was defined as a small loan. The firms used in the study were borrowers and guarantee recipients from

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[34] R.O. Edmister, "Financial Ratios and Credit scoring for Small Business Loans," Journal of Commercial Bank Lending, (September, 1971).

the SBA for the period 1954-1969. Failures were defined as loss borrowers and non-failure as nonloss borrowers.

Edmister analyzed 19 financial ratios which included most of those found to be important in previous studies. He focused his methodology on testing the following four hypotheses:

(1) a ratio's level as a predictor of a small business failure

(2) the three year trend of a ratio as a predictor of small business failure

(3) the three year average of a ratio as a predictor of small business failure

(4) the combination of the industry relative trend and the industry for each ratio as a predictor of small business failure

A zero-one regression technique was employed since Edmister believed the regression computer programs were somewhat better developed. He was intent upon limiting multicollinearity in his regression equation and employed an arbitrary stepwise procedure in which a variable was not permitted to enter the regression equation if its simple correlation coefficient with an included variable was greater than 0.31. A shortcoming to this arbitrary coefficient cutoff is that a powerful explanatory variable may be excluded.

Each independent variable was transformed into qualitative form due to the following rationale espoused by Edmister: (1) to prevent extreme values from unduly affecting estimated parameters, and (2) to permit level and trend variables to be combined into a single dichotomous variable.

The preceding methodology produced a seven variable, zero-one linear regression equation:

$$Z = .951(X1) - .293(X2) - .482(X3) + .277(X4) - .452(X5) - .352(X6) - .942(X7)$$

where

Z = the zero-one dependent variable. It equals one for non-failure and 0 for failure.

X1= the ratio of annual funds flow to current liabilities. It equals one if the ratio is less than 0.05, zero otherwise.

X2= the ratio of equity to sales. It equals one if the ratio is less than .07, zero otherwise.

X3= the ratio of net working capital to sales divided by the corresponding Robert Morris Associates(RMA) average ratios. It equals one if the ratio is less than -0.02, zero otherwise.

X4= the ratio of current liabilities to equity divided by the corresponding RMA average ratio. It equals one if less than .48, zero otherwise.

X5= the ratio of inventory to sales divided by the corresponding RMA industry ratio. It equals one if the ratio has shown an upward trend, zero otherwise.

X6= the quick ratio divided by the trend in RMA quick ratio. It equals one if the trend is downward and level just prior to the loan and is less than 0.34, zero otherwise.

X7= the quick ratio divided by RMA quick ratio. It equals one if the ratio has shown an upward trend, zero otherwise.

The model classification results had an overall accuracy of at least 90%. For example, using Z greater than or equal to .53 to determine non-failure and Z less than .53 for failure, all of the failed firms were classified for an overall accuracy rate of 93%. Edmister concluded that the predictive ability of ratio analysis depends upon both the choice of analytical method and the selection of ratios. He found (1) dividing a ratio by its representative industry average, and (2) classifying ratios by quartiles as two useful methods of analysis. Edmister also stated that no single ratio predicts as well as a small group; independent predictors are superior to nonindependent predictors; and some ratios that are insignificant by themselves add important information when combined with other variables.

Blum [1974][35] developed a model to aid the antitrust division of the Justice Department in assessing the probability of business failure for merger prosecution.

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[35]Mark P. Blum, "Failing Company Discriminant Analysis," Journal of Accounting Research, Vol. 12, No. 1 (Spring, 1974).

Blum's definition of failure was based upon the following criteria established in litigation[36] : (1) inability to pay debts as they become due; (2) entrance into bankruptcy proceedings; or (3) an explicit agreement with creditors to reduce debt. If any of the above conditions are met a firm is deemed a failure. Blum, like Beaver(1966), selected variables based upon the concept of a business firm as a reservoir of financial resources with the probability of failure expressed in terms of expected cash flows. His primary contribution was the inclusion of ratio trends and variance(stability over time) as predictors. With liquidity, profitability and variability as the underlying factors of his framework, 12 variables were selected by Blum to measure cash flow parameters. Twenty-one discriminant functions were derived for a like number of time ranges of data availability. The validation tests results concluded that the "middle" ranges of four, five and six years had higher predictive accuracy than the other ranges.

The best function was able to correctly classify approximately 94% of the firms based on financial ratios computed within a year of failure. Accuracy was

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[36] International Shoe v. FTC, U.S. 291 (1930).

80% two years before failure and 70% thereafter up to five years before.

Many of the studies reviewed have developed bankruptcy prediction models using data from large firms. For example, the average asset size of the firm's in Altman's 1977 ZETA model was approximately $100 million and no firm had less than $20 million in assets. However, in 1984 Fulmer, Moon, Graves and Erwin[37] developed a model using data obtained from firms that have assets totaling less than $10 million. The unavailability of data on such small firms has been a troublesome problem for researchers in attempting to develop a model. Data for their study were provided by banks in the Southeast for bankrupt and non-bankrupt clients. Financial statement data for one year prior to bankruptcy and two years prior to bankruptcy were acquired for the study.

Forty potentially significant ratios were analyzed using the discriminant analysis statistical technique. A nine-variable model was selected which best discriminated between the two groups. The bankruptcy classification model includes a liquidity ratio, three leverage ratios, a profitability ratio and three other

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[37] J. Fulmer, J. Moon, T. Gavin and M. Erwin, "A Bankruptcy Classification Model for Small Firms," Journal of Commercial Bank Lending, (July, 1984) pp. 25-37.

ratios. Factors that indicate the possibility of going concern problems were grouped into two main categories. These categories are financial and operating problems.

Characteristics that are included in the financial problem area are liquidity deficiency, equity deficiency, debt default and shortage of funds. Characteristics of operating problems are operating losses, doubtful revenues, legal problems and management's control over operations.

The model correctly classified 98% of the firms one year prior to failure and 81% of the firms two years prior to failure. The variables included in the model for small firms are different from those in other widely used models that are applicable to larger firms. Both models have measures of liquidity, leverage, activity and profitability. However, the researchers feel that within each type of measure different ratios are useful in classifying large versus small firms as bankrupt or non-bankrupt.

Specific Factor Studies

Studies in failure prediction moved away from the simple prediction of failure to research on the impact of specific accounting data and the comparison of failure models to human judgment. Ketz[38] and Norton and Smith[39] both studied the impact of price level adjusted statements on failure prediction while other studies focused on auditor and creditor predictions of failure.

Elam's[January 1975][40] study was to determine if capitalization of (nonpurchase) leases enhanced the ability of a failure prediction model to correctly classify firms. This was a timely and an important issue as leases have become an important means of financing. A sample of 48 firms with at least one financial statement prior to failure between the years 1966-1972 was required, with reporting of lease information in the footnotes of the financial statements. A matched pair sample was gathered according to (1) fiscal year, (2) Standard Industry Classification, (3) net sales in the fifth year prior to bankruptcy within the industry

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[38]F.J. Ketz, "The Effect of General Price-Level Adjustments on the Predictive Ability of Financial Ratios," Journal of Accounting Research (Supplement, 1978) pp. 273-84.

[39]C.L. Norton, and R.E. Smith, "A Comparison of General Price Level and Historical Cost Financial Statements in the Prediction of Bankruptcy," The Accounting Review 54 (January, 1979) pp. 72-87.

[40]R. Elam, "The Effect of Lease Data on the Predictive Ability of Financial Ratios," The Accounting Review, (January, 1975) pp. 25-43.

class, and (4) reporting of uncapitalized long-term leases.

Given the annual lease payments and lease life in the footnotes, Elam capitalized the future lease commitments for each firm using an interest rate of 6%. The ratio of capital leases to total assets(leases excluded) for the study's bankrupt and nonbankrupt groups are given in the following table.

TABLE 2-4 RATIO OF CAPITAL LEASES TO TOTAL ASSETS

FIRMS	# OF YEARS PRIOR TO BANKRUPTCY				
	1	2	3	4	5
BANKRUPT	.197	.173	.200	.311	.269
NONBANKRUPT	.154	.167	.090	.080	.082

Source:
Elam, R., "The Effect of Lease Data on the Predictive Ability of Financial Ratios," The Accounting Review (January, 1975) p.31.

Bankrupt firms on the average were leasing quite heavily five years before bankruptcy. This indebtedness increases, then decreases the next three years. On the contrary, nonbankrupt firms enter leasing much more gradually and not to the extent of bankrupt firms.

Single and multivariate analysis were used to test the hypothesis that lease data do not improve the accuracy of a failure prediction model. Based upon the single or multiple ratio test, Elam found that the effects of capitalized lease data do not significantly improve the overall classification accuracy of the model tested.

The study undertaken by Libby [March 1975][41] was designed to determine whether accounting ratios provide useful information to loan officers trying to predict business failure. He built upon Deakins' 1972 study by using a subset of the 14-variable set to develop Deakins' model. Loan officers were asked to analyze the ratios and to predict either "failure" or "non-failure". The usefulness of this information was judged on the basis of the accuracy of the loan officers prediction.

He found that the loan officers' predictive ability was superior to random assignment(i.e., failed-nonfailed) and concluded the ratio information was utilized correctly by the loan officers. On the basis of other tests, Libby concluded that (1) there was no significant differences between representatives; (2) there was no significant correlation between predictive accuracy and loan officer characteristics, such as age and experience; (3) there was no difference in short term, test-retest reliability between user groups; and (4) there was a uniform interpretation of accounting data across bankers.

These conclusions can be misinterpreted since there was bias as to the information. The loan officers were told beforehand that one-half of the firms being analyzed had failed. Another study in 1980 by Casey[42] found that loan officers who were not informed about failure frequencies could only correctly predict 27% of a sample of bankrupt firms.

Deakin[43] extended his 1972 analysis to a 1977 study building upon Libby's contribution to his earlier model. The extension of the earlier study was twofold: (1) to provide an indication of the frequency and nature of misclassification of nonfailing companies, and (2) to compare auditors' opinions with the models predictive ability.

The sample of the failed group consisted of 63 firms: the 32 companies from his 1972 study and 31 firms (from a 1974 study by Altman and McGough) that

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[41] R. Libby, "Accounting Ratios and the Prediction of Failure: Some Behavioral Evidence," Journal of Accounting Research, (March, 1975).

[42] C. Casey, "The Effect of Accounting Information Load on Bank Loan Officer's Prediction of Bankruptcy," Journal of Commercial Bank Lending, (August, 1978).

[43] E. Deakin, "Business Failure Prediction: An Empirical Analysis," in E. Altman and A. Sametz, eds., Financial Crisis: Institutions and Markets in a Fragile Environment. (New York N.Y.; Wiley and Sons, 1977).

failed in 1970 and 1971. The non-failed group consisted of 80 randomly selected firms from Moody's Industrial Manual and matched by year of data. Data two years prior to failure was employed, and for each of 143 firms, the five-ratio set derived by Libby was computed.

Using both linear and quadratic multiple discriminant analysis, Deakin classification results were 94.4% and 83.9% respectively. Due to the disparity in results, Deakin adopted the following fail-nonfail decision rule for his validation tests: (1) classify as failing if both the linear and quadratic function classify as failing; (2) classify as nonfailing if both functions classify as nonfailing; and (3) investigate further if the functions produce conflicting results.

The validation test was applied to 80 firms on the Compustat 1800 file for the fiscal year 1971. Both models agreed that 16.29% of the firms(290) had characteristics that were more similar to those of the failed group than those of the non-failed group. Characteristics inherent to the non-failed group amounted to 73.99% (1317 firms) of the sample. The investigate further group had 9.72% (173 firms) assigned to that category.

To verify the models prediction, the 290 failed firms financial performances were scrutinized along with 100 of the 1,317 firms predicted not to fail. No further analysis was performed on the "investigate further" category. The follow-up analysis was for a three-and-one-half year period from 1972 until June 30,1975. The criterion for judging the predictive accuracy of the model was based upon the failure definition by which the model was developed. Failure was narrowly defined as bankruptcy, liquidation or reorganization. Analyzing the firms under his definition of failure, only 18 (6.2%) of the 290 firms predicted to fail were classified correctly. Of the firms predicted not to fail, none of the 100 firms failed.

A study by Altman and McGough[44] described the relation between the multiple discriminant analysis prediction of failure and a auditor's qualification or disclaimer as to the going concern nature of a firm. A comparison of the auditors' reports and the statistical model for classifying failing companies shows the discriminant model results in fewer classification errors for failing companies. However, the auditors' reports

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[44]E.I. Altman, and T. McGough, "Evaluation of a Company as a Going Concern," Journal of Accountancy, (December, 1974) pp. 50-57.

resulted in fewer misclassifications of non-failing companies. This is explained by the costs associated with the auditors' misclassification. If an auditor classifies a non-failing company as failing this can result in the loss of the client and can also cause the firm to fail.

Altman's 1968 discriminant function was employed to evaluate 34 firms entering bankruptcy since 1970. The model would have predicted 28 of the firms to be bankrupt candidates based on their last financial statement. The auditors expressed going concern problems in their opinions in only sixteen of the thirty-four firms evaluated. A sample of 21 firms with a going concern problem as expressed in the auditor's opinion revealed that six subsequently went bankrupt as predicted by the MDA model. Seven of the sampled firms recovered and are no longer receiving a qualified opinion; of these seven, five had MDA scores which would not have predicted bankruptcy.

Thus, these findings yield strong implications for the use of multivariate models as a decision making aid for auditors attempting to assess the going concern probability of a firm.

Improving Prediction Models

Continuing research into the prediction of failure using accounting data has fostered the use of differing methodologies leading to the improvement of previous models.

Wilcox [1976][45] focused upon application of the gambler's ruin model of probability theory to business risk. His plan was to develop a useful generalization or model first and then to test it. The classic gambler's ruin problem was adapted to measure business risk and focused upon net liquidation value(NLV) and the factors that cause it to fluctuate. Net liquidation value is a dollar level fed by a liquidity inflow rate and drained by a liquidity outflow rate. He defined the inflow rate as net income minus dividends and the outflow rate as the increase in book value of assets minus the increase in the liquidation value of those assets. Net liquidating value is also defined as asset liquidation less total liabilities. The main concern of the model was with predicting when NLV will be negative, which often portends bankruptcy.

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[45]J.W. Wilcox, "The Gambler's Ruin Approach to Business Failure," Sloan Management Review, (March, 1976).

Wilcox contended that his gambler's ruin model yielded better results when compared with Beaver's and Altman's models, especially since (1) his did not represent the result of statistical searching; (2) his model was tested over a long period of time; during which inflation had altered typical financial ratios; and (3) his model was derived from a conceptual framework with implications for the managerial process. Santomero and Vinso[1977][46] provided an additional application of the gambler's ruin model using commercial bank data. No real tests of their model are provided although they do estimate the probability of ruin of each bank at a future point in time and search for the time when this probability will be at a maximum.

IN 1977 Altman, Haldeman, and Narayanan[47] used ZETA, a revised MULDIS(MDA) program, which can analyze both linear and quadratic functions. Even though the old Z-score approach had gained a great deal of respectability and popularity, there were at least five

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[46] A.M. Santomero, and J.D. Vinso, "Estimating the Probability of Failure of Commercial Banks and the Banking System," Journal of Banking and Finance, (September, 1977).

[47] E.I. Altman, R. Haldeman and P. Narayanan, "ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations," Journal of Banking and Finance, (June, 1977).

reasons espoused by the researcher that a new model could improve upon past structures. They are:

(1) The dramatic change in size and financial profile of the businesses failing in recent years.

(2) The new model should be as current as possible with respect to the temporal nature of the data.

(3) Past failure models concentrate on the broad classification of manufacturers or on specific industries.

(4) Data and footnotes to financial statements have been analyzed to include the most recent changes in financial reporting standards and accepted accounting practices for the study.

(5) A new model would enable the researcher to test and access several of the most recent advances and still controversial aspects of discriminant analysis.

The sample consisted of 53 bankrupt firms and a matched sample of 58 nonbankrupt entities for the 1962 -1975 time period. They were matched to the nonfailing firms by industry and year of data. The firms sampled are divided almost equally into manufacturers and retailers.

The researcher concluded that the ZETA model for bankruptcy classification appears to be quite accurate for up to five years prior to failure. The model successfully classified well over 90% of the sample one year prior to bankruptcy and 70% accuracy up to five years. Even though the statistical properties of the data indicate that a quadratic structure is appropriate, the linear structure of the same model outperforms the quadratic in tests of model reliability. Table 2-5 presents the classification accuracy of the original sample based on data from one year prior to bankruptcy.

TABLE 2-5 CLASSIFICATION ACCURACY OF 1977 STUDY

Years prior to bankruptcy	Bankrupt Firms		Nonbankrupt Firms		Total	
	Lin	Quad	Lin	Quad	Lin	Quad
1 Original sample	96.2	94.3	89.7	91.4	92.8	92.8
1 Lachenbruch[1] validation	92.5	85.0	89.7	87.9	91.0	86.5
2 Holdout	84.9	77.4	93.1	91.9	89.0	84.7
3 Holdout	74.5	62.7	91.4	92.1	83.5	78.9
4 Holdout	68.1	57.4	89.5	87.8	79.8	74.0
5 Holdout	69.8	46.5	82.1	87.5	76.8	69.7

Source:
Altman, E.I., Corporate Financial Distress, (New York, N.Y.: Wiley and Sons, 1983) p.136.

[1]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 observations. This is repeated until all observations are classified.

In the Summer of 1977 Moyer[48] published a paper that re-examined the Altman bankruptcy model. The study focused on some of the technical aspects of the study as criticized by Joy and Tollefson.[49] Moyer noted that although Altman tested his model's explanatory power on a holdout sample of firms, the data for this sample were drawn from the years used in the original fit. Because the parameters of the model could only be estimated when the period was over, the test does nothing to indicate whether the model has any predictive accuracy. That test requires the use of parameters estimated from earlier years in distinguishing firms that will or will not fail in later years.

Moyer tested the predictive power of the Altman model when it was applied to a new set of data from firms during the 1965-1975 time period. Next he re-estimated the model parameters and concluded that the Altman model may have included an excessive number of variables and that the model's predictive power is substantially less than the original work implied.

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[48]Charles Moyer, "Forecasting Financial Failure: A Re-Examination," <u>Financial Management</u>, (Spring, 1977) pp. 11-17.

[49]O.M. Joy, and J. Tollefson, "On the Financial Applications of Discriminant Analysis," <u>Journal of Financial and Quantitative Analysis</u>, Vol. 10, No. 5 (December, 1975).

The original Altman model when applied to the data set of larger firms from a different time span has an overall success rate of only 75% as compared to 95% for the original study. Moyer concluded that the original Altman model parameters are sensitive to either the time span used to develop the model or the firm sizes which were represented in his original samples, or both.

The Altman model parameters were next re-estimated to address issues raised by Joy and Tollefson. Using the stepwise as compared to the direct MDA approach, it was found that somewhat better "explanatory" power could be obtained from the model if the market value of equity/book value of debt and sales/total assets variables are eliminated from the model. The three variable function had a success rate of 90.48%. For the two years to bankruptcy function the direct model and the limited three variable stepwise model have an 83% success rate, indicating again that the two variables eliminated add little to the classification ability of the model. This contrasts with Altman's findings that the sales to total assets variable was the second most important variable in the model in terms of contribution to the model's discriminating ability.

In 1981 Scott[50] compared several of the leading empirical models[51] in terms of their observed accuracy to reflect the current state of the art. He then followed with a theoretical critique of bankruptcy prediction to his own conceptual bankruptcy framework.

Scott felt it was hard to determine which model discriminated best. The research results of these models incorporate different data and different procedures that underlie the test results. Of these multidimensional models, the 1977 Altman ZETA model was determined to be the most convincing. It had high discriminatory power, is reasonably parsimonious and includes accounting and stock market data as well as earnings and debt variables. Scott concluded[52] that "though the models are not based on explicit theory, their success suggests the existence of a strong underlying regularity."

The next aspect of his research was to derive bankruptcy-prediction formulas from the major bankruptcy theories. Two of the theories explained the

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[50] J. Scott, "The Probability of Bankruptcy: A Comparison of Empirical Predictions and Theoretical Models," Journal of Banking and Finance, (September, 1981) pp. 317-344.

[51] This study included the empirical work of Beaver(1967), Altman(1968), Deakin(1972), Sinkey(1975) and Altman, Haldeman and Narayanan(1977).

[52] Scott, p. 324.

empirical results the best. Scott's conceptual bankruptcy framework model includes assumptions regarding (1) imperfect access and (2) perfect access to external capital markets. The major conclusion from the study was that bankruptcy prediction is both empirically feasible and theoretically explainable. Although the overlap between the empirical and theoretical models is imperfect, it provides empirical support for existing theory as well as theoretical justification for the bankruptcy prediction models.[53]

Farm Failure Studies

Studies for the farming sector have been very limited due to the nonavailability of financial data. However, when studies have been performed the research was limited to certain geographical areas. Many of the studies incorporated qualitative data and data not disclosed in the financial statements in their model building process besides financial statement data.

A discriminant model constructed by Bauer and Jordan[1971][54] analyzed data from Tennessee Production

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[53] Other studies to see for this section are Ohlson(1980), Dambolena and Khoury(1982), Emery and Cogger(1982), and Zmijewski(1984).

[54] L.L. Bauer, and J.P. Jordan, "A Statistical Technique for Classifying Loan Applications," University of Tennessee Agricultural Experiment Station Bulletin 476, 1971.

Credit Associations for the period 1958-1969. Statistical analysis suggested the function should classify 85% of the cases correctly. Variables which they found to be significant were: the current ratio, the debt to asset ratio, reasonable farm value, total liabilities, marital status, and family living expense as a portion of total farm expense.

Missouri data were used by Johnson and Hagan[1973][55] to develop a model that would reduce the man-hours required by trained analysts to classify loans into acceptable and problem loan groups. Data used in the analysis were from 204 acceptable and 68 problem loans. They found loan repayment made plus marketable inventory divided by loan repayment anticipated, the current ratio and the debt to asset ratio to be significant. The model correctly classified just over 50% of the non-failed farms and 98% of the failed farms. The overall classification accuracy for the model was 62%.

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[55] R. Johnson, and A. Hagan, "Agricultural Loan Evaluation with Discriminant Analysis," <u>Southern Journal of Agricultural Economics</u>, Vol. No. 5 (1973) pp. 57-62.

A model developed by Dunn and Frey[1976][56] from the cash grain area of central Illinois also found that the debt to asset ratio was an important discriminating variable. Additional variables were: the amount of credit life insurance, the number of acres owned and the amount of the note divided by net cash farm income. The data for the study were taken from applications of borrowers between 1964 and 1968 who still had loans outstanding in 1971. Their model correctly classified 90% of the acceptable loans and 60% of the problem loans.

Alabama Production Credit Association data used by Hardy and Weed[1980][57] to construct a model correctly classified 81% of the loans correctly. The study was designed to develop an objective credit evaluation technique based upon loan repayment ability characteristics of farm borrowers. Data used in the study were collected from all Alabama Production Credit Associations. Each association president selected a sample of 40 loans which included both acceptable and problem loans. Of the total 220 usable observations

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[56] D. Dunn, and T. Frey, "Discriminant Analysis of Loans for Cash Grain Farms," Agricultural Finance Review, Vol. No. 36 (April, 1976).

[57] W. Hardy, and J. Weed, "Objective Evaluation for Agricultural Lending," Southern Journal of Agricultural Economics, Vol. No. 12 (1980) pp. 159-163.

obtained, 145 were classified by the PCA as acceptable and 77 as problem loans. The two variable model contained: the debt to asset ratio and the annual loan repayment anticipated divided by total assets. The model was only able to classify 44.8% of the acceptable loans, however, this was due to a cut-off score that virtually eliminated Type I errors, resulting in 93.5% of the problem loans being correctly classified.

An additional study by Hardy and Patterson[1983][58] was performed on Federal Land Bank data. A ten percent random sample was taken on loans closed during 1974 to 1978 from the Fifth Farm Credit District, yielding a total sample size of 1,980. Of this sample, 1,765 were classified as good loans, while 216 were in the problem category. Seventy-one percent of the loans were correctly classified by the final discriminant model. The model found the debt to asset ratio and the ratio of loan commitment to net worth to be the most important discriminating variables.

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[58] W. Hardy, and J. Patterson, "An Objective Evaluation of Federal Land Bank Borrowers," Highlights of Agricultural Research, 30:2 (1983).

Summary

This chapter has provided a brief overview of the previous research in the financial distress area. Studies have progressed from univariate analysis to multivariate analysis with the latter yielding reliable models for failure prediction. The objective and methodology of the studies have been diverse but the empirical results have shown the utility of accounting data for the prediction of failure.

CHAPTER III

METHODOLOGY

The methodology used in this research is discussed in this chapter. Probably one of the most significant primary items is the determination of the criteria for identification of a farm as either failed or non-failed. The source of data representing the population, characteristics of the farms, and sample selection procedures to derive the discriminant function and evaluating its effectiveness are also presented. Other sections on the identification of variables, farm financial statements, ratios, reporting limitations, statistical procedure, and the evaluation of the discriminant function are discussed in the remainder of the chapter.

Definitions of Failure

The answer to the question, What is a failing firm? is of prime importance to the research. In order for the discriminant statistical method to be effective the group definitions must be distinct and non-overlapping.[59] Unsuccessful business enterprises have been defined in various ways to depict the formal process confronting the firm and/or to categorize the economic problems involved.[60] Failure, insolvency, and bankruptcy have all been used to describe the same phenomenon of ceasing operations even though the three terms have different meanings. The economic criterion for failure signifies that the risk adjusted rate of return is significantly and continuously lower than similar investments. This economic situation makes no statement regarding the continuance or discontinuance of the entity. Insolvency is a technical term that exists when a firm cannot meet its current obligations. This lack of liquidity, also described as insolvency in the equity sense, may be a temporary condition but usually precipitates a formal bankruptcy declaration.

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[59]R. Eisenbeis, "Pitfalls in the Application of Discriminant Analysis in Business, Finance and Economics," Journal of Finance, (June, 1977) pp. 875-899.

[60]E.I. Altman, Corporate Financial Distress. (New York, N.Y.; John Wiley and Sons, 1983) p. 5.

Finally, bankruptcy is the act of a formal declaration by a firm to the courts to either liquidate its assets or to attempt a recovery program.

Several studies have focused upon the legal considerations when defining an unsuccessful or failed business enterprise. Altman (1968) defined his bankrupt group as those firms that filed a bankruptcy petition under Chapter X of the national bankruptcy act. Wilcox (1976) used a Chapter X or XI bankruptcy petition as his criteria for failure.

Technical definitions of failure were also employed in past research. Beaver (1967) defined failure as the inability of a firm to pay its financial obligations while Daniel (1968) used the combination consisting of legal bankruptcy, substantial losses for three or more years or nominal earnings in one year and substantial losses in two years, or a deficit in retained earnings for three or more years. Edmister (1972) designated borrowers that defaulted on loans from the Small Business Administration as failures for his study.

Classifying farms into successful and unsuccessful groups presented a formidable task. Many farms still in business are borrowing from a governmental agency, the Farmers Home Administration, usually considered the lender of last resort. These farms would possibly cease operations or restructure their debt if those lending agencies did not make funds available. Thus, many farms are essentially failures but are disguised as going concerns. Therefore, the approach to the classification of farms as failed or non-failed lies in the definition of failure and the subjective classification of these farms by this definition. Greater clarity in the segregation of the two groups translates to an increase in the usefulness of the results.

The criteria for the classification of a farm as a loss borrower (defaulted on loan) or failure include bankruptcy, foreclosure, the inability to obtain additional borrowings from the Federal Intermediate Credit Bank (FICB), or classification of the loan as a bad debt and the write-off of the loan by the FICB. All other farms are considered to be going concerns.

Data was examined for all farms and classifications were made on the basis of the above criteria. A farms was classified as a failure as of its last financial statement date if it met any of the criteria of the failure definition, otherwise it was classified as non-failed.

Data Collection

The primary source of data for the investigation was the Federal Intermediate Credit Bank data base for the Alabama, Mississippi and Louisiana district. The Federal Intermediate Credit Banks and their Production Credit Associations constitute one of the three major branches of the Farm Credit System. The Farm Credit System is divided into twelve geographic districts with each district being served by a Federal Land Bank, a Federal Intermediate Credit Bank and a Bank for Cooperatives. Production Credit Associations provide short- and intermediate-term financing with maturities ranging up to seven years to farmers and ranchers. These loans are used primarily to finance operating expenses and purchases of machinery and equipment.

The data base consisted of approximately ten thousand two hundred farm loan records for the three state area. These farms were stratified into three groups based on the gross sales of farm products sold each year. This stratification was necessary to limit the distortion of data of very large and very small farms.[61] The family-sized commercial farm (comprising the median group) has gross product sales between

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[61]Ibid. p. 105.

$50,000 and $500,000. Farm with gross sales below $50,000 and above $500,000 were not considered for this study since the family-size commercial farms (hereafter referred to as commercial farms) are experiencing the most financial distress.[62] The number of farm loan records in the data base with income statement information needed to identify commercial farms varied from one to three years prior to a failure determination. Four hundred farm records were identified one year prior to failure, of which 270 were classified as commercial farms. Two years prior to failure, 150 cases had the relevant financial information, of which 92 were commercial farms. Finally, 30 farms (all of which were commercial) were identified three years before failure. Sixty-four of the 92 cases(70%) two years prior to failure were a subset of the 270 cases one year prior to failure while 23 of the 30 cases(76%) three years prior to failure were a subset of the 270 year one cases. Only 9 farms contained all three years of data prior to failure.

Each farm record contained demographic, qualitative and quantitative information on the farm. The borrower's identity was not disclosed.

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[62]United States Department of Agriculture, Agriculture Information Bulletin NO. 492.

Balance sheet and income statement data previously mentioned were also included in the data base for each farm record. Many of these farm records were severely lacking in financial statement information for more than one year. This was expected, however, since detailed financial information for farming enterprises has only recently been required. The number of farms giving detailed financial data is still small but progress by the FICB is being made to correct this problem. For example, of the 270 commercial farm records in the data base one year prior to failure only 9(3.3%) farms had complete balance sheet and income statement data for three consecutive years prior to their latest financial statements. Income statement information was the most common lacking element, since over 100 farms had complete balance sheet information for a three year period.

Data Base Characteristics

The FICB data base contained 10,233 farm loan records which were available for use in the study. The population of farmers was almost equally split among Alabama, Louisiana and Mississippi borrowers, as shown in Table 3-1.

TABLE 3-1 BORROWERS BY STATE

State	Number of Farm Records	Percent
Alabama	3,083	37.2
Louisiana	3,530	34.5
Mississippi	2,637	25.8
Uncoded	263	2.5
Totals	10,233	100.

The percentage of failed farms was approximately thirty percent, as seen in Table 3-2. The failure determination was made based upon the definition mentioned earlier in this chapter.

TABLE 3-2 DETERMINED FAILURES

Group	Frequency	Percent
Failure	3,059	30
Non-Failure	7,174	70
Totals	10,233	100

A further breakdown of the data base by the primary enterprise code for each farm revealed that field crops, beef and poultry enterprises were the most common for the three state area. Other less numerous enterprises were vegetables, pecans, ornamental/horticulture, dairy, swine, forestry, aquatic and miscellaneous other products as shown below.

TABLE 3-3 PRIMARY ENTERPRISE CLASSIFICATION

Enterprise	Number of Farms	Percent
Field Crops	3,766	36.8
Vegetables	34	.3
Pecans	24	.2
Orn/Horticulture	63	.6
Beef	2,991	29.2
Dairy	565	5.5
Swine	98	1.0
Poultry	816	8.0
Aquatic	199	1.9
Forestry	444	4.4
Miscellaneous	1,000	9.8
Uncoded	233	2.3
Totals	10,233	100.

Another interesting breakdown (Table 3-4) of the data base was performed upon the year each borrower began farming as an occupation. The years 1970-79 had the greatest influx of beginning farmers for this three state area. Surprisingly, even with the significant decline of the farm economy, about 13% of the farmers entered the farming occupation during the 1980's.

TABLE 3-4 YEAR BORROWER BEGAN FARMING

Year	Number of Farmers	Percent
1980-86	1,359	13.0
1970 79	1,854	18.0
1960-69	1,227	12.0
1950-59	1,166	11.0
1940-49	655	6.5
1930-39	212	2.0
1920-29	130	1.5
1910-19	56	.5
Uncoded	3,574	35.0
Totals	10,233	100.

Finally the farms were categorized by their latest balance sheet date (Table 3-5). The majority of farmers had balance sheet data filed between the 1984 thru March 1986 time period. The others were scattered over the 1970 to 1983 time span.

TABLE 3-5 LATEST BALANCE SHEET DATE

Year	Number of Statements	Percent
1986	1,389	13.6
1985	4,729	41.8
1984	2,296	22.4
1983	921	9.0
1982	493	4.8
1981	256	2.5
80-70	299	2.9
Uncoded	300	3.0
Totals	10,233	100.

Types of Data

Farm Financial Statements

The accuracy, reliability, and interpretation of accounting data are increasingly important as agricultural loans grow in size, complexity and degree of risk.[61] Loan decisions must be made based on historical and projected accounting data furnished by borrowers. However, as an industry, farm and ranch firms generally are unsophisticated in their accounting systems. Most farmers have only a single-entry system used primarily for income tax purposes. Financial statements are typically prepared by the farm lender based largely upon the memory of the farmer. This process is very time consuming, yields minimum information and raises questions about information accuracy.[64]

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[63] T. Frey, and R. Behrens, Lending to Agricultural Enterprises. (Boston, Mass.; Bankers Publishing Company) p. 85.

[64] A move has been made to use a coordinated set of financial statements in agriculture for joint use by lenders and borrowers. These statements, currently being intergrated into the loan documentation process by the FICB, incorporate many accounting principles but do vary on several significant issues from generally accepted accounting principles, due to the unusual asset characteristics of agriculture. These coordinated financial statements are shown in Appendix A.

The balance sheet classifications for agricultural concerns are divided into three classes as opposed to the two of the traditional format. These three classes are used for assets and liabilities. Relative liquidity determines categorization of assets, while maturity establishes categorization of liabilities. The three categories are current, intermediate and fixed or long term. The addition of the intermediate classification to the traditional format represents "working" assets that yield services to the business over time but are generally used up in a time frame of 1-10 years. Assets in this category include machinery, equipment, and breeding livestock, along with retirement accounts, cash value of life insurance, household goods, and personal effects. The intermediate liabilities are existing obligations with an original maturity of one to ten years, while long term liabilities are those with maturities beyond ten years.

Income measurement is a complex issue. For a long time agricultural enterprises used physical observation or efficiency measures as a proxy for an indication of net income. There was no intense focus on the overall measure of performance. Net farm income is the single most important measure of performance for a farm business.[65] It represents a return to labor, equity, capital and management supplied by the farm family.

Net income, as compared to net farm income, is simply the excess of revenue over expenses on an after tax basis which reflects a combination of farm and non-farm income. Revenues include cash inflows plus an inventory adjustment while expenses include operating expenses, interest, and depreciation. Adjustments for current liabilities and gain or loss on capital assets sold are also required. Sample balance sheets and income statements are presented in Appendix A.

Variables

Worthwhile analysis of financial statements requires identification of significant factors for consideration, evaluation and comparison.[66] Significance depends upon the nature of the question to be resolved, which, in this analysis, was whether or not a farm was failing.

A determination of significant variables was necessary to aid in the model classification process. Balance sheet and income statement data were collected for assessment of the relative significance of items of

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[65] T. Frey, and D. Klienfelter, Coordinated Financial Statements for Agriculture. (Skokie, Illinois; Agrifinance, 1981).

[66] Ibid. p.67.

financial statement information. The potentially significant variables gathered for the study consisted of financial statement classifications and ratios which are transformations of these classifications. Many of the ratios used in the study were unique to farming operations while others were found to be significant indicators of corporate and farm problems in past research. A listing of the ratios found to be significant for selected corporate and farm failure studies is located in Appendix B. The trend or yearly change in all ratios selected as the year of failure approaches was another variable examined.

Financial Statement Classifications

The financial statement classifications chosen for this study were selected on the basis of conventional classifications for farm operations and the requirements for the ratios selected in particular. The choice of classifications was important because improper grouping of items can impair or destroy the significance of the individual items. Information contained in the classifications about the financial position of a farm may be significant. An undue multiplicity of classifications can make the analysis much more difficult, if not impossible by classifying essentially similar items of different categories and making the important intercorrelations of variables much less clear.[67] The financial statement classifications used in this study were:

Current Assets (CA)

Current Liabilities (CL)

Intermediate Assets (IA)

Intermediate Liabilities (IL)

Fixed Assets (FA)

Long Term Liabilities (LL)

Total Assets (TA)

Total Liabilities (TL)

Net Worth (NW)

Net Farm Income (NFI)

Interest Expense (INT)

Net Income (NI)

Value of Farm Production (VFP)

Operating Expenses (OE)

Depreciation (DEP)

Two classifications, net nonfarm income and net family living expense were not used due to the fact that nearly 90 percent of the cases were missing the necessary data.

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[67] T.E. Daniel, "Discriminant Analysis for the Prediction of Business Failure," (Unpublished PhD. dissertation, University of Alabama, 1968) pp. 71-72.

Ratios

The analysis of financial statements is a compilation and study of relationships and trends.[68] The financial statements are separated into component parts and each part is studied in relation to relevant items and in relation to the whole. As a tool for analysis, ratios are measures of the relationships between two relevant items. These measures are expressed as rates or percentages and expedite comparison and reduce groups of figures to a form more readily comprehended and more easily retained.

Financial ratios are transformations of financial statement data, usually made by statement users to aid decision making. These ratios are not intended to provide definite answers; their real value is derived from the questions they provoke.[69] Therefore, ratios are symptoms of the firm's economic condition intended to guide the analyst in his investigation. Thus, the investigation of potential farm failure should be facilitated by the use of financial statement ratios

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[68] J.O. Horrigan, editor, Financial Ratio Analysis. (New York, N.Y.; Arno Press, 1978) p. 5.

[69] Baruch Lev, Financial Statement Analysis: A New Approach. (Englewood Cliffs, New Jersey; Prentice-Hall, Inc., 1974) p. 34.

since they are barometers of the financial position and the results of operations of a farm.

Some of the financial ratios expected to be significant in this study (see Table 3-6) were those commonly discussed in the financial literature and textbooks and those peculiar to farming operations.[70] Many of the ratios were also chosen due to their significance in other failure prediction studies. Since ratios are relative measures, it is hypothesized that many of the financial ratios significant in industrial failure studies will also be significant for the model in this study. The basis for making decisions should come from the accounting data taken from a particular farm's financial statements. The ratios derived from this year end fair market value data are usually separated into various classifications of ratios, as seen in Table 3-6. These classifications combine similar relationships and trends that yield focused information to the analyst about the different facets of a farm operation.

[70]Elam, p.26.

TABLE 3-6 FINANCIAL STATEMENT RATIOS USED IN THE STUDY

LIQUIDITY
Current assets/Current liabilities
Current liabilities/Total Liabilities
Current Assets-Current Liabilities/Intermediate Assets
Intermediate Assets/Intermediate Liabilities
Current Assets-Current Liabilities/Total Assets

SOLVENCY
Total Liabilities/Net Worth
Total Assets/Net Worth
Fixed Assets/Long term Liabilities
Total Liabilities/Total Assets
Current Liabilities/Value of Farm Production
Net Income/Interest

EFFICIENCY
Value of Farm Production/Total Assets
Operating Expenses/Value of Farm Production
Depreciation/Value of Farm Production
Interest/Value of Farm Production
Value of Farm Production/Current Assets
Value of Farm Production/Intermediate Assets

PROFITABILITY
Net Farm Income+Interest/Total Assets
Net Farm Income/Net Worth
Net Farm Income/Total Assets
Net Income/Current Liabilities
Net Farm Income+Interest/Value of farm Production
Net Income/Value of Farm Production

CASH FLOW
Net Income+Depreciation/Value of Farm Production
Net Income+Depreciation/Total Assets
Net Income+Depreciation/Net Worth
Net Income+Depreciation/Total Liabilities

Sources:

Elam, R., The Accounting Review, January, 1975.

Penson, Klienfelter and Lins, Farm Investment and Financial Analysis. (Prentice-Hall, 1982).

Limitations of Ratios

When used as tools of financial statement analysis, ratios are effective only if the items on the financial statements are accurate and if the analyst has the ability to choose the appropriate ratios to fulfill the purpose for which the analysis is being conducted.[71] The extent to which financial statements may be relied upon is an important factor in the analysis. Since judgment and accounting conventions affect statements materially, the reliability of financial statements depends upon the competency and integrity of those responsible for the compilation in order to generate meaningful analysis. However, there are some factors which affect the financial condition and operating results of businesses that cannot be expressed in dollar terms. One such factor, managerial ability, will not be evident in the statements but will have a definite effect on the financial condition of the farm.

Financial analysis involves many alternative approaches of which ratio analysis is only one of several means of discerning an understanding about a business enterprise from financial data. Ratios are statistical tools which, like other statistical devices,

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[71]Horrigan, p. 26.

must be used within the range of their efficiency to prevent misuse. Because ratios are summary statistical data, it is expedient that the decision maker take into consideration the possible changes that may be concealed in the summarized data and the resultant change due to the alteration of two summarized economic variables.[72] It is erroneous to attach a high degree of reliability or significance to ratio measures, since the valuation of the elements are based upon assumptions and estimates. Their significance lies in their characteristics as barometers of financial position and operations which stimulate questions and lead to points of inquiry within the analysis. When used in its proper context, ratio analysis facilitates an understanding and determination of a farm's economic position.

However, by empirically testing ratios as predictors of failure, a body of evidence can be gathered that will lead to a better understanding of what measures serve the users. This predictive ability only determines if the particular measure has a significant correlation with an event and is not intended to be used as the sole criteria for making decisions.

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[72]Ibid. p. 6.

Conversely, the usefulness of ratios should be increased if it can be demonstrated that they reliably indicate a future event.

Selection of Sample

A search of the population was made to identify failed farms based on their latest financial statements between the years 1981 thru March, 1986. Failed farms must meet the failure criteria as being bankrupt, foreclosed, unable to obtain additional capital from the FICB, or written-off as bad debts by the FICB. All other farms were considered to be non-failed.

The initial intent in selecting cases for use in this study was to begin with the total population and then reduce it to include only those commercial farms with three or more years of complete, consecutive financial statement data. The three-year period was established as a minimum period of operation to allow for a smoothing of disruptive events that may destroy the significance of the results. The time restriction (1981 thru March, 1986) reduced the number of failures, however, this restriction was necessary to make the failed and non-failed farms as comparable as possible.

Due to the lack of farms with complete financial statement data for the three-year period (9 farms), the original sample design was abandoned and three samples were taken to obtain cases for each of the three years prior to a failure determination. This alternative approach was expected since the FICB data base operation is in a formative period and the task of acquiring farm data by the PCA's from their borrowers is a cumbersome project.

The failed and non-failed farms with complete data for each specified sample was pooled across years. For every identified failed farm between 1981-1986 there was at least one non-failed farm for that year. The financial statements were pooled over the three years so that no comparison of farm variables would come from two different economic periods.

The next step was to randomly partition the 270 cases in the year one sample into two subsamples. One of the subsamples was used to derive the discriminant function while the other subsample, a hold-out sample, was used for validation of the discriminant function.[73] The discriminant function for one year prior to failure was then used to classify the sampled cases two years and three years before failure. The same procedure was also used to derive the discriminant function on the

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[73]The hold-out sample is used, since, as with any inferential technique based upon sample data, the percent correct prediction tends to overestimate the power of the classification procedure. This occurs since validation is based on the same cases used to derive the classification function.

sample of 92 farms two financial statement periods before failure, with the function also classifying the 30 farms selected in the sample for three years prior to failure. The discriminant function for the three year model was developed using all 30 farms with a validation sample of 67 farms with the appropriate variables three years prior to failure to classify the model.

Classification

Once the values of the discriminant function are estimated, it is possible to calculate discriminant scores for each of the observations in the sample, or any farm, and to assign the observations to one of the groups based on this score. In a multigroup case, results are shown in a classification chart or accuracy matrix. Table 3-7 illustrates how the chart is arranged.

TABLE 3-7 ACCURACY MATRIX

Actual Group	Predicted Group Membership Failure	Non-Failure
Failure	H	M_1
Non-Failure	M_2	H

H - Hits or correct classification
M - Misses or incorrect classification

Source:

Altman, Corporate Financial Distress. p.111.

The actual group membership is equivalent to the *a priori* groupings, and the model attempts to classify these farms correctly. The H's in Table 3-7 stand for correct classifications (hits) and the M's stand for misclassifications (misses). Misclassification can occur in one of two ways: a failed farm can be incorrectly classified as a non-failure or a non-failed farm can be misclassified in the failed group. Therefore, if a null hypothesis was developed for the observations being classified, such as, the farm is going to fail, misclassifications would be based upon the incorrect rejection or incorrect acceptance of the null hypothesis. M_1 represents a Type I error (misclassification of a failed farm) and M_2 is a Type II error (misclassification of a non-failed farm). Type I errors occur when there is a rejection of the null hypothesis (farm is going to fail) when it is actually true and a Type II error is the acceptance of the null hypothesis (farm is going to fail) when it is actually false.

The sum of the diagonal elements equals the total correct hits, and when divided by the total number of observations classified, yields a measure of the models success in classifying farms.

Missing Data

Due to the lack of adequate financial statement data there were some farms selected that had values missing for some variables. There were a total of fifteen financial statement variables for each farm record to be used in the analysis. Upon inspection of the data base, two of the variables (net nonfarm income and net family living expense) were found to have over 90% of the values missing and were subsequently dropped from consideration. In order to be selected in the sample a farm record had to contain assets, liabilities and income statement information for the year under analysis. Most farm records selected were missing values on only one of the twelve variables used in the analysis. The computerized discriminant procedure will not include a case in the derivation of the discriminant function with a missing value and it is not reasonable to discard all the other useful information contained in a record simply because it is missing one variable value.

Therefore, in order to assign values to any missing data for the farms selected, which were approximately 10% of the total variables over all cases, the sample was stratified by value of farm production to appropriate average values f^r the missing values of variables. This stratification allowed for a more accurate measurement of a farm's missing value of a variable so that it would be in accordance with other farms of similar size. It was assumed that since data of these farms were taken from a similar time period, equivalent size operation and from the same industry (farming), the average values were viable approximations of a farm's missing values for the particular strata to which they belong.

Statistical Procedure

Discriminant analysis begins with the desire to statistically distinguish between two or more groups of cases. The groups are determined by the particular research situation. The discriminant analysis technique is a statistical technique used to classify an observation into one of several *a priori* groupings dependent upon the observations' similar characteristics. This method is used primarily to classify and/or make predictions in problems where the dependent variables appear in qualitative form, e.g. failure or non-failure.[74] To distinguish between groups, a collection of discriminating variables are selected that measure characteristics on which the groups are expected to differ. This technique involves deriving the linear combination of two (or more) independent variables that will discriminate best between the previously defined groups. This is achieved by the statistical decision rule of maximizing the between-group variance relative to the within-group variance--this relationship is expressed as the ratio of the between-group to within-group variance.[75] The linear combination for a discriminant analysis is derived from the equation which takes the following form:

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[74]Altman p. 59.

[75]Joseph Hair, Rolph Anderson, Ronald Tatham and Bernie Grablowsky, *Multivariate Data Analysis*, (New York, N.Y.: McMillan Publishing Company, 1984) p. 85. The ratios to be used in the model will be chosen by this method.

$$Z = W_1X_1 + W_2X_2 + \ldots. + W_nX_n$$

where

Z = the discriminant score
W = the discriminant weight
X = the independent variables

This equation, also known as the discriminant function, will yield a single composite discriminant score for each farm in the analysis. By averaging the discriminant score for all farms within a particular group the mean (centroid) is computed. The centroids indicate the most typical location of an individual farm for a particular group, and a comparison of the group centroids reveals how far apart the groups are along the dimension being tested.[76]

The distinction between the group centroids allows for the test of statistical significance of the discriminant function. It is computed by comparing the distribution of the discriminant scores for the failed and non-failed groups. If the overlap (misclassification of failed and non-failed) in the distribution is small, the discriminant function separates the groups well. If the overlap is large, the function is a poor discriminator between the groups.

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[76]Ibid. p. 86.

Once the discriminant function has been derived, two research objectives of this technique can be pursued. These objectives are analysis and classification.

The analysis aspect of this technique provides several tools for the interpretation of data. Among these is a statistical test for measuring the success with which the discriminating variables actually discriminate when combined into the discriminant function. Also the weighting coefficients can be interpreted much as in multiple regression and factor analysis.[77]

The use of discriminant analysis as a classification technique comes after the initial computation. Once a set of variables are found to be satisfactory discriminators for cases with known group membership, a classification function can be derived which will permit the classification of new cases with unknown membership.

When utilizing a comprehensive list of financial ratios and elements in assessing a farm's failure potential, there is reason to believe that some of the measurements will have a high degree of correlation, or

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[77]William Klecka, "Discriminant Analysis," Quantitative Application in the Social Sciences, editor John L. Sullivan (Beverly Hills, CA.; Sage University Press, 1980).

collinearity, with each other. While this aspect necessitates careful selection of the predictive variables, it also has the advantage of yielding a model with a relatively small number of selected measurements which has the potential of conveying a great deal of information.[78] The information might very well indicate differences between groups, but whether or not the differences are significant and meaningful is a more important aspect of the analysis. The multicollinearity problem was controlled by the tolerance level in the SPSS statistical program. The tolerance of an independent variable being considered for inclusion is the proportion of the variance of the variable not explained by the independent variables already in the equation.[79] The tolerance index has a possible range of 0 to 1 with a tolerance of 1 indicating no correlation with the other independent variables. Thus the tolerance level for the study was set at an intermediate value of .7 which would indicate that 30% of the variance of a potential independent variable is explained by predictors already entered.[80] This

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[78] Altman, p. 60.

[79] N. Nie, C. Hull, J. Jenkins, K. Steinbrenner, and D. Bent, Statistical Package for the Social Sciences. (New York, N.Y.; McGraw-Hill Book Company, 1975) p. 364.

[80] Ibid, pp. 340-341.

intermediate value of .7, also used in other studies,[81] was chosen to eliminate variables which add very little to the explanatory power of the model.

The primary advantage of multiple discriminant analysis in dealing with classification problems is the potential of analyzing the entire variable profile of the object simultaneously, rather than sequentially examining its individual characteristics.

In order to derive the discriminant function, a stepwise procedure was incorporated to eliminate variables that added little to the discriminating ability of the function. The stepwise procedure halts when all the variables are found that contribute to further discrimination. Further analysis is consequently performed upon the selected variables.

Discriminant functions for one, two and three years prior to failure were derived using all variables except the ratio trends. Similarly, a discriminant function was derived using the change in ratios between one and three years prior to failure. The following criteria were used in the selection of the discriminant functions:

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[81]Edmister, pp. 10-23.

(1) observation of the statistical significance of various alternative functions including determination the relative contribution of each independent variable;

(2) observation of the classification accuracy of the various profiles on the sample to derive the function and;

(3) judgment of the analyst.

Thus, with the best discriminant function, the desired outcome of the research was to have a model that could predict, with a high degree of accuracy, whether a farm would fail or succeed in the next twelve months.

CHAPTER IV

ANALYSIS AND FINDINGS

The results of the model building process outlined in Chapter III are reported throughout this chapter. The selection of variables for the model, an explanation of these variables and classification results are also presented.

Analysis of Models

One Year Prior Model

Most of the potentially useful variables were eliminated for consideration for inclusion in the one year prior to failure prediction model by using the stepwise discriminant analysis statistical technique. A two variable model was developed which best discriminates between failed and non-failed farmers. The one year prior model was developed from 133 farms selected randomly from the commercial size farm loan sample of 270. Of the 133 farms selected to derive the model, 58 of the farms were identified as failed and 75 were non-failed.

After two steps the stepwise discriminant procedure produced the variables for the model one year prior to failure. The variables included in the model were X_1 (Working Capital to Total Assets) and X_2 (Net Farm Income to Net Worth). The working capital to total asset ratio was significant at the .0013 level (1, 131 degrees of freedom) while the net farm income to net worth variable was significant at the .0007 level (1, 131 degrees of freedom). The Wilks' Lambda statistic for the function was .893293 and the Canonical correlation was .326607. The Chi-Square statistic for the model was 14.669 which was significant at the .0007 level. This data is summarized in Table 4-1. The two variable model yielded the discriminant function of:

$$Z = .1811643 + 4.876926(X_1) + .8158185(X_2)$$

where

Z = Overall Score

X_1 = Working Capital/Total assets -- The working capital to total asset ratio, frequently found in failure studies, is a measure of the net liquid assets of a farm relative to its total capitalization. Working capital is defined as the difference between current assets and current liabilities.

X_2 = Net Farm Income/Net Worth -- This profitability ratio is comparable to the earnings before taxes to equity ratio. This ratio ignores any tax effects.

Ordinarily, a farm experiencing consistent operating losses or over-capitalization will have shrinking current assets in relation to total assets. Of the five liquidity ratios evaluated, net working capital to total assets proved the most valuable. The selection of this variable in the model corresponds with Beaver(66), Altman(68), Daniel(68) and Deakin's(72) assessment of the working capital/total assets ratio as a good discriminator.

Net farm income (NFI) is the residual after subtracting operating expenses from the value of farm production (VFP). It is the commonly used pre-tax return on equity and indicates that the more profitable farms are likely to be classified as non-failed. This ratio was also part of the model developed by Fulmer, Moon, Gavin and Erwin(84) for small industrial firms.

TABLE 4-1 ONE YEAR PRIOR MODEL

Variable	Coefficient	Mean Failed	Mean Non-Failed
X_1	4.876926	-.10518	-.00675
X_2	.815818	-.07142	.18802
constant	.181164		
Group Centroids		-.39006	.30164

Canonical Correlation	.3266607
Wilks' Lambda	.8932928
Chi-Square	14.669 (.0007 sig.)

Variable	Standardized Coefficient	Unstandardized Coefficient
X_1	.83697	4.876926
X_2	.55902	.815818

X_1 = Working Capital/Total Assets
X_2 = Net Farm Income/Net Worth

Standardized and unstandardized canonical discriminant function coefficients allow for the assessment of the contribution made by each variable relative to the other variables in the model. The value of the coefficients depend upon a comparison with the other variables in the function. While the unstandardized coefficients are used in the discriminant model, both sets of coefficients identify variable X_1 as making the greater contribution to the model.

Initial Selection

The initial selection of 133 farms to derive the model, 58 failed and 75 non-failed, was classified using data compiled one financial statement prior to failure. Since the discriminant coefficients and the group distributions are derived from this sample, a high degree of successful classification is usually expected. This should occur since those 133 farms are classified using a discriminant function which is based upon the individual measurements of these farms. The accuracy matrix for the farms chosen to derive the model is presented in Table 4-2.

TABLE 4-2 ACCURACY MATRIX -- ORIGINAL SELECTION OF 133 FARMS

Actual Group	Number of Cases	Predicted Membership Failure	Predicted Membership Non-Failure
Failure	58	11 (19%)	47 (81%)
Non-Failure	75	3 (4%)	72 (96%)

Overall Accuracy 62.41%

The model is only accurate in classifying 62.41% of the farms used to derive the model. Type I errors proved to be overbearing at 81% while Type II errors were minute at 4%. The upward bias of this classification should be remembered while further validation techniques are appropriate to test the reliability ot the model.

Validation Samples

A holdout sample of 137 farms, 47 failed and 90 non-failed borrowers, were used to validate the discriminant function for one year prior to failure. An additional 92 cases were classified using financial statement data compiled two years prior to failure to observe the discriminating ability of the model. Likewise, 30 farms with data compiled from financial statements three years prior to failure were also classified. The results of this classification process are shown in Tables 4-3 thru 4-5.

TABLE 4-3 ACCURACY MATRIX -- HOLDOUT SAMPLE

Actual Group	Number of Cases	Predicted Membership Failure	Predicted Membership Non-Failure
Failure	47	4 (8.5%)	43 (91.5%)
Non-Failure	90	3 (3.3%)	87 (96.7%)

Overall Accuracy 66.42%

TABLE 4-4 ACCURACY MATRIX -- 2 YEARS PRIOR

Actual Group	Number of Cases	Predicted Membership Failure	Predicted Membership Non-Failure
Failure	28	3 (10.2%)	25 (89.3%)
Non-Failure	64	2 (3.1%)	62 (96.9%)

Overall Accuracy 70.65%

TABLE 4-5 ACCURACY MATRIX -- 3 YEARS PRIOR

Actual Group	Number of Cases	Predicted Membership Failure	Non-Failure
Failure	9	2 (22.2%)	7 (77.8%)
Non-Failure	21	0 (.0%)	21 (100%)

Overall Accuracy 76.67%

The Type I as compared to the Type II error rates for the model are either very high or very low. A trend of the error rates for the one year prior to failure model is presented in Table 4-6.

TABLE 4-6 TYPE I AND II ERROR TRENDS

Sample	Type I	Type II
Derivation	81.0%	4.0%
Holdout	91.5%	3.3%
2 Yr	89.3%	3.1%
3 Yr	77.8%	0.0%

From a financial statement user's point of view, it is possible that classifying a farm that eventually fails in the non-failed group may be a much more costly error than classifying a farm that survives as a potential failure. The cost of not making a loan to a current successful repayment customer is based on the opportunity cost concept. The investor foregoes the return on the rejected loan but can invest the funds elsewhere. However, a loau made to an unsuccessful repayment customer corresponds in most cases to the net loss from loan foreclosure. Thus, the user of the model, knowing the costs of the different types of misclassifications, can adjust the model in order to minimize total costs.

Model Two Years Prior

The model developed two annual financial statements prior to failure was verified from a sample of 92 commercial farms. Of the 92 farms selected, 28 were were deemed failed and 64 non-failed on an *a priori* basis. This sample was then randomly split yielding 42 farms to derive the discriminant function, 12 failed and 30 non-failed, while the remaining 30 farms were used as a holdout sample to verify the model.

The model derived for two years prior to failure contained two variables, the level of current assets and intermediate liabilities. The models' Canonical correlation was .4907856 while the Wilks' Lambda was .7591259. The Chi-Square statistic of 10.748 was significant at the .0046 level. These statistics are summarized in Table 4-7. The relative contribution made to the model, as assessed by the standardized coefficients, was virtually equal at .76064 for the current asset variable(X_1) and .74663 for the intermediate liability variable (X_2). The function for this model is:

$$Z = -1.426386 + .3300603\text{-}005(X_1) + .1132316\text{-}004(X_2)$$

where

Z = Overall Score

X_1 = Current assets -- This group of assets represents cash and near cash items. They are assets that could be converted to cash without disrupting the business and are assets that will be either used up or converted to cash during the year or the normal operating cycle.

X_2 = Intermediate liabilities -- These liabilities are those obligations with an original maturity of one to ten years.

The financial statement element, current assets, is usually found to be significant as a part of a ratio but has not been identified as a variable in a model of a previous study. Intermediate liabilities are generally incurred when financing farm machinery and equipment. Although this element has not shown up in other studies, Daniel(68) reported long term liabilities as a significant variable in his model.

TABLE 4-7 TWO YEAR PRIOR MODEL

Variable	Coefficient	Mean Failed	Mean Non-Failed
X_1	.3300603-005	$293882	$105653
X_2	.1132316-004	$117067	$ 64469
constant	-1.426386		
Group Centroids		.86918	-.34767

Canonical Correlation	.4907856
Wilks' Lambda	.7591295
Chi-Square	10.748 (.0046 sig.)

Variable	Standardized Coefficient	Unstandardized Coefficient
X_1	.76064	.3300603-005
X_2	.74663	.1132316-004

X_1 = Current Assets
X_2 = Intermediate Liabilities

An inspection of the variables selected for this model show that intermediate liabilities are, on the average, over 1.5 times higher for failed farms than for non-failed farms. This is an indication of an overutilization of borrowed funds to invest in farm machinery and equipment. Some of these farms may have disposed of many of these productive assets but the fair market value of the property was not sufficient to extinguish the debt. On the other hand, the failed group sampled had more than double the current assets of their non-failed counterparts. This number deflates to 1.5 when all 92 farms are averaged. The disproportion may indicate a lack of ability in managing the day-to-day assets of the farm. There may be over-investment in growing crops, excess cash on hand, or excessive amounts of crop and feed inventory which is not needed. Whatever the reason for the high level of current assets, it is apparent that such levels are not conducive to successful farming operations two years prior to failure. The model classified 78.57% of these farms correctly as presented in the next table.

TABLE 4-8 ACCURACY MATRIX -- 2 YEARS PRIOR

Actual Group	Number of Cases	Predicted Membership Failure	Predicted Membership Non-Failure
Failure	12	5 (41.7%)	7 (58.3%)
Non-Failure	30	2 (6.7%)	28 (93.3%)

Overall Accuracy 78.57%

The Type I error was 58.3% while the Type II error was 6.7%. The validation sample of 50 farms yielded an accuracy rate of 60% (Table 4-9). This is substantially lower than the classification for the farms used to derive the model since there is an upward bias involved in classifying the farms from which the discriminant function was derived.

TABLE 4-9 ACCURACY MATRIX -- 2 YEARS PRIOR
HOLDOUT SAMPLE OF 50 FARMS

Actual Group	Number of Cases	Predicted Membership Failure	Predicted Membership Non-Failure
Failure	16	0 (.0%)	16 (100%)
Non-Failure	34	4 (11.8%)	30 (88.2%)
Overall Accuracy 60.0%			

The model was then used to classify the 30 farms three financial statements prior to failure. The accuracy matrix (Table 4-10) yielded correct predictions on 70% of the farms.

TABLE 4-10 ACCURACY MATRIX -- 2 YEARS PRIOR MODEL CLASSIFYING FARMS 3 YEARS PRIOR

Actual Group	Number of Cases	Predicted Membership Failure	Predicted Membership Non-Failure
Failure	9	2 (22.2%)	7 (77.8%)
Non-Failure	21	2 (9.5%)	19 (90.5%)

Overall Accuracy 70.0%

However, the model two years prior is lacking, like the one year prior model, in its ability to classify correctly the failed farms. The overall Type I error rate for the holdout sample and the sample three years prior to failure was 92%. Very few farmers would be denied loans if the model were used as the sole criterion for loan decisions. This presents a troublesome problem and is discussed in Chapter V.

Model Three Years Prior

Thirty farms were used to derive the model for three financial statement periods prior to failure, consisting of 9 failed and 21 non-failed farms. Since data was unavailable the fourth year prior to failure, the model was validated by using a sample of farms also three years prior to failure that had the variables included in the model. This validation sample consisted of 67 farms composed of 16 failed and 50 non-failed farms.

Only one variable was included in this model to predict failure. The intermediate liability variable was again significant in the assessment of farm failure. The discriminant function for this model is:

$$Z = -1.058864 + .9943338\text{-}005(X_1)$$

where

Z = Overall Score

X_1 = Intermediate liabilities

This function has a Wilks' Lambda of .8458599 and a Chi-Square statistic of 3.5991 which is significant at the .0578 level. The Canonical correlation is .3926069 as shown in the following table.

TABLE 4-11 THREE YEAR PRIOR MODEL

Variable	Coefficient	Mean Failed	Mean Non-Failed
X_1	.9943338-005	$107504	$80113
constant	-1.058864		
Group Centroids		.63693	-.26226

Canonical Correlation	.3926069
Wilks' Lambda	.8458599
Chi-Square	3.5991 (.0578 sig.)

Variable	Standardized Coefficient	Unstandardized Coefficient
X_1	1.0	.9943338-005

X_1 = Intermediate Liabilities

The average amount of intermediate liabilities was over 2 times more for failed farms than for non-failed farms. This is consistent with the analysis of the intermediate liability variable two years prior to failure.

Classification accuracy for this model was 73.33% while the Type I error was 77.8% and Type II error was 4.8%, as seen in Table 4-12.

TABLE 4-12 ACCURACY MATRIX -- 3 YEARS PRIOR MODEL

Actual Group	Number of Cases	Predicted Membership Failure	Non-Failure
Failure	9	2 (22.2%)	7 (77.8%)
Non-Failure	21	1 (4.8%)	20 (95.2%)

Overall Accuracy 73.33%

The validation sample (Table 4-13) of 67 commercial farms had a classification accuracy of 73.13% but the Type I error rose in spite of an increase in overall model accuracy.

TABLE 4-13 ACCURACY MATRIX -- 3 YEARS PRIOR CLASSIFYING A HOLDOUT SAMPLE

Actual Group	Number of Cases	Predicted Membership Failure	Non-Failure
Failure	17	2 (11.8%)	15 (88.2%)
Non-Failure	50	3 (6.0%)	47 (94.0%)

Overall Accuracy 73.13%

A summarization of the three models and their predictive accuracy is presented in Table 4-14.

TABLE 4-14 SUMMARIZATION OF MODEL CLASSIFICATION ACCURACY

Year		1 Yr Holdout Prior	1 Yr Holdout Sample	2 Yr Holdout Prior	2 Yr Holdout Sample	3 Yr Holdout Prior	3 Yr Holdout Sample
YR 1	Cases	133	137	92	--	30	--
	% Accuracy	62.41	66.42	70.65	--	76.67	--
YR 2	Cases	--	--	42	50	30	--
	% Accuracy	--	--	78.57	60.00	70.00	--
YR 3	Cases	--	--	--	--	30	67
	% Accuracy	--	--	--	--	73.33	73.13

Cases listed under the prior column are the number of cases used to derive the discriminant model.

Change-in-Ratio Model

A final model was developed independent of the others to identify those variables that would be significant by observing the change in ratios from year three to year one. Only one ratio entered the discriminant equation, that being the change in the depreciation/value farm production ratio. The function for the model is:

$$Z = .04957895 + 27.0108(X_1)$$

where

Z = Overall Score

X_1 = Depreciation/Value Farm Production -- This ratio is a measure of the capitalization as a percentage of revenue.

When the change in this ratio is negative, it may be interpreted as a sign of over capitalization or a decrease in value of farm production. Also as the value of farm production decreases and there is an increasing portion of depreciation to the value of farm production this may be a sign of underutilized equipment. Table 4-15 presents the averages for the financial statement elements and ratios used in this model one and three years prior to failure.

TABLE 4-15 DEPRECIATION AND VALUE OF FARM PRODUCTION TRENDS

	Averages Yr 3		Averages Yr 1	
	Failed	Non-Failed	Failed	Non-Failed
DEP	$ 43218	35138	$ 49055	28964
VFP	$314743	362344	$321659	362847
DEP/VFP	19%	9%	21%	8%

DEP - Depreciation
VFP - Value of Farm Production

The average depreciation to value of farm production(VFP) ratio in year three for failed farms was 19% while in year one the same ratio rose to 21%. In comparison, depreciation as a percentage of value of farm production was 9% in year three for non-failed farms and decreased to 8% one year prior to failure. For this time period the non-failed farmer had an average of $362,344 of VFP in year three and an average depreciation allowance of $35,138, while, for one year prior to failure, the average VFP was $362,847 and the average depreciation allowance was $28,964. During this same time frame the failed farmer had $314,743 of VFP and $43,218 of associated depreciation three years prior to failure. One year prior to failure these same farms had VFP of $321,659 and an increasing depreciation allowance of $49,055.

The increasing level of depreciation for the failed group may represent the replacement of machinery and equipment which corresponds to a heavier intermediate debt burden. The non-failed group did not replace as many of these assets and effectively utilized their current machinery and equipment to produce a higher value of farm production. They were more conservative than the failed group and more efficient in the use of their intermediate assets.

The Wilks' Lambda and the Chi-Square statistics (Table 4-16) were .7892547 and 4.8517 significant at the .0276 level, respectively. The Canonical correlation for the function was .4590701. The failed group centroid was -.67611 while the non-failed group centroid was identified at .36059.

TABLE 4-16 CHANGE IN YEAR THREE TO YEAR ONE RATIO MODEL

Variable	Coefficient	Mean Failed	Mean Non-Failed
X_1	27.01080	-.02687	.01151
constant	.4957895-001		
Group Centroids		-.67611	.36059

Canonical Correlation	.4590701
Wilks' Lambda	.7892547
Chi-Square	4.8517 (.0276 sig.)

Variable	Standardized Coefficient	Unstandardized Coefficient
X_1	1.0	27.01080

X_1 = Depreciation/Value of Farm Production

The 23 commercial farms, 8 failed and 15 non-failed, identified with complete data for year three and year one were classified using the Lachenbruch method.[82] The classification results as seen in Table 4-16 were comparable to the other models at 69.56%.

[82]The Lachenbruch classification technique was used as noted in chapter II for small samples as a means of validation.

TABLE 4-16 ACCURACY MATRIX -- CHANGE IN YEAR 3 TO YEAR 1 RATIOS

Actual Group	Number of Cases	Predicted Membership Failure	Predicted Membership Non-Failure
Failure	8	1 (12.5%)	7 (87.5%)
Non-Failure	15	0 (.0%)	15 (100.%)

Overall Accuracy 69.56%

Again, the Type I error rate is quite large at 87.5% and the ability to identify only 12.5% of those farms that will eventually fail necessitates that the model be adjusted to reduce these errors.

CHAPTER V

SUMMARY, CONCLUSIONS AND SUGGESTED DIRECTIONS FOR FURTHER RESEARCH

The studys more important findings are highlighted in the summary and conclusions presented in this chapter. Suggested directions for further research are also provided.

Summary of Findings

A review of approximately 10,200 farm records in a data base provided by the Federal Intermediate Credit Bank of the Fifth Farm Credit District for adequate data identified 270 usable cases that were in the commercial farm category one year prior to failure. For two financial statement periods prior to failure, 92 farms had the relevant data available while only 30 farms were usable three financial statement periods prior. Farms that were failures, as defined in this study, were identified in the years 1981 thru March 1986.

Discriminant functions were derived for each of the three years prior to failure. Each discriminant model was validated by a holdout sample in the year the model was derived and the long range accuracy of the model was assessed by classifying samples from prior periods. Prior probabilities were used to assign cases to the failed and non-failed groups after the discriminant scores were calculated for each farm. Another model derived independently of the others, was built by taking the change in financial statement ratios from three years prior to failure and one year prior to failure. This final model was built in order to identify those variables that were the best discriminators due to the increase or decrease of the elements that compose the ratio.

Year One Model

The model developed from farm data one year prior to failure identified two financial statement ratios as being significant discriminators between failed and non-failed farms. These variables were working capital/total assets and net farm income/net worth. The 133 farms used to derive the model were classified at a 62.41% accuracy rate. The validation sample of 137 farms had a classification accuracy of 66.42% while the 92 farms two years prior to failure were classified by the one year model at a 70.65% classification accuracy and 76.67% for the 30 farms three years prior to failure.

Type I errors were smaller when data from two and three years prior to failure was used in the model. These errors declined from 91.5% for the holdout sample to 89.3% for two years prior and further to 77.8% for three years prior. Due to the high costs of misclassification for failed farms, neither of these error rates is acceptable for reducing loan losses and the model must be adjusted for this shortcoming.

Two Year Model

The level of current assets and intermediate liabilities were the two variables included in the discriminant model developed from data two years prior to failure. The intermediate liabilities for the failed group were 1.5 times higher than the non-failed group. Likewise, the failed group had a current asset level over 2 times higher than their non-failed counterpart.

Classification accuracy for the 42 farms used to derive the model was 78.57% whereas the holdout sample of 50 farms had a classification accuracy of only 60%. The classification accuracy was 70% when the 30 farms three years prior to failure were classified with this model. Type I errors were also large for this model with a 100% error rate for the holdout sample and a 77.8% error rate for the 30 farms classified three years prior.

Three Year Model

Thirty farms, 9 failed and 21 non-failed were used to derive the failure prediction model three financial periods prior to failure. Only one variable was included in this model to predict failure. The intermediate liability variable was again significant as a discriminator between failed and non-failed farms. The classification accuracy of this one variable model was 73.33% for the 30 farms used to derive the model and 73.13% for a holdout sample of 67 cases. Again, Type I errors were large at 77.8% for the cases used to derive the model and 88.2% for the holdout sample. Table 5-1 presents an accuracy matrix for each model classifying all cases in each of the three years.

TABLE 5-1 OVERALL MODEL ACCURACY IN EACH YEAR

	Correct Classification		
Models	Yr 1 Cases	Yr 2 Cases	Yr 3 Cases
Year 1 Model	64.5%	70.65%	76.67%
Year 2 Model		68.00%	70.00%
Year 3 Model		---	73.19%

Type I Errors

Rejection of the null hypothesis (a farm is a failure) when it is actually true is referred to as an error of the first kind or a Type I error.[83] No benefit is derived from a model that has a large overall classification error resulting from one group. The purpose of the model is to distinguish between groups, thus allowing financial statement users the ability to predict the future viability of farming operations. Type I errors occur when there are misclassifications of failed farms as non-failed. Predicting a future failed operation to be a successful concern usually means the eventual loss of principal and interest to the investor. However, if the model does identify correctly only one potential borrower as a future failure,

[83] Robert Schlaifer, Probability and Statistics for Business Decisions. (New York, N.Y.: McGraw-Hill, 1959) p. 608.

the model has helped to save the investor that principal and interest which would have been lost.

The models developed in this study have a very large Type I error rate as seen in Table 5-2. If all borrowers are classified as non-failed and some actually fail, the model yields no benefit to the user. On the other hand, the model to predict failure is not to be used as the sole criterion in making investment decisions. The score derived from the model is a signal to the user about that enterprise's future health.

TABLE 5-2 SUMMARIZATION OF MODEL TYPE I ERRORS

		1 Yr Holdout		2 Yr Holdout		3 Yr Holdout	
Year		Prior	Sample	Prior	Sample	Prior	Sample
YR 1	Cases	133	137	92	--	30	--
	% Error	81.00	91.50	89.30	--	77.80	--
YR 2	Cases	--	--	42	50	30	--
	% Error	--	--	58.30	100.0	77.80	--
YR 3	Cases	--	--	--	--	30	67
	% Error	--	--	--	--	77.80	88.20

Cases listed under the prior column are the number of cases used to derive the discriminant model.

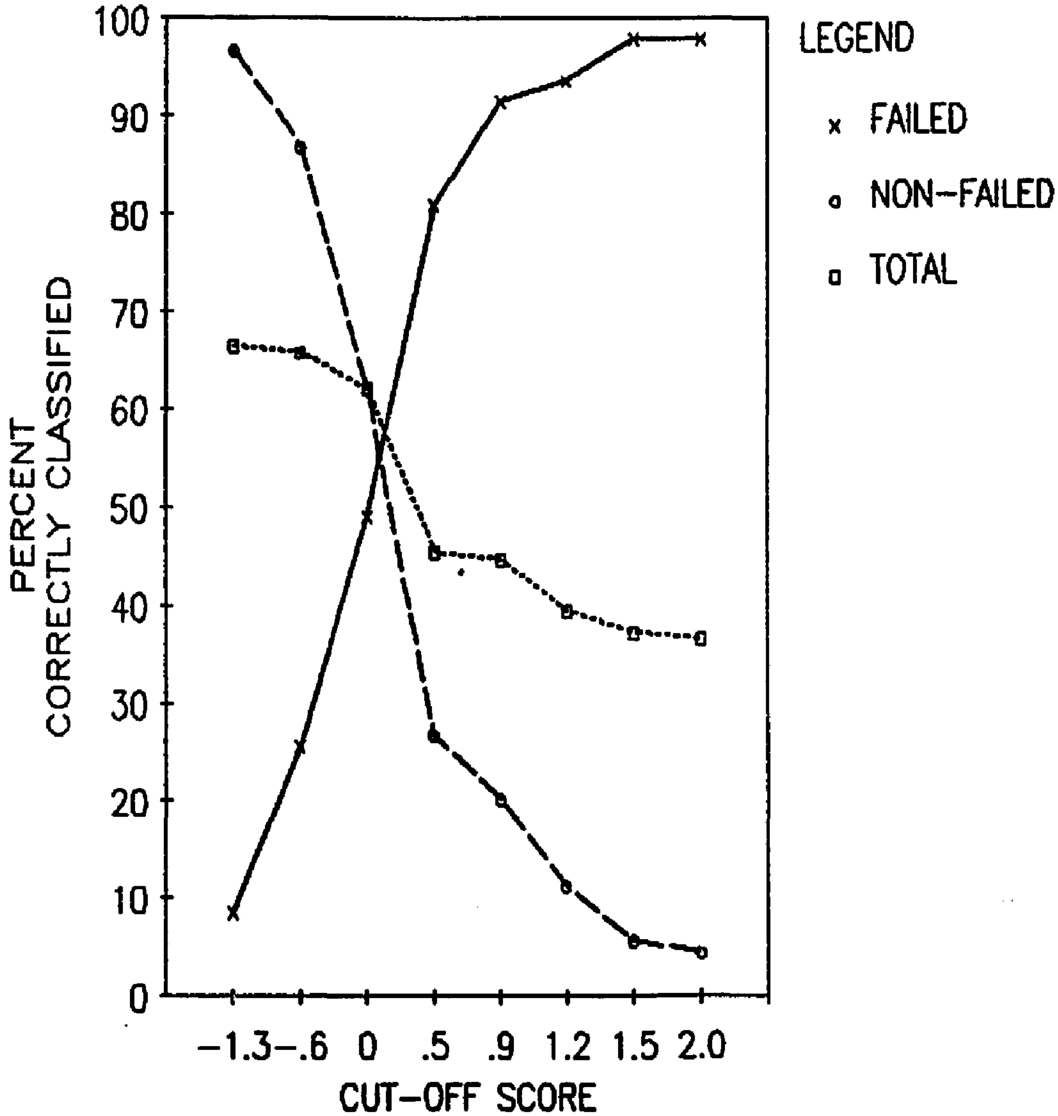
When using the model in order to reduce Type I errors, which in turn increases Type II errors, a cut-off score is established before classifying a farm as failed or non-failed. For example, if a cut-off score was set at 0, farms would be classified as failed or non-failed dependent upon their score being above or below the cut-off score. However, which farms are predicted to fail or what is the appropriate cut-off level? Clearly, if detection of failures is the sole objective, one selects a cut-off rate that eliminates Type I errors. Unfortunately, this leads to high Type II errors since a large amount of scores would fall within the failed category. Therefore, this optimal cut-off score could be set subjectively by the user under a decision rule that would yield an acceptable Type I error while minimizing the non-failed farms that would be incorrectly classified by this cut-off score. A few alternative cut-off scores for the one year prior to failure model are shown in Table 5-3. The percent of failed, non-failed and total farms correctly classified are contained in the table for each alternate score, and Figure 6 yields a graphical presentation of this data.

TABLE 5-3 ALTERNATE CUT-OFF SCORES -- ONE YEAR PRIOR MODEL

Cut-Off Score	Percent Correctly Classified: Failed	Non-Failed	Total
-1.30	8.5	96.7	66.42
- .60	25.5	86.7	65.69
0.00	48.9	62.0	62.04
.50	80.9	26.7	45.26
.90	91.5	20.0	44.53
1.20	93.6	11.1	39.42
1.50	97.9	5.6	37.23
2.00	97.9	4.4	36.50

The use of an optimal cut-off score to eliminate Type I errors has been used in prior farm failure studies. Hardy and Weed(1980) classified 81% of all farms accurately, but were only able to accurately classify 44.8% of the non-failed farms. This was due to a cut-off point that virtually eliminated Type I errors, classifying 93.5% of the failed farms correctly. Johnson and Hagan(1973) classified just over 50% of the non-failed farms correctly and 98% of the failed farms correctly, while yielding an overall accuracy of 62% for the study. Another study by Frey and Dunn(1976), classified 90% of the non-failed farms and only 60% of the failed farms correctly. Therefore the optimal cut-off score can be set at a point to achieve the user's goals.

FIGURE 6
ALTERNATE CUT-OFF SCORES
ONE YEAR PRIOR MODEL



A method to reduce Type I errors without manipulating the cut-off score involves specifying a range of scores most commonly misclassified so that they will be investigated further before a decision is made. For example, with a cut-off score of -1.30 for the one year prior to failure model, the most common range of scores for misclassifed failed farms was between -1 and 0. Therefore, when classifying the holdout sample one year prior to failure, if all farms with scores between -1 and 0 were further investigated, a possibility exists of identifying those farms misclassified as Type I errors. Nineteen misclassified farms possibly could have been identified for the holdout sample with a score within this range. If these farms were further investigated and all were correctly reclassified the Type I error would fall to 51% and the total classification accuracy could rise to 80% if all non-failed farms were properly identified. This must be tempered by the knowledge that some correctly classified non-failed farms that have scores within this range may be denied loans when investigated further (raising Type II errors). Also, some of the misclassified failed farms may filter through the screen and be able to borrow funds.

However, a combination of both methods could also be quite useful. Instead of trying to totally eliminate Type I errors, from both an economic and administrative standpoint, a more efficient objective would be to maximize the returns by applying a screening device. This would be accomplished by setting an appropriate cut-off score to reduce Type I errors and then investigating a range of scores to try to identify those non-failed farms misclassified by the cut-off level. For example, if the cut-off score was set at 0, nineteen misclassified failed farms would now be correctly classified (lowering Type I errors) but twenty-five non-failed farms would be additionally misclassified for the one year prior holdout sample. Therefore, further investigation of those farms within a particular range of scores may lead to the identification of some misclassified non-failed farms.

The overall impact of using a cut-off point and further investigation of farms within a particular range of scores will result in lower Type I errors, possibly raise Type II errors and reduce the amount of loss loans.

Change-in-Ratio Model

A final model using the change in ratios from year three to year one was developed. The change in depreciation/value farm production was the only significant variable for the model. The model classified 69.56% of the 23 farms correctly using the Lachenbruch technique. Over capitalization, poor machinery and equipment purchase decisions, and declining farm production possibly contributed to the significance of this variable.

Conclusion

This study was performed to investigate the use of financial statement elements and traditional financial statement ratios as predictors of farm failure. In many respects, the study results for the year one model differed materially from what was anticipated. Very few variables were incorporated into the model as discriminators and the accuracy of predicting failure decreased as the year of failure approached. Variables not found to be significant in prior farm failure studies were discriminators for this research.

A failure prediction model for farming enterprises developed strictly from financial statement elements and ratios can possibly be utilized to assess the future viability of farm operations. Even though the models in this study did not yield a classification accuracy that was as high as prior industrial failure studies, this study was comparable to other farm failure studies. Four farm failure studies, which incorporated both financial statement data, qualitative data and data not disclosed in the financial statements, had an overall accuracy of 62, 71, 75 and 85 percent.[84] To the contrary, this study used only financial statement elements and ratios and yielded an accuracy one year prior to failure of approximately 67 percent.

The financial statement ratios found to be significant in prior studies were in the liquidity and leverage categories. Bauer and Jordan found the current ratio, total liabilities/total assets ratio, and the level of total liabilities to be significant. Four other studies[85] found the debt to total asset ratio to be a good discriminator. These ratios are consistent with the findings of this study, since measures of liquidity (working capital/total assets, current assets, intermediate liabilities) were also found to be significant variables in the discriminant models. Besides

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[84]These studies were by Bauer and Jordan(1971), Johnson and Hogan(1973), Hardy and Weed(1980), and Hardy and Patterson(1983).

[85]Johnson and Hagan(1973), Dunn and Frey(1976), Hardy and Weed(1980), and Hardy and Patterson(1983).

measures of liquidity, this study also found a profitability ratio, net farm income/net worth, to be significant, whereas prior farm failure studies did not indicate profitability measures as good discriminators.

These prior farm failure studies developed discriminant models which incorporated qualitative data and data not disclosed in the financial statements. Some of these variables were acres owned, credit life insurance, loan repayment made plus marketable inventory divided by the loan repayment anticipated, and the loan commitment to net worth measure. This study, as compared to other farm failure studies, strictly observed financial statement elements and ratios as predictors of farm failure. The relatively low classification accuracies for this study and prior studies do not strongly support the contention that there are significant differences between the financial statements for farms which will eventually fail and those which will continue to succeed. The complete and verified data as seen in the audited financial statements for the industrial studies as compared to the data used in this study could also contribute to the classification differences. As the FICB continues its accumulation of financial statement data, the accuracy and reliability of this data will improve and more accurate models (reducing Type I errors) could be developed.

The accuracy rate in this study may be an indication that traditional financial statement ratios and financial statement elements alone may not be able to accurately distinguish between failed and non-failed farms. The addition of qualitative data and data not presented in the financial statements may prove to be good discriminating variables for predictive purposes. Also, the ability of farm operators to secure continuous financing in the past from governmental agencies over periods of losses without restructuring operations may explain why the failed and non-failed groups were more distinct the further they were from failure. Moreover, the current economic crisis in the farm economy has necessitated that federal lending agencies practice more stringent lending procedures, which should lead to better investment decisions in order to decrease the number of loss loans. Therefore, future research in the agricultural area will have access to more reliable, and more complete, data of farming operations that are more businesslike due to these changes.

One contribution made by this research is the awareness provided to financial statement users concerning the utilization of financial statement ratios and elements in the assessment of the future failure or success of farming operations. Future models derived from more complete and reliable data for the prediction of failure are a necessity for agricultural lending agencies, especially if they show a correlation between the selected variables and the future event of failure or success. Discriminant models derived from financial statement data, in spite of the shortcomings of farm financial statements, may indicate that the relationships observable on the statements can provide the basis for drawing valid conclusions about the farms they represent.

Constraints

Using the relative predictive power of models created solely from financial ratios, ratio trends and financial statement elements has the advantage of allowing the research to concentrate directly on those variables. However, excluding economic indicators and other useful information may weaken the conclusions.

The farms are stratified over several time periods and not by the type of farming operation. There is a geographic limitation since the study only incorporates farms from the three state area of Alabama, Louisiana and Mississippi. Therefore, conclusions about the research can only be indicative for the Fifth Farm Credit District of the agricultural economy and inclusive for all types of farming operations, since no specific type of operation was examined. The predictive ability of the model was based on farm loans already in the Federal Intermediate Credit System and may not be applicable to new loans. This limitation is due to the fact that data used dealt with existing loans and no data was used on that portion of the population applying unsuccessfully for loans.

The inability to draw concrete comparisons and conclusions for the three models and classification accuracies between each year is a limiting factor in the research. This limitation arises due to the unavailability of an adequate number of farms with complete, consecutive financial statement data for a three year period. The particular type of sample selected to provide a basis for gathering sufficient data necessitated the selection of three samples with adequate data for each year prior to failure. Although the two and three year samples can be considered a part of the one year sample, this does not insinuate that these samples were representative of the one year sample. Therefore, on the basis of these findings a conclusion can not be drawn that the one year prior to failure model increased in accuracy two and three years prior to failure, since all of the farms used one year prior to failure were not classified in years two and three prior to failure. Also, it was impossible to conclude that one model was more accurate than another model since the same farms were not used to derive all of the models.

Observations

Even though there is an inability to compare models or data between years some observations are noteworthy. The success rate of the year one model increased 4% when classifying the holdout sample. However, Type I errors also increased for this classification while Type II errors decreased. The classification accuracy increased to 70.65% and 76.67% for observations two and three years prior to failure while both types of errors declined.

The model one year prior seems to be able to classify farms more accurately the further away farms are from failure rather than the closer the year of failure approaches. This suggests that failed and non-failed farms are more discernible when failure is more than a year away. Prior studies, namely Altman's, found that the failed and non-failed firms were more similar the further they were from failure and more distinguishable the closer failure loomed. A possible explanation for this difference between failed and non-failed farms may be explained by the differences in the fair market valuation of assets. As a loan officer observes the deterioration of a farm operation, a more accurate fair market valuation is presented to estimate the risk position of the investor. Therefore as the farms approach failure, a more approximate fair market value is presented which is similar to the successful operations. Thus, the differences further away from failure may be due more to data manipulation rather than to differences between farms.

Directions For Further Research

With the limitations of information imposed by the nonavailability and incompleteness of financial statement data from farm operations, further research is necessitated in the agricultural sector to develop models with higher predictive accuracy. Other variables such as acres owned and loan repayment made to loan repayment anticipated, not included in the financial statements, should be included in the model building process to test for relationships and discriminating ability that might exist between failed and non-failed groups. Further research should evaluate the number of acres owned as a classification of size instead of the value of farm production generated. This distinction could possibly yield more differentiation between failed and non-failed groups.

Alternative statistical methods should also be evaluated. Quadratic multiple discriminant analysis, probit and logit quantitative techniques may improve discrimination and predictive accuracy in further studies. Also a two step procedure of clustering the observations into various groups (not just failed and non-failed) and then discriminating according to those groups may help in discrimination and classification accuracy.

Finally, further research should focus upon each state and the primary enterprise classifications in order to evaluate the differences between models and variables peculiar to the different types of farming operations and geographical locations.

APPENDIXES

APPENDIX A
SAMPLE FARM BALANCE SHEET

ASSETS			LIABILITIES		
CURRENT ASSETS	cost or basis	market value	CURRENT LIABILITIES	cost or basis	market value
Cash on hand			Accounts Payable		
Savings Account			Medical and other Personal		
Hedging Account Equity			Notes Payable		
Marketable Bonds and Securities			Intermediate Notes Payable(current)		
Notes and Accounts Receivable			Long term Notes Payable(current)		
Livestock to be Sold			Estimated Accrued Interest		
Crops and Feed Inventory			Estimated Accrued Tax Liability		
Cash Investment in growing Crops			Accrued Rents and Leases		
Supplies			Contingent Income Tax Liability:		
Prepaid Expenses			Current Assets		
Other			Marketable Securities		
Total Current Assets			Total Current Liabilities		
INTERMEDIATE ASSETS			INTERMEDIATE LIABILITIES		
Notes and Accounts Receivable			Notes Payable		
Machinery and Equipment			Sales Contracts		
Less: Accumulated Depreciation			Life Insurance Policy Loans		
Breeding Stock			Other		
Less: Accumulated Depreciation			Contingent Income Tax Liability:		
Retirement Account			Machinery		
Cash Value of Life Insurance			Breeding Stock		
Securities not readily Marketable			Securities not Marketable		
Personal and Recreational Vehicles			Retirement Accounts		
Household Goods and Personal Effects					
Other					
Total Intermediate Assets			Total Intermediate Liabilities		
FIXED ASSETS			LONG TERM LIABILITIES		
Contracts and Notes Receivable			Mortgage on Farm real estate		
Farm Real Estate			Land Contracts		
Less: Accumulated Depreciation			Mortgage on Nonfarm Real Estate		
Nonfarm real Estate			Other		
Other			Contingent Income tax Liability:		
			Farm real Estate		
Total Fixed Assets			Total Long Term Liabilities		
TOTAL ASSETS			TOTAL LIABILITIES		

APPENDIX A
SAMPLE FARM INCOME STATEMENT

REVENUE:

Crops and Feed - Cash Sales
Crops and Feed - Inventory Change
Livestock and Poultry - Cash Sales
Livestock and Poultry - Inventory change
Breeding Stock - Cash Sales
Breeding Stock - Inventory Change - Raised
Breeding Stock - Inventory Change - Purchased
Livestock and Poultry Products
Custom Work
Governmental Payments and Patronage Dividends
Income from Hedging Transactions
Adjustments in Notes and Accounts Receivable
  Gross Revenue
  Less Livestock and Poultry Purchased
  Less Feed Purchased

  VALUE OF FARM PRODUCTION

EXPENSES

Cash Operating Expenses
Expense Adjustment (unused asset)
Expense Adjustment (unpaid items)
Depreciation
Total Operating Expense
Income from Farm operations
Less Interest Expense
Gain or Loss on Disposal of Intermediate Farm Assets
Gain or Loss on Fixed Farm Asset

  NET FARM INCOME

NONFARM INCOME

Operators Off Farm Income
Spouses Wage Off Farm
Interest and Dividends
Gain or Loss on Sale of Nonfarm Asset
Net Income - Other Farms
Net Income - Nonfarm Real estate

  NET NONFARM INCOME

Income before Income Taxes and Extraordinary Items
Provision for Income and Social Sec. Taxes
Income before Extraordinary Items
Extraordinary Items
  NET INCOME

APPENDIX B

Financial Ratios Found Useful In Selected Studies

	Beaver 1966	Altman 1968	Daniel 1968	Daekin 1972	Edmister 1972	Blum 1974	Elam 1975	Altman 1977	Fulmer 1984
Net Worth/Total Liabilities						x	x		
Net Income/Total Assets	x			x					
Quick Assets/Current Liabilities				x	x		x		
NI + DDA/Total Debt[1]	x			x		x	x		x
Total Debt/Total Assets	x			x			x		x
Working Capital/Total Assets	x	x		x					
Current Assets/Current Liab.	x			x			x	x	
Quick Assets/Operating Expenses[2]	x								
EBIT/Total Assets[3]		x						x	
Sales/Total Assets		x					x		x
Retained Earnings/Total Assets		x						x	x
Current Assets/Sales				x					
Working Capital/Sales				x	x				
NI + DDA/Current Liab.[1]					x				
Net worth/Sales					x				
Current Liab./Net Worth					x				
Inventory/Sales					x				
Quick Assets/Inventory						x			
Quick Flow[4]						x			
Current Assets/Total Assets				x					
Cash + Mkt. Sec./Total Assets				x					
NI + DDA/Sales[1]							x		
NI + DDA/Total Assets[1]							x		
NI/Sales							x		
Operating Income/Sales							x		
Net Profit After Taxes			x						
Investments/Sales			x						
Long Term Liab./Total Liab.			x						
Net Profit After Tax/Net Working Cap.			x						
Net Income/Net Worth							x		
Cash + Mkt. Sec./Current Liab.				x					
NI + DDA/Net Worth[1]							x		
Quick Assets/Total Assets				x					
Sales/Cash + Mkt. Sec.				x					
Current Liab./Total Assets							x		x
Sales/Quick Assets				x					
Long Term Debt/Current Assets							x		
Net Income.Common Equity						x			
Net Worth/Debt		x							
SE (EBIT/Total Assets)[5]								x	

APPENDIX B

Financial Ratios Found Useful In Selected Studies

	Beaver 1966	Altman 1968	Daniel 1968	Daekin 1972	Edmister 1972	Blum 1974	Elam 1975	Altman 1977	Fulmer 1984
Log of Int. Coverage + WC/LTD[6]								x	
Net Worth/Total Assets								x	
Log Total Assets								x	x
EBT/Net Worth[7]									x
Working Capital/Total Debt									x
Log EBIT/Interest[3]									x
Long Term Liab.			x						
Sales/Fixed Assets			x						
Long Term Liab./WC			x						
Investments/Current Assets			x						
Working Capital/Net Worth			x						

[1]NI + DDA = Net Income plus depreciation, depletion and amortization.

[2]Quick Assets/Operating Expenses = Quick Assets minus Cur. Liab./Operating Expenses minus depreciation, depletion and amortization.

[3]EBIT = Earnings before interest and taxes.

[4]Quick Flow = Cash = Mkt. Sec. + Acc. Rec. + (Annual sales + 12)/ [(CGS - Depreciation + Selling and Admin. + Interest) + 12].

[5]SE = Standard Error.

[6]Log int. cov. + WC/LTD = Log of interest coverage + Working capital/Long Term Debt.

[7]EBT = Earnings before taxes.

APPENDIX B

Financial Ratios Found Useful In Selected Farm Studies

	Bauer & Jordan 1971	Johnson & Hagan 1973	Dunn & Frey 1976	Hardy & Weed 1980	Hardy & Patterson 1983
Current Assets/Current Liabilities	x	x			
Total Liabilities/Total Assets	x				
Reasonable Farm Value	x				
Total Liabilities	x				
Marital Status	x				
Family Living Expenses/Tot. Exp.	x				
Debt/Total Assets		x	x	x	x
LR + Mkt. Inv./LRA[a]		x			
Credit Life Insurance			x		
Acres Owned			x		
Loan Amount/Net Cash Farm Income			x		
Annual Loan Req. Antic./Tot. Assets				x	
Loan Commitment/Net Worth					x

[a]LR + Mkt. Inv./LRA = Loan Repayment Made + Marketable Inventory divided by Loan Repayment Anticipated.

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