THE DETERMINATION OF WORTHLESS SECURITIES UNDER INTERNAL REVENUE CODE SEC. 165(g): EMPIRICAL EVIDENCE FROM JUDICIAL DECISIONS

By

BOB GRISSOM KILPATRICK

Bachelor of Science
University of Southern Mississippi
Hattiesburg, Mississippi
1975

Master of Science
University of Southern Mississippi
Hattiesburg, Mississippi
1976

Submitted to the Faculty of the Graduate College
of the Oklahoma State University
in partial fulfillment of the requirements
for the Degree of
DOCTOR OF PHILOSOPHY
May, 1984

THE DETERMINATION OF WORTHLESS SECURITIES UNDER
INTERNAL REVENUE CODE SEC. 165(g): EMPIRICAL
EVIDENCE FROM JUDICIAL DECISIONS

Thesis Approved:

Dale E. Armstrong
Thesis Adviser

Lawrence H. Hammer

U. D. Wade

Michael R. Edgmand

Norman N. Durham
Dean of the Graduate College

ACKNOWLEDGMENTS

First and foremost, I would like to express my sincere appreciation to the members of my committee, Dr. Dale E. Armstrong, Dr. William D. Warde, Dr. Michael R. Edgmand, and especially Dr. Lawrence H. Hammer, whose guidance and expertise made this study managable. Additional thanks are extended to the other accounting faculty at Oklahoma State University for their assistance during my pursuit of this degree.

I am grateful to my friends at the University of Southern Mississippi, especially Dr. Jerold J. Morgan, for their encouragement and support during my doctoral studies.

I would also like to thank my fellow doctoral candidates for their assistance throughout the program and, more importantly, for their friendship. A very special thanks is due to Larry and Roxanne for their unselfish support and friendship.

To Nancy, whose love and support helped me through the rough times, and to my daughter, Tiffany, I dedicate this dissertation.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

The purpose of this chapter is to introduce the basic problem in the determination of a deduction for worthless securities, to define the objectives of the research, and to describe the organization of the remainder of the dissertation.

Statement of the Problem

Section 165(g)(1) of the Internal Revenue Code of 1954 provides that

> . . . if any security which is a capital asset becomes worthless during the taxable year, the loss resulting therefrom shall, for purposes of this subtitle, be treated as a loss from the sale or exchange, on the last day of the taxable year, of a capital asset (Prentice-Hall, 1983b, p. 14, 032).

According to Section 165(g)(2), the term "security" includes corporate stock, an option to purchase corporate stock, bonds, notes or other certificates of indebtedness issued by a corporation or by a government or a political subdivision thereof. Although the Code does not actually define the term "worthless", it is generally construed to have the same meaning as that attributable to the normal usage of the word, i.e., something without value. Reg. Sec. 1.165-4(a) defines a worthless security in a negative way by saying that stock is not worthless if it has any recognizable value on the date that it is claimed to be worthless.

In some cases, the determination of worthlesness is a relatively simple, straightforward task. For example, if a publicly traded security has a zero value and the corporation is terminated, a prudent investor would consider the security to be worthless. In other cases, however, the determination of worthlesness is not so obvious. For example, in closely held companies, no active trading market exists to determine the value of the security. In such cases the date that a stock becomes worthless may be difficult to determine. In the case of Minnie K. Young v. Comm., 123 F2d 597 (2nd Cir. 1941) at 600, Judge Augustus N. Hand commented:

> In cases like this the taxpayer is at times in a very difficult position in determining in what year to claim a loss. The only safe position, we think, is to claim a loss for the earliest year when it may possibly be allowed and to renew the claim in subsequent years if there is any reasonable chance of its being applicable to the income for those years (p. 368).

The difficulty of determining the exact year of worthlessness was apparently recognized by Congress when it enacted Code Sec. 6511(d)(1), which extends the statute of limitations for filing claims for refunds arising from worthless securities from three years to seven. This provision permits taxpayers to amend prior year returns in the event pertinent facts subsequently become known which change the estimated timing of the loss.

The degree of flexibility available to the taxpayer in determining the actual year of worthlessness has led to controversy. The taxpayer benefits the most from the deduction for worthlessness by claiming the worthlessness occurred in a year in which there is a large net short-term capital gain. On the other hand, the IRS, in its role of "protection of the fisc," may contest the loss year claimed by the taxpayer if it appears that an attempt was made by the taxpayer to shift the loss to another year which would result in a greater benefit. The significance of this problem is evidenced by the fact that well over 150 cases dealing with the determination of the timing of worthlessness were litigated between 1926 and 1982.

The determination of worthlessness and the year in which it occurs is a question of fact. If the taxpayer and the IRS disagree on the facts, the burden of proof is placed on the taxpayer. Basically, the taxpayer must prove two things: (1) the security has no value, evidenced by an excess of liabilities over assets (properly valued) with no potential or liquidation value reasonably foreseeable; and (2) the actual worthlessness occurred in the year claimed and not in a prior year, as evidenced by an "identifiable event," or in the absence thereof, that sufficient evidence exists to support the timing of the claim (Reading Co. v. Comm., 42-2 USTC ¶9700 (CA-3)).

Objectives of the Study

The primary objective of this research was to analyze Tax Court decisions to find specific events, their timing, and their effect on the court's determination of the timing of the year of worthlessness. Once the events and their timing were found, statistical models were employed to determine whether patterns were present which could be modeled for the purpose of predicting the outcome of the Tax Court's determination of the year of worthlessness. The models developed in this study can be used by taxpayers and the government to evaluate the probability of a favorable decision by the Tax Court. If used, these models could help reduce litigation and the related costs to taxpayers and the government. In addition, the taxpayers can use these models as a planning device when contemplating a claim for a worthless security deduction.

A secondary objective of this research was to compare two alternative statistical models, the logit model and the discriminant model, in their ability to predict the outcome of the cases in this study. (These models are discussed in depth in Chapter III.) This comparison can provide some insight for choosing the appropriate model in future tax case studies employing statistical prediction techniques.

Organization of the Remaining Chapters

The remaining chapters develop the problem, describe the methodology employed, and report the results along with any limitations encountered in the study. More specifically, Chapter II contains a review of the literature concerned with the determination of worthless securities and a review of studies that employed similar research methodologies; Chapter III develops more fully the methodology employed in the study; Chapter IV reports the results of the study; and, finally, Chapter V contains a summary and conclusions of the study.

CHAPTER II

LITERATURE REVIEW

This chapter has two objectives. The first is to provide an overview of previous research in the area of worthless securities. This overview will explain the basic problem involved with the use of traditional tax research techniques in the area of worthless securities. The second objective of this chapter is to describe the different approaches taken in previous statistical tax case studies. This discussion will provide a sufficient justification for the inclusion of the statistical models used in this study.

Prior Research on the Determination of Worthless Securities

All prior research in the area of the determination of worthless securities has been performed using traditional tax case research (Worthy, 1964; Hasselback, 1978). Typically, relevant court cases are analyzed and common factors are extracted on a judgmental basis. Although the significance of the variables found in the prior research was subject to the researchers' ability to synthesize the relevant factors, some variables appear consistently in the literature.

Some of the variables cited in the literature on worthless securities include: insolvency, foreclosure on certain assets, discontinuance of business, dissolution or revocation of charter, assessment of stockholders to pay liabilities, absence of a market for the security, confidence of owners and the public, bankruptcy and receivership, reorganization, and seizure by government authorities. Such factors are often cited and then qualified with a statement that although it appears in the case, it does not necessarily mean that it is a determining factor in itself, but only that it may be important when considered in conjunction with other factors present in the case (Worthy, 1964).

In many cases, the Tax Court is confronted with several factors which span different taxable periods. In the aggregate, these factors render the security worthless. The challenge to the Court is to specify which of those factors actually rendered the security worthless. Because there are several related factors, it is difficult to extract any single event as decisive in fixing the year of worthlessness of the security.

This difficulty is recognized throughout the literature. For example, Werner (1978) stated that:

> . . . any extended analysis of the decisions in the area makes it abundantly clear that no element can be singled out as indicative of worthlessness, but rather that most decisions are the result of not only a combination of factors but a judicial reaction of those factors (p. A-71).

Herein lies the basic problem with the use of traditional tax research techniques in the area of worthless securities. While it is relatively simple to detect single variables which are considered pertinent to the decision, it is difficult on a judgmental basis to ascertain the significance of specific variables when they are observed in conjunction with other significant variables. With the use of a formal statistical model, however, this significance should be more readily determinable.

Previous Tax Case Studies Employing Statistical Prediction Techniques

Madeo (1979) performed a statistical analysis of post-1954 cases on accumulated earnings. Explanatory variables used in the analysis were drawn from the applicable regulations and the IRS Audit Guidelines. The analysis was performed on 59 cases, employing stepwise discriminant analysis. The cases were broken down into three categories: winners, losers, and split decisions (where a split was defined as some tax paid, but not the amount assessed by the IRS). Multiple discriminant analysis was used on both the Regulations' and the Guidelines' variables, all of which were dichotomous. The resulting models accurately predicted 78% (for the Regulations) and 94% (for the Guidelines) of the cases used to form the model. However, no holdout cases (i.e., cases not used to construct the model) were analyzed to independently verify the predictive accuracy of the models.

Whittington and Whittenberg (1980) employed factor analysis and discriminant analysis on cases of classification of debt versus equity in closely held corporations. Their explanatory variables were chosen from those cited in the literature as judicial determinants of the issue, rather than variables defined in the Regulations. Their reasoning was that only a primary list was provided in the Code and that the Courts had used additional variables. These dichotomous variables were factored into four categories. These final categories correctly predicted 96% of the 50 cases used to make the model and 90% of holdout cases.

Englebrech and Rolfe (1982) used discriminant analysis to determine dividend equivalent in stock redemptions by closely held corporations.

The seven variables identified in the 54 analyzed cases consisted of five discrete variables (present or absent) and two continuous variables. They were obtained from the literature, as well as the cases themselves. Interestingly, three models were computed in the analysis; one for those cases decided before a landmark decision in the area, another for those cases decided after a landmark case, and a final one covering all of the cases. Jackknifing showed that the models predicted 76%, 85.7%, and 79.5% of the cases, respectively. In addition, the segregation of the model into pre- and post-landmark cases proved to contain different explanatory variables, indicating that the landmark case did indeed establish some new guidelines for the determination of the dividend equivalence of stock redemptions.

Recently, Stewart (1982) employed a logit transformation model in determining the classification of employees versus independent contractors. Eleven trichotomous variables (present, absent, not mentioned), obtained from the IRS Audit Manual and two landmark cases, were evaluated with a sample of 148 cases. The logit model was estimated using a maximum likelihood program (curvi-linear) developed by Nerlove and Press, followed by a stepwise logistic regression program in the BMPD Biomedical Computer Programs. The model correctly classified 97.3% of the cases used to estimate the parameters; no holdout sample was evaluated.

The preceding studies are representative of empirical statistical tax case research. With the use of formal statistical models, the researchers were able to determine the significance of specific explanatory variables, as well as relationships among those variables. The use of similar statistical techniques should help to solve the problem asserted with the use of traditional tax research techniques in the area of worthless securities, because the formal statistical significance of concurrent causal factors may be derived. These formal statistical relationships are more objective than the judgmental relationships obtained with traditional tax research techniques.

Summary

This chapter presented a brief overview of prior traditional tax research in the area of worthless securities. It was asserted that traditional tax research techniques were remiss in their ability to detect the significance of individual variables when those variables were observed in combination with other relevant variables normally inherent in worthless security litigation.

The chapter also presented several different approaches taken in prior statistical tax case studies. These studies provide conclusive evidence that statistical prediction techniques are appropriate in tax case analysis. These statistical techniques are more objective than traditional tax research techniques in their ability to detect the significance of concurrent variables used in the judicial decision-making process.

CHAPTER III

METHODOLOGY

The objective of this chapter is to develop a theoretical framework for quantifying the judicial decision process, to explain the design of the study, to discuss the statistical model formulations, and to discuss the approaches taken to analyze the data.

Theoretical Framework

The Judicial Decision Process

The judicial decision process consists of two phases: fact finding and decision making. In any court case, several facts will be presented, not all of which are pertinent to the decision which is to be made. The first task of the judge is to distinguish those facts which are pertinent to the decision from those facts which are not.

Once these facts are distinguished, the judge applies a rule of law to this combination of facts contained in the case in order to reach a decision. This is the concept known as ratio decidendi, which is defined as the legal reasoning for a decision. Ratio decidendi is an analysis performed by the judge in which the facts of a particular case are transformed into some conclusion or judgment. Using a notation similar to Cullison (1966), ratio decidendi requires that the set of operative F would imply conclusion C, i.e.:[1]

$$F \longrightarrow C$$

Behaviorists argue that judicial reasoning also involves a subconscious process which is influenced by the personal attributes of the judge (Duncanson, 1980). Conceding that argument, the judicial decision must still be linked to the underlying facts of the case, because judicial opinions are viewed as signals which provide information about the judge's perception of the presented facts and the relationship that those facts have upon the decision (Jensen and Horvitz, 1979).

Another closely-related legal concept is the doctrine of stare decisis, where a judge's action in any given case is influenced by prior decisions. That is, when a court has established a principle of law to be applicable to a certain set of facts, then that court will attempt to follow that principle and apply it to all future cases in which the operative facts are substantially the same.

Following Cullison's (1966) notation again, assume all precedent cases and their corresponding sets of operative facts and conclusions were ordered from 1 to n, i.e.:

$$\begin{array}{lcl} F1 & \longrightarrow & C1 \\ F2 & \longrightarrow & C2 \\ F3 & \longrightarrow & C3 \\ \vdots & & \vdots \\ Fn & \longrightarrow & Cn \end{array}$$

---

[1]Operative facts are those which are sufficient to yield a judicial decision (Cullison, 1966, p. 61).

Stare decisis implies that a case with the same operative facts F1 should also have the same outcome C1.

The doctrines of ratio decidendi and stare decisis together form the basis for quantitative analysis of the judicial decision process. Stated simply, ratio decidendi implies that a relationship exists between the operative facts in a case and that case's outcome; stare decisis implies consistency in the application of the law. Together, the application of these doctrines by the courts should result in reasonably predictable rules of law.

Human Information Processing

Although the statistical tax case studies discussed in Chapter II do not explicitly mention it, each study could be evaluated in light of the lens model paradigm, which is a theory of human information processing developed by Brunswik (1952). Both the judicial decision process and the taxpayer's (or his advisor's) decision about whether or not to litigate an issue may be evaluated within this framework.

The lens paradigm divides the state of the world into two parts: (1) the environment (or event); and (2) the individual's judgment of the environment, with the two parts separated by time or space. Within this framework, it is assumed that the decision maker wishes to make some evaluation (Y_s) about the current or future value of an event (Y_e). The environmental event (Y_e) is assumed to be objectively determinable, ex post. Because the decision maker cannot directly observe the event, he must evaluate it through a "lens" of items (cues) of information (X's) which are imperfect predictors of the environment (see Figure 1).

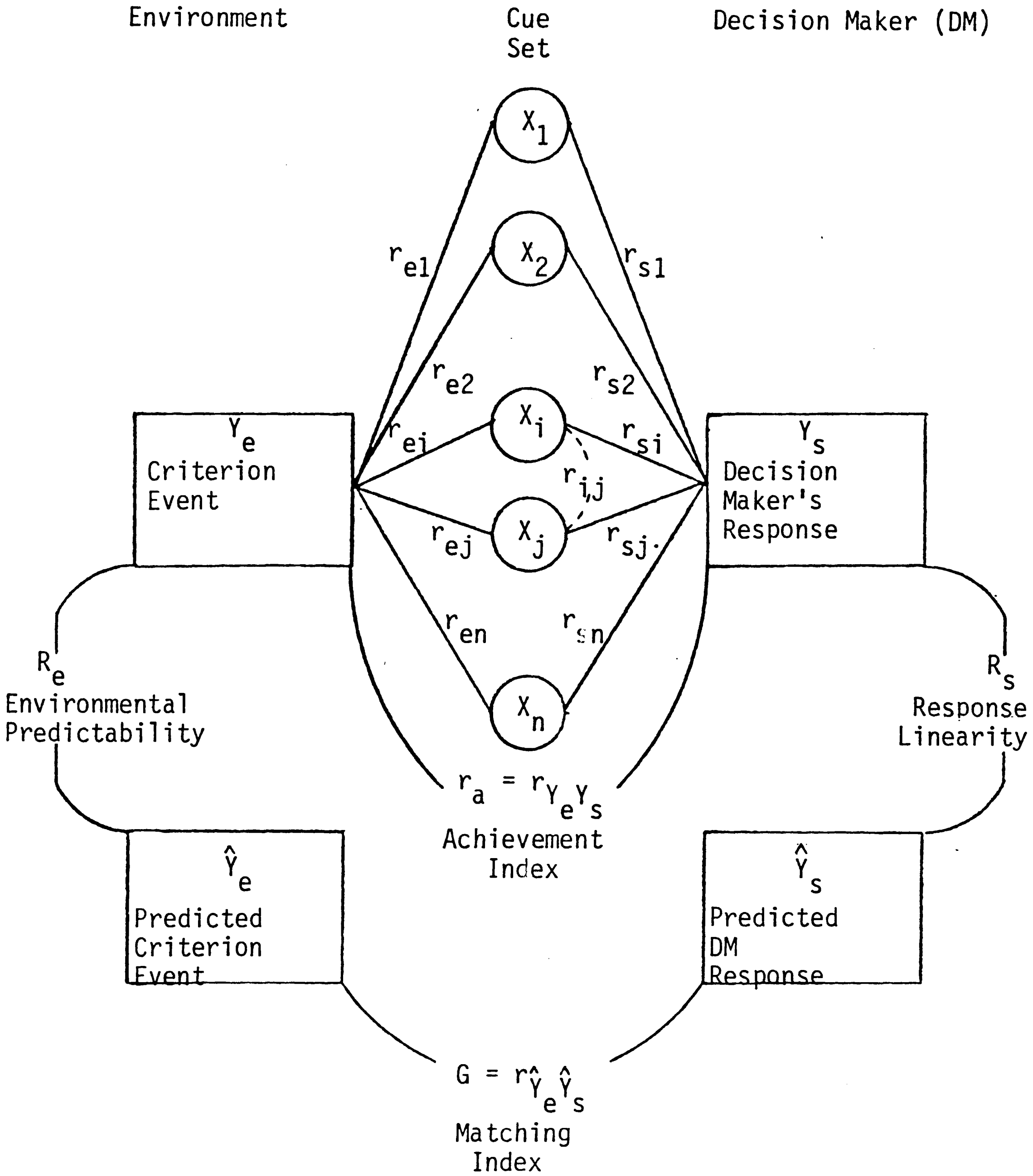

Figure 1. Brunswik's Lens Model

As Figure 1 implies, the relationship between the decision maker's response and the event which he is evaluating is described by a combination of several sub-relationships. These various relationships are typically formulated with the use of statistical techniques such as multiple linear regression, analysis of variance, multivariate scaling, or some other multivariate technique, depending upon the assumed statistical distributions of the data.[2]

Among the relationships on the environmental side of the model is the ecological validity of the cues (r_{ei}), which measures the correlation between the individual cues and the criterion event. When all of the cues are combined to form a multivariate relationship with the criterion event (e.g., a regression model), the resulting environmental predictability statistic (R_e) measures the relevance of the cue set in predicting the event.

Similar relationships are computed on the decision maker side of the lens model. The utilization coefficient (r_{si}) measures the decision maker's reliance on individual cues. The combination of all of the cues to form a relationship similar to the environment side yields a measure of the decision maker's consistency in judgment known as the response linearity (R_s).

The overall objective of the lens model studies is to produce a measure of the decision maker's accuracy in evaluating the event. This measure is known as the achivement index (r_a). However, the achievement index is an ex post measure of decision accuracy. To evaluate the

---

[2]For an excellent summary of several lens model studies in the area of accounting, see Libby (1981), pp. 142-150.

decision maker's processing of information, researchers measure the achievement index indirectly by connecting the environmental side of the model with the decision maker side with the matching index (G). This matching index measures the similarity of the decision maker's weightings of cues with the environment's weightings. Combining the environmental side (R_e) and the decision maker side (R_s) with the matching index (G) yields the following lens model equation:

$$r_a = GR_eR_s$$

The lens model equation shows that decision accuracy (r_a) is a multiplicative combination of the similarity of cue utilization for each side of the model (G), the environment's predictability (R_e), and the consistency of the decision maker (R_s). Intuitively, one would expect the achievement index will be less than one, because each of the three components (G, R_e, and R_s) would most likely be less than one. R_e would normally be less than one because, by definition, the environmental event is usually not perfectly predictable from the cues of information. R_s would normally be less than one because decision makers do not apply their knowledge about the event with perfect consistency. Finally, the failure of the decision maker to incorporate the optimal cue weightings from the environmental side of the model will cause G to be less than one. The significance of this lens model equation is that it reveals the various possible causes of suboptimal information processing by decision makers by combining these three potential sources of error which yields an overall measure of decision accuracy.

Judicial Decisions and the Lens Model[3]

Jensen and Horvitz (1979) used a lens model formulation to develop a theoretical framework for quantifying judicial decisions (see Figure 2). According to Jensen and Horvitz's depiction, the environmental side of the model represents the "true" events of the case. The cues of the information (X's) represent evidence about the existence of facts which the judge sees as relevant to the issue being decided in the particular case (as cited in the basis for his decision). Finally, the decision maker's response (Y_s) represents the actual judicial decision.

Within the prediction framework of the lens model, the goal of the decision maker is to make correct predictions about the event by utilizing the information set. The most relevant index of that goal is the achievement index (r_a), which measures the accuracy of the decision maker's predictions. The Jensen and Horvitz depiction of the judicial decision (Figure 2) does not provide this measure of prediction accuracy, due to the tautology caused by setting up the environmental side of the lens model as the "true" events of the case. For example, with respect to the question being addressed here, a security is deemed worthless because the judge declares it to be. Thus, the decision maker's prediction (Y_s) defines the criterion event (Y_e).

From the preceding discussion, it appears that the Jensen and Horvitz depiction of the judicial decision process excludes decision makers other than the judge and is, therefore, not truly user-oriented. As was previously stated in Chapter I, the objective of this study is

[3]The arguments developed in this section are similar to Libby's (1975) expansion of the Beaver, Kennelly, and Voss (1968) article on the predictive ability criterion of accounting measurement.

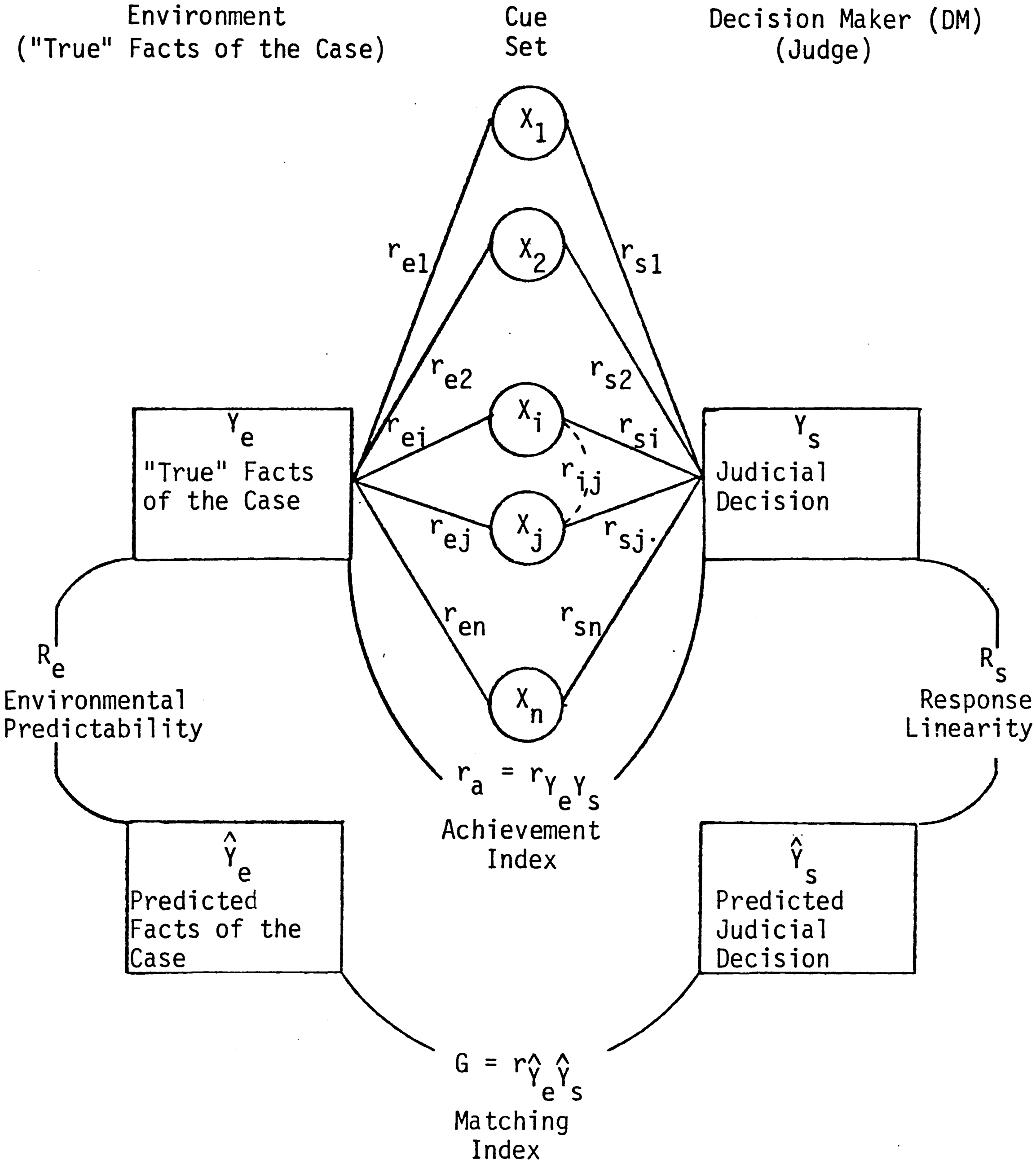

Figure 2. Judicial Decisions and the Lens Model: Jensen and Horvitz (1979) Depiction

to provide a model which can be used by taxpayers and their advisors to assess probable Tax Court outcomes of worthless security litigation. Accordingly, the framework for prediction of judicial decisions should include the taxpayers as a decision maker as in Figure 3.

In Figure 3, the judicial decision is considered to be the environmental event which is to be predicted by the taxpayer and his advisor. This framework will provide a basis for the calculation of the achievement index, which can provide some insight into the usefulness of such a predictive model.

Design of the Study

The General Model

As previously stated, the primary objective of this research is to develop a statistical prediction model of Tax Court judicial decisions of cases involving the determination of worthless securities. This environmental prediction model is represented by the variable Y_e in the lens model portrayal of the judicial decision process in Figure 3. The general format of this environmental prediction model is:

$$Y_e = f(X;B),$$

where Y_e = outcome of the case,

X = the matrix of explanatory variables, and

B = the matrix of parameters to be estimated.

The Y_e variable, outcome of the case, was coded as a (0,1) categorical variable where (0) meant that the year of claimed worthlessness by the taxpayer was rejected by the Tax Court and (1) meant that the year of claim was accepted. The X variables, the events which

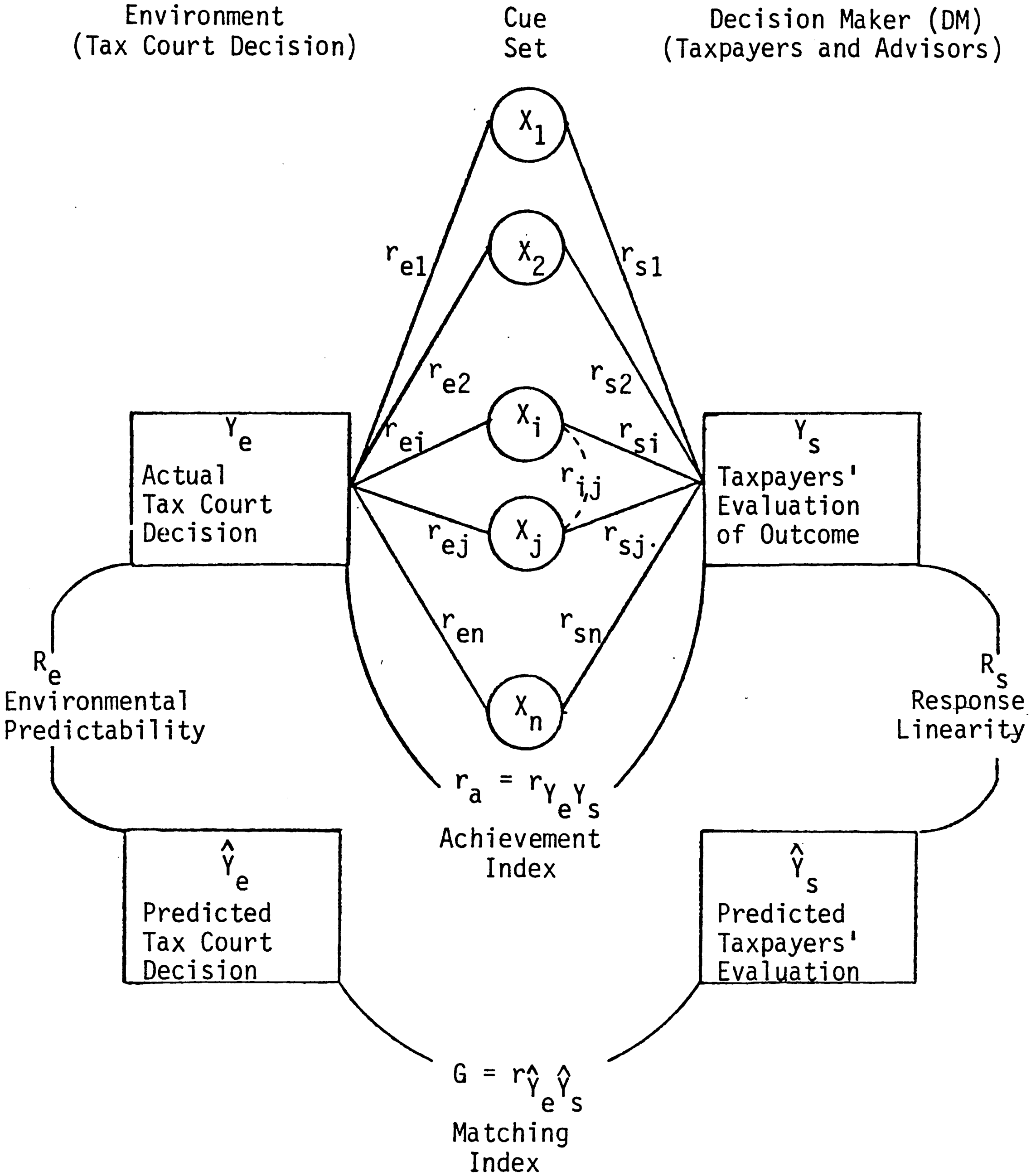

Figure 3. Predictive Framework of the Lens Model and Judicial Decisions

purportedly determine the outcome of the case, were extracted from the literature and from the cases themselves. A total of 26 variables was obtained for the analysis (see Appendix A). Since the timing of the events as well as their existence were both deemed relevant to this research, a coding scheme was devised to account for both aspects. An example of the coding scheme used for the X values follows:

X = Ai, where A is the discontinuance of operations, and
i is the time period (1, 2, or 3) e.g.:

A1 = 1, if operations were discontinued in a year prior to the claim year,
0, otherwise.

A2 = 1, if operations were discontinued during the claim year,
0, otherwise.

A3 = 1, if operations were discontinued in a year subsequent to the claim year,
0, otherwise.

<u>Selection of Cases</u>

The 76 cases listed in Appendix B were identified from the Prentice-Hall <u>Federal Taxes</u> (1983) service and the Prentice-Hall <u>Citator</u> (1983). From these 76 cases, 84 worthless security issues were identified and used in the model-building.

Cases tried in original trial courts other than the Tax Court were excluded from this study. One significant reason for including only Tax Court cases is the fact that the Tax Court's basis for its decision (i.e., its <u>ratio decidendi</u>) is included in the text of each case. For example, in the District Court the taxpayer may elect a jury trial if the issue to be decided is one of fact. If and when a security is worthless are questions of fact. If the case is decided by a jury, only the decision is included in the text of the case. The basis for the jury's decision is not included.

The problem suggested by behaviorists (that decisions may vary in similar fact cases because judicial reasoning is influenced by the personal characteristics of each judge) is mitigated in the Tax Court because of its review procedures. The individual judge who hears a case must submit his decision and the reasons for his decision to the Chief Judge of the Tax Court. The Chief Judge then reviews the decision and decides whether it may stand or whether it should be reviewed by a panel of Tax Court judges. This review process not only requires the original trial judge to explicitly state the reasonings for his decision in the text of the case, but it also provides a mechanism that increases the consistency of decisions among cases with similar facts.

Tax Court decisions are more apt to reflect a more uniform application of the tax laws than the numerous District Courts for two reasons. First, the Tax Court hears only federal tax issues which means that Tax Court judges are able to concentrate on the Federal tax law. In contrast, District Courts hear numerous non-tax cases as well as tax cases. Since the Tax Court judges deal only with Federal tax issues, they should develop greater expertise in Federal tax law than District Court judges who must spend substantial amounts of time on non-tax issues. Additional expertise in the Tax Court should result in more consistency in the interpretation and application of the tax law. Second, the Tax Court is a single court comprised of 16 judges who are appointed for overlapping 15 year terms. The doctrine of <u>stare decisis</u> applied to the Tax Court scenario implies that panels of judges will feel constrained by peer pressure to follow prior decisions made by other panels of judges currently serving on the Tax Court (Jensen and Horvitz, 1979).

Model Formulation

The two modeling approaches discussed in Chapter II (discriminant analysis and logit analysis) have been successfully used in different areas of business and economics. Following is a general discussion of each model, its assumptions, and any limitations encountered with the model.

Discriminant Analysis[4]

The objective of discriminant analysis is to produce a rule based upon values of the explanatory variables which classifies observations into the correct population. The usual assumptions of discriminant analysis are that the explanatory variables are normally distributed and that the variance-covariance matrices are equal in each population. In discriminant analysis, no "dependent variable" exists. Instead, a linear combination of explanatory variables classifies observations into the correct population by deriving coefficients which maximize the differences between the means of the population for a given standard deviation of the sample. When there are two populations, the discriminant rule classifies an observation based on the following conditional probabilities:

---

[4]For more background on discriminant analysis, see Lindeman (1980), Chapter 6.

$$P_i(Y=1) = \frac{e^{XB+\ln(p/q)}}{1 + e^{XB+\ln(p/q)}} \text{, and}$$

$$P_i(Y=0) = \frac{1}{1 + e^{XB+\ln(p/q)}} \text{,}$$

where Y = the population (assumed dichotomous),

X = the matrix of explanatory variables,

B = the vector of unknown parameters, and

p and q = the a priori probabilities of group membership 1 and 0, respectively.

Both Eisenbeis (1977) and Ohlson (1980) point out some of the limitations of discriminant analysis. When discrete explanatory variables are used (as in this study), the assumption of their normal distribution is clearly violated. However, Gilbert (1968) asserts that in examining the robustness of standard linear discriminant analysis, there is only a small loss in predictive accuracy as the number of variables and observations increase.

Another violation caused by discrete explanatory variables is the assumption of equal group dispersion (variance-covariance matrices). Gilbert's (1969) results indicate that when standard linear discriminant anlaysis is used with discrete data, significant differences in classification errors and conditional probabilities occur which are directly related to the differences in the dispersion of the groups. However, non-linear discriminant estimation overcomes this violation.

Logit Analysis[5]

Logit analysis is a transformation in which the log of the odds of group membership is linearly related to the matrix of explanatory variables and the matrix of unknown parameters estimates. This transformation is based on the cumulative standardized logistic probability density function:

$$P_i = \frac{1}{1 + e^{-XB}}$$

where P_i = probability values,

e = base of natural logarithm (i.e., 2.71828...),

X = matrix of explanatory variables, and

B = matrix of unknown parameter estimates.

This logistic transformation produces a cumulative standardized probability density function quite similar to the normal distribution (Pindyck and Rubenfeld, 1981, p. 288). In addition, the transformation constrains probabilities of group membership to the (0,1) interval.

The logit model is usually estimated by maximum likelihood techniques. As a result, the statistics of the logit model follow the chi-square distribution, which is the usual distribution when data are nominally measured as in this study. Following the traditional assumptions of the chi-square distribution, the logit model makes no assumptions about the probability distributions of the explanatory variables (in contrast to the normal distribution assumption in discriminant analysis), except for the assumption of a multinominal

---

[5]For additional background on logit analysis, see Forthofer (1981) and Amemiya (1981).

probability distribution.[6] Decision rules for classification of cases into the dichotomous populations are:

$$P_i(Y=1) = \frac{e^{XB}}{1 + e^{XB}} \text{ , and}$$

$$P_i(Y=0) = \frac{1}{1 + e^{XB}} \text{ .}$$

The advantages of the logit model over the discriminant model are in its assumptions, or more specifically, its lack of assumptions about the shape of the distributions of the data. There seem to be no major disadvantages to the logit model, except when it is estimated using a weighted least squares (WLS) approach. Forthofer and Lehner (1981) suggest that when using WLS to estimate the logit model, no more than one-fourth of the functions should be based on subpopulations with fewer than 25 observations, and in no case should a subpopulation have fewer than 10 observations. To avoid these data restrictions, Amemiya (1981) recommends using the maximum likelihood technique to estimate the logit model which permits model estimation with many or only a few observations per cell.

Analysis of Data

Relative Importance of Variables

In determining the allowance of a claim for the deduction of a worthless security, the Court must look not only to the value of the security, but to the timing of the occurrence of worthlessness as well.

---

[6]This assumption imposes no contraints, except for allowing for any of all the possible outcomes to be yielded from a single trial.

The Court looks for one or more events that indicate if and when a security becomes worthless. The impact of the timing of these events on the Court's decision to allow or disallow a claimed worthlessness within a particular taxable period was one of the objectives of this research.

As previously mentioned, 26 variables were identified for the model formulation. Inclusion of the three-tier timing scheme developed earlier in this chapter increased the total number of variables to 78. Because the number of explanatory variables was so large, the relative importance and statistical significance of each variable had to be determined in order to obtain a more parsimonious model of the decision.

To accomplish this task, stepwise techniques were used. The basic forward stepwise procedure (in a multiple regression context) is as follows. First, the explanatory variable which has the highest partial correlation with the dependent variable is selected. Second, the explanatory variable with the highest partial correlation coefficient is tested for significance at some prespecified level and added to the model if significantly nonzero. Third, the explanatory variables which have not yet been included in the model are searched to find the one which has the highest partial correlation with the dependent variable, given the other explanatory variables already in the model. Fourth, the variable with the highest partial correlation with the dependent variable, given the other independent variable(s) already in the model, is tested for significance at some predetermined level and added to the model if significantly nonzero. The procedure is continued until there are no explanatory variables which have a partial correlation with the dependent variable, given the other explanatory variable(s) already in the model, significantly nonzero at the predetermined significance level.

The stepwise procedures available in the SAS User's Guide: Statistics (1982) and the SAS Supplemental Library User's Guide (1980) were used for the discriminant model and the logit model, respectively. For discriminant analysis, variables entering the model are selected based upon their contribution to the discriminatory power of the model, as measured by Wilks' lambda. For logit analysis, entering variables are selected based upon Rao's efficient score statistic. For both models, a significance level of .05 was chosen for variables entering and exiting the model.

Classificatory Power of the Models

To determine classification accuracy, a comparison was made of the two statistical models (discriminant and logit) with a naive, or chance, model. The comparison was the simple difference between the actual percentage of observations classified into their correct groups provided by the statistical models and the expected percentage of correct classifications from the chance model. The chance model, as defined for this study, is based solely on the ratios, or proportions, of the groups (decisions) and is a result of the Law of Total Probabilities:

$$P(C) = P(C|i)\ P(i)\ ,$$

where $P(C)$ = probability of overall correct predictions,

$P(C|i)$ = conditional probability of correct predictions given group i, and

$P(i)$ = probability of occurrence of group i.

For the two-group population (denoted as 1 and 0 for consistency with earlier notation), the probability of overall correct prediction is:

$$P(C) = P(C|1)\ P(1) + P(C|0)\ P(0).$$

If the conditional probabilities are based upon the proportion of the groups, then:

$$P(C|i) = P(i).$$

Thus, the probability of correct predictions of the chance model based solely on proportions of group memberships is the sum of the squared percentages of each group, i.e.:

$$P(C) = [P(1)]^2 + [P(0)]^2$$

Hair et al. (1979, p. 102) suggest that, as a general rule of thumb, the probability of correct predictions for the classification models should be at least 25% higher than for this chance model.

It is generally accepted, however, that an upwardly biased predictive accuracy results when the observations used in the construction of the models are classified by that same model. To eliminate this bias, two verification methods are generally available--the holdout sample and the jackknife method. Because the sample size was relatively small, the holdout sample was rejected in favor of the jackknife method. This method holds out one observation at a time while a classification model is computed from the remaining observations. This hold-out observation is then group-classified by the resulting model. The procedure is repeated until all observations have been classified.

In light of several recent articles advocating a preference for the logit model over the discriminant model when qualitative variables are present (Eisenbeis, 1977; Ohlsen, 1980; and Stewart, 1982), an additional comparison of the classificatory power of the logit model with the discriminant model seemed warranted.

Following an approach similar to Talvitie (1974), the logit model and the discriminant model were ranked according to a classification criterion and a criterion based upon expected values. The classification criterion used in this study was the total number of misclassified cases in the overall sample. The model with the smallest number of misclassified cases would have the greatest predictive power. The expected value criterion involved a computation of an average absolute error, computed as follows:

$$E = \frac{\Sigma|Op - Oa|}{N},$$

where E = average absolute error,

Op = posterior probability of group classification,

Oa = actual groups classification (0 or 1), and

N = number of cases.

This average absolute error was viewed as an indication of the power of the models, i.e., the increase of the models' posterior probability of group membership over the chance model's prior probability of group membership. For example, one model's classification of group membership with a posterior probability of .90 would be viewed as more powerful than another model's classification of the same group membership with a posterior probability of only .65. In other words, the model which has the smaller error rate would be considered more accurate, even if both models have the same rate of correct group classifications.

With the use of this dual measure ranking procedure, it was hoped that one of the models would emerge as the superior classificatory model for this type of analysis. Clearly, if one model is ranked higher than (or at least as high as) the other model for both measures, this would provide strong evidence regarding its superiority. On the other hand, if neither model was dominant (i.e., each model was ranked higher in one of the measures), any conclusions concerning the superiority of either model would be speculatory, perhaps swayed by personal preferences for a particular model.

Stability of the Variables

The 84 issues on worthless securities used in this study span a 56 year time period (1926 through 1982). Because of this lengthy time space, a test of the inter-temporal stability of the models' parameters was performed in order to determine whether the variables included in the overall model were applied uniformly over time, or whether a shift in the importance of the variables occurred.

Prior studies in the area have used different methods to test for inter-temporal stability (Whittington et al., 1980; Stewart, 1983). Because there was no dramatic change in judicial determinations of worthless securities over the identified time period (such as significant changes in the Federal tax law or landmark decisions), the approach taken in this study was to divide the 84 observations into two equally-sized groups of 42, according to the year of the decision. This resulted in a subsample of pres-1951 cases and a separate subsample of post-1950 cases.

The analysis performed on the post-1950 cases followed the approach taken for the overall model. First, stepwise procedures were used for the logit and discriminant models. Second, the classification accuracy of the two statistical models was compared to the chance model based on the post-1950 proportions of successful and unsuccessful cases. Third, the jackknife technique was used to verify the classification accuracy and to eliminate any inherent upward bias in the measure. Fourth, the logit model was compared with the discriminant model and ranked as before. Finally, the rankings of the overall statistical models (computer over the 1926-1982 time space) were compared with the rankings of the statistical models made for the post-1950 subsample of cases.

Summary

The purpose of this chapter was to describe the methodology employed in the study. As a first step, a theoretical framework for quantifying the judicial decision was developed within the lens model paradigm. It was argued that, in order to be more user-oriented, the judicial decision should be portrayed as the environmental side of the lens model rather than the decision maker side, as was previously depicted by Jensen and Horvitz (1979).

The next phase in describing the study's methodology developed the general model which defined the relationships among the variables, as well as describing the coding system used for the model formulation. Additionally, the discriminant model and the logit model were introduced as the preferred statistical models to be used in the analysis of the data.

The final section of this chapter described the approaches taken to analyze the data. This phase described the selection process of the explanatory variables to be used in the statistical prediction models. Also described in this section was the approach taken to compare the two statistical models. Finally, this section specified the procedures used to test for the stability of these variables over time.

CHAPTER IV

RESULTS

The objective of this chapter is to discuss the analysis performed on the data, along with the results derived from the analysis. The chapter is divided into the following sections:

1. Relative importance of Variables
2. Classificatory Power of the Models
3. Stability of the Variables
4. Summary of the Results

Relative Importance of Variables

The objective of this study was to search for the events (and the timing of those events) upon which the Tax Court appears to be relying in determining worthless security issues. In order to obtain a functional statistical predictive model, the 78 variables (Appendix A) had to be reduced to a more reasonable number. As mentioned in Chapter III, stepwise techniques for the discriminant model and the logit model were utilized to accomplish this reduction.

The Models

As a result of the stepwise model building, five variables were found to be significant at the .05 level.[1] These five variables, in order of acceptance into the stepwise models were: (1) insolvency observed during the claim year (D2); (2) discontinuance of operations during the claim year (A3); (3) dissolution of the company occurred during the claim year (F2); (4) bankruptcy filed in a year subsequent to the claim year (G3); and insolvency observed in a year subsequent to the claim year (D3). These five variables were included in the standard discriminant and logit models to facilitate comparability of the classificatory power of the two models. The models and statistics for the logit function and the discriminant function are presented below in Table I and Table II, respectively.

TABLE I

LOGIT FUNCTION AND STATISTICS FOR THE OVERALL MODEL

Variable	Beta	Chi-Square Statistic	Significance Level
Intercept	-1.569		
D2	4.466	15.18	0.0001
A2	2.576	8.95	0.0028
F2	1.949	5.01	0.0252
G3	-3.328	4.96	0.0259
D3	-3.448	5.15	0.0232

[1]One variable, the entity viewed as a going concern at the end of the claim year (N2), was significant for the discriminant model, but was eliminated because of limited dispersion, which causes calculation difficulties in the logit model.

TABLE II

LINEAR DISCRIMINANT FUNCTION AND STATISTICS FOR THE OVERALL MODEL

Variable	Classification		F	Significance
	Reject	Accept	Statistic	Level
Constant	-0.367	-2.508		
D2	0.575	4.822	34.531	0.0001
A2	0.572	2.839	11.405	0.0011
F2	1.171	3.592	8.899	0.0037
G3	1.900	-0.565	5.596	0.0204
D3	1.829	-0.266	4.915	0.0294

Close inspection of the coefficients in both functions yields similar interpretations. Positive coefficients drive the probability of successful outcome upward (toward 1.0), and negative coefficients drive the probability of successful outcome downward (toward 0.0). Since the logit function has been established to provide the probability of a successful outcome, or acceptance by the Court, a direct comparison with the discriminant function's classification of successful (accepted) cases shows the signs of all coefficients are the same. Three variables, D2, A2, and F2, have positive coefficients, while the remaining two variables, G3 and D3 and the intercept have negative coefficients.

Because the interpretations of the 32 possible combinations of the presence or absence of these five variables are relatively straightforward, a discussion of each possible combination seems unwarranted. However, because of the coding scheme used, a few observations about the logit function should be made. With the use of a (0,1) coding (absent or present), simple addition of all factors cited as present yields the logit value. In transforming the logit into a probability value (see Chapter III for classification rules), it is readily seen that when the logit value is positive, a greater-than-50% probability of success is predicted (i.e., a success prediction). When the logit value is negative, a less-than-50% probability of success is predicted (i.e., a loss prediction). If any one of the three variables with positive coefficients (those occurring during claim year) is present, then, ceteris paribus, a successful outcome of varying degree of probability (depending on the specific variable) is predicted. On the other hand, if none of the three variables is present (i.e., no identifiable event), the prediction is a loss by the taxpayer. Note also that if either of the two negative-coefficient variables are present, its combination with the intercept is sufficient to outweigh any single positive-coefficient variable, thus producing a loss prediction.

Specific Variables

Those variables which increase the probability of a successful outcome (i.e., those with positive coefficients), in order of significance are: insolvency occurring during the claim year, discontinuance of operations during the claim year, and dissolution during the claim year. These variables seem intuitively valid because they can be viewed as "identifiable events" occurring during the year of a claim. The remaining variables which decrease the probability of a successful outcome (i.e., those with negative coefficients) are: bankruptcy filed in a year following the claim year, and insolvency occurring in a year following the claim year. The fact that both of these variables are events occurring in a year subsequent to the claim year indicates that there may have been some potential or liquidating value of the security at the end of the claim year. Although a discussion of each combination of variables seems unwarranted, a discussion of each of the specific variables may prove enlightening.

Insolvency Occurring During the Claim Year. This event should be the single most intuitively appealing factor in determining worthlessness of stock. When a corporation's liabilities exceed its assets, the stockholders have a claim to nothing, i.e., a worthless security. Indeed, this reasoning is verified by the fact that this was the first variable entered in the stepwise building process, i.e., it is the variable with the highest statistical significance in determining the outcome of a case.

In determining insolvency, the Tax Court usually looks beyond book values of assets and liabilities to their market values, as submitted in the facts of the case (Camp v. Comm., TC Memo 1953-273). One fact that should not be overlooked, however, is that if insolvency was present prior to the claimed year of worthlessness, this could indicate that the stock may have been worthless at some earlier date (Universal Consolidated Oil v. Comm., TC Memo 1961-24). Another fact which should not be overlooked is that the presence of other factors could outweigh the court's view that this is an "identifiable event". For example, in Goodrich v. Comm., 40 BTA 960, although insolvency first occurred during the claimed year, the fact that the business continued to operate indicated to the Court that a potential value of the stock existed. Accordingly, the Court rejected the claim.

Discontinuance of Operations During the Claim Year. This second statistically significant factor which is positively correlated with a successful outcome for the taxpayer is another "identifiable event" occurring within the claim year to which the court may look in determining worthlessness of the security. Of course, discontinuance of operations is an indication of worthlessness only if there are no remaining assets to be distributed to the shareholders. On the other hand, even though there are no assets to be distributed to shareholders in liquidation, there may be a potential value for the stock as long as the company is operating (Maguire v. Comm., TC Memo 1943-471).

Dissolution During the Claim Year. Admittedly, this was the most surprising event to be included as a significant factor in determining the worthlessness of a security. While there are a few cases in which the formal dissolution of a company was considered to be an "identifiable event" (Harmon v. Comm., TC Memo 1950-204), actual worthlessness of stock typically precedes formal dissolution and revocation of the corporation's charter (Est. of Triplett v. Comm., TC Memo 1950-198).

Inclusion of this variable in the model may not be well advised as indicated by the value of its beta coefficient (F2) in the logit function presented in Table I. Note that its value is just large enough to cause the logit value to be positive (i.e., a success prediction). Indeed, of the six cases in which this was the only variable (of the five significant variables) present, only three cases (Gittman, Heiss, and Iron Fireman Manufacturing) were correctly classified as successful outcomes; the remaining three (Morton, Est. of Triplett, and Universal Consolidated Oil Co.) were incorrectly classified as successful outcome (see Appendix C).

Bankruptcy Filed in a Year Subsequent to the Claim Year. It was suggested earlier that since the variables which occurred in a year subsequent to the claim year both had negative coefficients (which decrease the probability of a successful outcome), some potential or liquidation value probably existed at the end of the claim year. Indeed, this argument held true, as evidenced by cases where the company was regarded as a going concern until bankruptcy was filed (Ryan v. Comm., TC Memo 1956-169) or where the taxpayers failed to prove that worthlessness had occurred prior to the filing of bankruptcy (Lunsford v. Comm., TC Memo 1952-169).

One exception to this scenario occurred in the case of Richards v. Comm., TC Memo 1959-64. The company was so hopelessly insolvent at the end of the claim year that the formal filing of bankruptcy in the following year merely "served to further substantiate the claimed loss."

Insolvency Occurring in a Year Subsequent to the Claim Year. As was the case with bankruptcy filed in a year subsequent to the claim year, the fact that insolvency occurred in a year subsequent to the claim year could indicate that a potential value existed at the end of the claim year. This possibility is demonstrated by a rather interesting case, in which the taxpayer's claim for a worthless security was rejected by the court because there was still hope at the end of the claimed year for an ongoing business (Kleberg v. Comm., 43 BTA 277). The taxpayer then filed a claim for worthlessness occurring in the year immediately following the original claim year, which shifted the insolvency-occurring-in-a-subsequent-period variable (D3) to the insolvency-occurring-in-the-claim-year variable (D2) (Kleberg v. Comm., 2 TC 1025). In this second case, the claim was allowed.

Classificatory Power

The Basic Models

An indication of the validity of the logit model (presented in Table I) and the discriminant model (presented in Table II) is their ability to classify the observed cases as a successful (accepted) or an unsuccessful (rejected) outcome. To classify the cases as successful or unsuccessful, a prior probability level of 0.50 was used (i.e., equal prior probabilities of acceptance or rejection by the Court). Therefore, if the posterior probability was greater (less) than the cutoff of 0.50, the case was classified as successful (unsuccessful).

Table III shows that the logit model currently classified 73 of the 84 observations (86.9%), while the discriminant model correctly classified 74 of the 84 observations (88.1%). Note that Table III shows a slight discrepancy in the number and type of misclassified cases for the two models. Appendix C shows that there were nine misclassifications which were common to the two models.

The naive model introduced in Chapter III for predicting outcomes based upon the simple ratio of successful cases (46 of 84, or 54.8%) to unsuccessful cases 39 of 84, or 45.2%) would be correct $(54.8\%)^2 + (45.2\%)^2$ or 50.4% of the time. The two models developed in this study are substantially higher (36.5% higher for logit and 37.7% higher for discriminant) than this naive model.

TABLE III

CLASSIFICATION ACCURACY MATRIX--OVERALL MODEL

Actual Outcome	Number of Cases	Predicted Outcome Logit: Successful	Predicted Outcome Logit: Unsuccessful
Successful	46	40	6*
Unsuccessful	38	5*	33
		Predicted Outcome Discriminant: Successful	Predicted Outcome Discriminant: Unsuccessful
Successful	46	42	4*
Unsuccessful	38	6*	32

*Misclassification.

The Jackknife Model

Table III presented the classification accuracy rates for the logit model and the discriminant model. However, because the observations used to develop the models were also classified by that same model, the accuracy rates presented in Table III are biased upward. To eliminate this bias, the jackknife technique was used.

Since the classification accuracy of the logit and discriminant models was virtually equal, the jackknife method was performed only on the logit model. This decision was justified on the grounds that the logit model was considered theoretically preferable because of its assumptions about the probability distributions of the data. Table IV shows that the jackknifed-logit model was not substantially lower in its prediction accuracy than the upwardly biased logit model. The jackknifed-logit model correctly classified 71 of the 84 observations (84.5%) which was a reduction of only 2.4% accuracy (2 cases) from the upwardly biased logit model.

TABLE IV

JACKKNIFED-LOGIT CLASSIFICATION ACCURACY MATRIX--OVERALL MODEL

Actual Outcome	Number of Cases	Predicted Outcome	
		Successful	Unsuccessful
Successful	46	40	6*
Unsuccessful	38	7*	31

*Misclassifications.

The reduction in classification accuracy was, of course, not surprising. An interesting note can be made in reference to Appendix C where the probability of successful outcome is presented for each case and for each model, including the jackknifed-logit model. As previously mentioned, there was a slight discrepancy in the misclassifications of the logit model and the discriminant model (see Table III). The jackknifed-logit model misclassified every observation which was misclassified by each of the two original models. Close inspection of the four cases which were not commonly misclassified by all three models (Goodrich, Hankey, Melick, and Ryan) shows that the posterior probability levels were relatively "close" to the predetermined cutoff level of 0.50, which is perhaps indicative of a "toss-up" of the classification of the outcome of the case.

Comparison of the Logit Model and the Discriminant Model

Recently, several articles on qualitative variables have advocated a preference for the logit model over the discriminant model because of the discriminant's violation of normality assumptions as discussed in Chapter III (Eisenbeis, 1977; Ohlsen, 1980; and Stewart, 1982). To provide more insight into the appropriateness of the two models in these types of studies, comparisons were made between the two models following an approach similar to Talvitie (1974), in which the models were ranked according to a classification criterion and a criterion based upon expected values.

The classification criterion was based on the numbers of misclassified cases used in the construction of the two models. This classification criterion considered three types of misclassifications: misclassified successful cases (Type I misclassification); misclassified unsuccessful cases (Type II misclassifications); and finally, the total number of all misclassified cases. Division of the total number of all misclassifications into the Type I and Type II categories was made to account for the different potential losses which could be incurred by the taxpayer. To facilitate this ranking criteria, the following three assumptions were made: (1) the tax benefit for the claimed year of worthlessness exceeds the litigation fees for the defense of the claim; (2) if the taxpyaer chooses not to enter litigation, then he accepts the IRS position and loses the tax benefit for the claimed year of worthlessness; and (3) the taxpayer makes his decision of whether or not to enter litigation based on the posterior probability of group classification from the model, i.e., he enters litigation when the posterior probability of success exceeds 0.5, and does not enter litigation (accepts the IRS position) when the posterior probability of success is less than 0.5. Based on these assumptions, the loss incurred by the taxpayer from a Type I misclassification (in which the posterior probability of the model indicates a loss when the actual outcome was successful) exceeds the loss incurred by the taxpayer from a Type II misclassification (in which the posterior probability of the model indicates a successful outcome when the actual result was unsuccessful). The misclassifications for the individual cases are presented in Appendix C and were summarized earlier in Table III.

The expected value criterion was based on an average absolute error of prediction of the posterior probability of group classification for each model. This criterion, whose computational formula was given in Chapter III, was viewed as an indication of the strength of each model's posterior probability of group classification. Appendix D contains the absolute prediction errors of both models for the individual cases. Table V, below, contains a summary of the ranking criteria used to compare the logit model with the discriminant model.

Table V indicates that neither model clearly dominates the other, according to this ranking procedure, because each model was ranked narrowly ahead of the other in one category. In fact, a t-test of the average absolute errors showed there was no significant (α = 30%) difference between the two models. Hence, despite the theoretical preferences of the logit model over the discriminant model, the two models performed with virtual equivalence.

TABLE V

RANKINGS OF THE LOGIT AND DISCRIMINANT FUNCTIONS--OVERALL MODEL

Function	Number of Misclassifications Type I	Type II	Total	Average Absolute Error
Logit	6	5	11	.2090
Discriminant	4	6	10	.2191

Stability of the Models

A test of the temporal stability of the models' parameters was performed to determine whether the variables derived from the overall model (1926-1982) were being applied consistently over time. As discussed in Chapter III, the cases were arbitrarily divided into two equally-sized subgroups according to the year in which the case was decided. An analysis of the post-1950 subgroup of cases (which followed the same approach used for the overall model) follows.

The Models and Variables

The post-1950 stepwise model-building process for the discriminant model yielded six variables which were significant at the .05 level. These variables, in order of acceptance into the model were: (1) insolvency observed during the claim year (D2); (2) the chief executive officer or owner resigned or died in the year prior to the claim year (O1); (3) operations were discontinued during the claim year (A2); (4) a plan of liquidation was adopted during the claim year (C2); (5) operations were discontinued prior to the claim year (A1);

and (6) owner advances or guarantees were made prior to the claim year (L1). The discriminant model and its statistics are presented below in Table VI.

TABLE VI

LINEAR DISCRIMINANT FUNCTION AND STATISTICS--POST-1950 MODEL

Variable	Classification Reject	Classification Accept	F Statistic	Significance Level
Constant	-0.1951	-3.8096		
D2	1.0761	5.2782	11.563	0.0015
O1	0.8923	7.8570	6.147	0.0176
A2	0.9008	3.7349	4.845	0.0339
C2	-0.0798	5.3466	4.636	0.0379
A1	1.1369	6.8011	4.734	0.0362
L1	0.5032	-3.3465	3.963	0.0544

An attempt to build a logit model for the post-1950 cases using stepwise techniques proved relatively unsuccessful. The stepwise logit procedure ceased model-building after the first variable, D2. To facilitate comparability of the post-1950 logit and discriminant models, the six significant variables produced from the stepwise discriminant procedure were used to compute a logit model, presented in Table VII.

A comparison of the overall models (Tables I and II) with the post-1950 models (Tables VI and VII) yields the following conclusions. Only two variables, D2 (insolvency occurring during the claim year) and A2 (discontinuance of operations during the claim year), were common to the overall model and the post-1950 model. This clearly indicates that these two variables have been considered as significant identifiable events over the entire time period.[2] The four remaining variables of the post-1950 model, however, do not appear in the overall model. Interpretation of these four variables in a statistical sense is extremely difficult because of the problems of limited dispersion (see Table VII). However, the following inferences can be offered. As in the overall model, a comparison of the signs of the coefficients of the variables entering the logit model with those of the discriminant model shows that all the signs of the coefficients in the different models are again identical. All variables in the post-1950 model, except for the L1 variable, have positive signs for their coefficients, increasing the probability of a successful outcome for the taxpayer. The L1 variable (owners advances prior to the claim year) and the intercept both have negative coefficients, decreasing the probability of a successful outcome.

Classificatory Accuracy

Despite the difficulty encountered concerning the four new variables in the post-1950 model, both the logit model and the discriminant model performed with relative satisfaction. Appendix E contains the posterior probabilities of groups classification of the post-1950 cases for each model. The classifications of these cases are summarized in Table VIII.

---

[2]These two variables were also entered into the pre-1951 cases subsample in a stepwise discriminant model.

TABLE VII

LOGIT FUNCTION AND STATISTICS--POST-1950 MODEL

Variable	Beta	Chi-Square Statistic	Significance Level
Intercept	-2.9509		
D2	3.4876	7.40	0.0065
01*	12.3799	--	--
A2	2.6733	4.41	0.0357
C2*	24.4002	--	--
A1*	10.7738	--	--
L1*	-15.6812	--	--

*These parameters were considered to be infinite in the logit model (i.e., standard errors were zero) and were estimated by the logit procedure. This situation is usually the result of empty cells in the contingency table, because the variable's value was always equal to the dependent variable's value.

TABLE VIII

CLASSIFICATION ACCURACY MATRIX--POST-1950 MODEL

Actual Outcome	Number of Cases	Predicted Outcome Logit: Successful	Predicted Outcome Logit: Unsuccessful
Successful	19	16	3*
Unsuccessful	23	2*	21
		Predicted Outcome Discriminant	
Successful	19	16	3*
Unsuccessful	23	2*	21

*Misclassifications.

Table VIII shows that the discriminant function and the logit function obtained for the post-1950 model had the same classification accuracy--37 of the 42 cases were correctly classified (88.1%). (In fact, the misclassified cases in the post-1950 model were the same for each function.) This accuracy is an improvement over the naive model for the post-1950 cases of 37.7%, which is essentially equivalent to the improvement obtained for the overall model.[3]

Following the approach taken for the overall model, the jackknifing technique was performed for the post-1950 logit model. This resulted in correct classification of 35 of the 42 post-1950 cases (83.3%), which was a reduction of 4.8% in classification accuracy (2 cases) from the biased post-1950 logit model. These two additional misclassified were again "close" to the predetermined cutoff level of 0.50.

The Overall Models v. The Post-1950 Models

The analysis concerning the stability of the variables thus far suggests that some explantory variables were not stable over time, since there were different sets of variables for the overall models and the post-1950 models. To test for the significance of this apparent difference, the ranking procedure used earlier (to compare the overall logit model with the overall discriminant model) was performed on both models over both time periods. This resulted in a ranking of four models: the overall logit, the post-1950 logit, the overall discriminant, and the post-1950 discriminant.

---

[3]The naive model (discussed in Chapter III) would be correct $(19/42)^2 + (23/42)^2$, or 50.4%, of the time.

The posterior probabilities of group classification for the individual post-1950 cases for all four models are presented in Appendix E. From these posterior probabilities, average absolute errors of prediction were computed as before and are presented in Appendix F. Table IX summarizes the ranking for all four models.

TABLE IX

RANKINGS OF THE LOGIT AND DISCRIMINANT FUNCTIONS--OVERALL AND POST-1950 MODELS FOR POST-1950 CLASSIFICATIONS

Model	Number of Misclassifications			Average Absolute Error
	Type I	Type II	Total	
Logit				
Overall	4	3	7	.2198
Post-1950	3	2	5	.1571
Discriminant				
Overall	3	3	6	.2389
Post-1950	3	2	5	.1845

Table IX indicates that the post-1950 logit model narrowly dominates the other models, since it was ranked at least as high as any other model in each of the ranking criteria. The post-1950 discriminant model followed closely, with the two overall models ranked last. However, the improvement provided by the post-1950 model was not statistically significant from any of the other models.[4]

[4]t-tests indicated that the largest difference was significant only at the 18% level.

Since there were no statistically significant differences among the four models in Table IX, one could conclude that the overall models' predictions were equivalent to the post-1950 models' predictions. Thus, the conclusion concerning the temporal stability of the five variables in the overall model is somewhat speculatory. However, additional readings of the three cases which had the largest changes in posterior probabilities between the overall models and the post-1950 models (Ainsley, Boyer, and Jessups #2) indicated that the new variables introduced in the post-1950 models appear to have been included for "noise reduction" in the model, perhaps caused by the smaller post-1950 sample size. The posterior probability in each of these three cases was changed because of one variable (L1, A1, and O1, respectively), which seemed to have nothing at all to do with the decision. To confirm the suspicion that these three variables were included as "noise reducers," a stepwise model was built for the post-1950 sample, excluding these three cases. The three variables were not found to be significantly nonzero. Therefore, based on this additional analysis, the five variables in the overall model appear to be stable over the entire period studies, 1926-1982.

Summary of the Results

The purpose of this chapter was to discuss the analysis of the data and to report the results obtained from the analysis. The chapter first reported the results of the stepwise building models used to identify variables which were statistically significant in classifying case outcomes. Second, the classification accuracy for each model was presented and demonstrated to be a significant improvement over the chance model. Third, a ranking procedure was used to compare the classificatory power of the logit model with the discriminant model, and the results of the procedure indicated that the two models performed with virtual equivalence. Finally, the analysis to test for inter-temporal stability suggests that the variables used in the models appear to be stable over the time period used in the study.

CHAPTER V

SUMMARY AND CONCLUSIONS

The major objective of this research was to idenfity specific events, and the timing of those events, upon which the Tax Court appears to rely in determining the outcome of worthless security litigation. To accomplish this objective, 84 worthless security cases decided by the Tax Court were identified and used to build statistical models for the purpose of classifying and predicting Tax Court determinations of the year of worthlessness of a security. A secondary objective of this research was to compare two commonly used statistical prediction models in order to determine which model was more appropriate for this type of research.

The objective of this chapter is to summarize the study's major findings, to discuss the limitations of the study, and to introduce some possible extensions of this research.

Major Findings and Implications

Ability of the Variables to Classify Outcomes

A five-variable logit model and a five-variable discriminant model were built using stepwise techniques for the purpose of classifying Tax Court decisions concerning worthless security issues. The jackknife technique was used as an independent verification of the model's classification accuracy. The results of this process (presented earlier in Table IV) indicate a relatively high classification accuracy, 84.5%, which was significantly higher than the naive model described in Chapter III.

Due to the high degree of the model's classification accuracy, it appears that the Tax Court is relatively consistent in its decisions concerning worthless security issues. The Tax Court appears to rely heavily upon the five variables which are summarized below in Table X.

TABLE X

SIGNIFICANT FACTORS USED BY THE TAX COURT
IN DECIDING WORTHLESS SECURITIES CASES

Factors Positively Related to Successful Outcomes:

1. Insolvency occurring during the claim year
2. Discontinuance of operations during the claim year
3. Dissolution of the company during the claim year

Factors Negatively Related to Successful Outcomes:

4. Bankruptcy filed after the claim year
5. Insolvency occurring after the claim year

These factors are consistent with research findings obtained by traditional tax research techniques which were discussed in Chapter II. The importance of this finding is its reduction of numerous potential identifiable events typically found in the traditional research literature (Hasselback, 1978) to a few statistically significant events. This is not to say, however, that the presence of other factors is unimportant. Indeed, some of the factors found to be statistically significant in this study may be more relevant in <u>specific</u> cases than others.

Temporal Stability of the Model

Two sets of statistical classification models were constructed to determine whether the five variables in Table X were used consistently across time. One set of models was constructed over the entire time span of cases used in the study (1926-1982), while the other set of models was constructed over the most recent half of the cases in the study (1951-1982). Although the post-1950 set of models contained some different variables than the overall set of models, there was no significant increase in classification accuracy. Furthermore, the difference in the variables included appear to be the result of the influence of three unusual cases in the small sample size. It was therefore concluded that the five factors in Table X appear to be stable over time.

Comparison of Logit and Discriminant Models

A secondary objective of this study was to compare the logit model with the discriminant model in their abilities to classify Tax Court decisions. This was accomplished by ranking the models in a manner similar to the Talvitie (1974) study. Despite theoretical preferences for the logit model, the results of the comparison indicated that the two models performed with virtual equivalence. It was concluded that either model could be used with equal success in these types of studies.

Use of the Model by Taxpayers

The findings of this study should prove most helpful to taxpayers. They could use this model to evaluate their decision of whether to contest an IRS position which denied the claimed year of a worthless security deduction. Assuming a high posterior probability of success is predicted by the model, perhaps the taxpayer could even introduce this model to the IRS or to the Tax Court as evidence in support of his position.

In addition to using the model as a predictor of litigation outcome, taxpayers could also use the model in planning the year of deduction for claimed worthlessness. In some situations, the taxpayer could have some degree of control over the timing of certain events. For example, if a taxpayer has control of a corporation which is experiencing insolvency and he desires to write off his investment as worthless, then to some extent, he could perhaps "arrange" the date which the company discontinues operations to yield a more advantageous tax benefit.

Limitations of the Study

The process of reading and coding the opinions of the Tax Court judges was performed solely by the author. Copeland et al. (1981) found that certain inconsistencies and biases are present in such circumstances. Fortunately, however, an independent source, Warner et al. (1978) was available for verifying 26 of the 84 cases in the study. Although there was no statistical analysis performed by Warner, a similar analysis for detecting the presence of certain variables in specific time periods was performed. In all 26 cases, no discrepancies were found between the codings in this study and the codings in the Warner study.

The conclusions concerning the significant factors in determining a worthless security claim were based solely upon the analyses of Tax Court decisions. These conclusions do not necessarily apply to worthless security cases heard in the various district courts or the Court of Claims. Consequently, generalization of these results to cases-tried in the other courts should be made with caution. However, because the study found a high degree of consistency in the application of these variables by the Tax Court, these variables should be given strong consideration by the other courts.

Suggestion for Further Research

In Chapter III, a theoretical framework for predicting judicial decisions was established within the Lens Model paradigm. This depiction suggested that the judicial decisions should be the environmental event to be predicted by taxpayers and their advisors (see Figure 3). As an extension of this research, an experimental study could be designed using tax "experts" (or surrogates) and disguised facts from a selection of the cases used in this study for the purpose of predicting the judicial decisions. This would not only give some indication about the difficulty or ease in predicting the outcomes of the cases used in this study, but it would also complete the Lens Model framework.

SELECTED BIBLIOGRAPHY

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

Amemiya, T. "Qualitative Responses Models: A Survey." Journal of Economic Literature (December, 1981), pp. 1483-1536.

Ashton, R. H. Studies in Accounting Research #17: Human Information Processing in Accounting. Sarasota, FL: American Accounting Association, 1982.

Beaver, W. H., J. W. Kennelly, and W. M. Voss. "Predictive Ability as a Criterion for the Evaluation of Accounting Data." The Accounting Review (October, 1968), pp. 675-683.

Brunswik, E. The Conceptual Framework of Psychology. Chicago: The University of Chicago Press, 1952.

Copeland, R. M., R. L. Taylor, and S. H. Brown. "Observation Error and Bias in Accounting Research." Journal of Accounting Research (Spring, 1981), pp. 197-207.

Cullison, A. D. "An Orientation for Formalized Hohfeldian Analysis." Model Uses of Logic in Law (June, 1966), pp. 58-77.

Cox, D. R. The Analysis of Binary Data. London: Methuen and Co., 1970.

Deakin, E. H. "A Discriminant Analysis of Predictors of Business Failure." Journal of Accounting Research (Spring, 1972), pp. 167-179.

Draper, N. R. and H. Smith. Applied Regression Analysis. New York: John Wiley and Sons, Inc., 1981.

Duncanson, I. and G. Samuel. Jurisprudence in a Nutshell. London: Sweet and Maxwell, 1980.

Eisenbeis, R. A. "Pitfalls in the Application of Discriminant Analysis in Business, Finance, and Economics." Journal of Finance (June, 1977), pp. 875-900.

Englebrecht, T. D. and R. J. Rolfe. "An Empirical Inquiry into the Determination of Dividend Equivalence in Stock Redemptions." Journal of the American Taxation Association (Summer, 1982), pp. 19-25.

Forthofer, R. N. and R. G. Lehnen. Public Program Analysis: A New Categorical Data Approach. New York: Wadsworth, Inc., 1981.

Gilbert, E. S. "On Discrimination Using Qualitative Variables." Journal of the American Statistical Association (December, 1968), pp. 1399-1412.

__________. "The Effect of Unequal Variance-Covariance Matrices on Fisher's Linear Discriminant Function." Biometrics, 25 (September, 1969), pp. 505-515.

Green, T. "Outline of Points to be Considered in Bad Debts and Worthless Security Writeoffs." 5th NYU Institute on Federal Taxation (1946), pp. 646-653.

Grizzle, J. E., C. F. Starmer, and G. G. Koch. "Analysis of Categorical Data for Linear Models." Biometrica, 25 (September, 1969), pp. 489-504.

Hair, J. F., R. E. Anderson, R. C. Tatham, and B. J. Grablowsky. Multivariate Data Analysis. Tulsa, OK: Pennwell Publishing Company, 1979.

Hasselback, J. R. "Security Losses: The Importance of Being Worthless." Tax Advisor (December, 1978), pp. 102-110.

Jensen, H. L. and J. S. Horvitz. "A Theoretical Framework for Quantifying Legal Decisions." Jurimetrics Journal (Winter, 1979), pp. 121-139.

Libby, R. "Accounting Ratios and the Prediction of Failure: Some Behavioral Evidence." Journal of Accounting Research (Spring, 1975), pp. 150-161.

__________. "The Use of Simulated Decision Makers in Information Evaluation." The Accounting Review (July, 1975), pp. 475-489.

__________. Accounting and Human Information Processing: Theory and Applications. New York: Prentice-Hall, Inc., 1981.

Lindeman, R. H., P. F. Merenda, and R. Z. Gold. Introduction to Bivariate and Multivariate Analysis. Glenview, IL: Scott, Foresman and Co., 1980.

Madeo, S. A. "An Empirical Analysis of Tax Court Decisions in Accumulated Earnings Cases." The Accounting Review (July, 1979), pp. 538-553.

Ohlson, J. A. "Financial Ratios and the Probabilistic Prediction of Bankruptcy." Journal of Accounting Research (Spring, 1980), pp. 109-131.

Pindyck, R. and D. Rubenfeld. Econometric Models and Economic Forecasts. New York: McGraw-Hill, 1981.

Prentice-Hall American Federal Tax Reports, Vol. 28. New York: Prentice-Hall, Inc., 1943.

Prentice-Hall Citator. New York: Prentice-Hall, Inc., 1983a.

Prentice-Hall Federal Taxes. New York: Prentice-Hall, Inc., 1983b.

SAS Institute, Inc. SAS Supplemental Library User's Guide, 1980 Edition. Cary, NC: SAS Institute, Inc., 1980.

________. SAS User's Guide: Statistics, 1982 Edition. Cary, NC: SAS Institute, Inc., 1982.

Shuckman, P. Readings in Jurisprudence and Legal Philosophy. Boston: Little, Brown and Co., Inc., 1979.

Stewart, D. "Use of LOGIT Analysis to Determine Employment Status for Tax Purposes." Journal of the American Taxation Association (Summer, 1982), pp. 5-12.

Talvitie, A. "Comparison of Probabilistic Modal-Choice Models: Estimation Methods and System Inputs." Highway Research Record, 392 (1972), pp. 111-120.

Tye, C. W. "Pointers in Bad Debts, Worthless Securities, and Other Business Losses." 6th NYU Institute on Federal Taxation (1947), pp. 681-702.

Warner, J. P., L. J. Lee, and A. H. Schreiber. 96-3rd Tax Management Portfolio, Losses: General Requirements. Washington, D.C.: Tax Management, Inc., 1978.

Werner, J., W. Wendling, and N. Budde. "A Comparison of Probit, Logit, Discriminant, and OLS: The Physician's Location Choice Problem." 1979 Proceedings of the Business and Economic Statistics Section, American Statistical Association, pp. 631-635.

Whittington, R. and G. Whittenburg. "Judicial Classification of Debt Versus Equity--An Empirical Study." The Accounting Review (July, 1980), pp. 409-418.

Worthy, K. M. "Stock Losses: Establishing Worthlessness." 22nd NYU Institute on Federal Taxation (1964), pp. 289-314.

APPENDIXES

APPENDIX A

VARIABLES USED IN STUDY

VARIABLES USED IN STUDY*

Variable Identification	Variable
A	Discontinuance of Operations
B	Sale of Major Assets
C	Adoption of Liquidation Plan
D	Insolvency
E	Creditor or Government Foreclosure
F	Dissolution
G	Bankruptcy Filed
H	Reorganization Initiated
I	Trustee or Receiver Appointed
J	Net Operating Loss
K	Retained Earnings Deficits
L	Owner Advances or Guarantees
M	Default on Current Obligations
N	Company Regarded as a "Going Concern"
O	Chief Executive Officer Resigned, Died, etc.
P	Major Asset(s) Determined Worthless
Q	Attitude of Owner in Determination of Worthlessness
R	No Market for Securities
S	Intervention or Takeover by Government or Creditors
T	Inability to Raise Outside Debt
U	Owners Discontinues Advances of Funds
V	Debt Refinanced Successfully
W	Liquidation Completed
X	Business Upturn
Y	Additional Stock Issues
Z	Reorganization Attempts Abandoned or Completed

*Note that each variable had 3 levels, depending on the timing of its occurrence. For example,

A1 = Discontinuance of Operations was observed in a year prior to the claim year,

A2 = Discontinuance of Operations was observed in the claim year, and

A3 = Discontinuance of Operations was observed in a year subsequent to the claim year.

APPENDIX B

CASES USED IN STUDY

Number	Year of Decision	Case and Citation
1	1971	Aagaard v. Comm., 56 TC 191
2	1928	Adamson v. Comm., 17 BTA 17
3	1931	Adirondack Sec. Co. v. Comm., 23 BTA 61
4	1963	Ainsley Corp. v. Comm., TC Memo 1963-183
5	1962	American Steel & Pump Co. v. Comm., TC Memo 1962-24
6	1971	Austin Co. v. Comm., 71 TC 955
7	1962	Benton v. Comm., TC Memo 1962-292
8	1955	Boyer v. Comm., TC Memo 1955-105
9	1960	Brandtjen & Kluge, Inc. v. Comm., 34 TC 416
10	1931	Braun v. Comm., 34 BTA 536
11	1922	Brown v. Comm., 27 BTA 176
12	1958	Butler v. Comm., TC Memo 1958-150
13	1931	Byrd v. Comm., 21 BTA 1183
14	1972	Byron v. Comm., 58 TC 731
15	1953	Camp v. Comm., TC Memo 53-273
16	1940	Connelly v. Comm., 42 BTA 237
17	1927	C. E. Conover Co. v. Comm., 7 BTA 1234
18	1954	Drachman v. Comm., 23 TC 558
19	1928	Eysenbach v. Comm., 10 BTA 716
20	1955	Funke v. Comm., TC Memo 1955-156
21	1931	Gahagen v. Comm., 22 BTA 828
22	1974	Gilmore v. Comm., TC Memo 1974-41
23	1974	Ginsburg v. Comm., TC Memo 1974-191
24	1939	Goodrich v. Comm., 40 BTA 960
25	1937	Estate of Gran v. Comm., 36 BTA 1233
26	1949	Gussow, Kahn & Co. v. Comm., 13 TC 580
27	1929	Grittman v. Comm., 11 BTA 122
28	1931	Gwynne v. Comm., 22 BTA 164
29	1975	Hankey v. Comm., TC Memo 1975-97
30	1950	Harmon v. Comm., TC Memo 50-204
31	1937	Heiss v. Comm., 36 BTA 833
32	1977	Herrick v. Comm., TC Memo 1977-71
33	1957	Estate of Howe v. Comm., TC Memo 1957-58[1]
34	1945	Iron Fireman Mfg. Co. v. Comm., 5 TC 452
35	1927	Jackling v. Comm., 9 BTA 312
36	1977	Jessups v. Comm., TC Memo 1977-289[1]
37	1944	George M. Jones Co. v. Comm., TC Memo 1944.[2]
38	1926	Jones v. Comm., 4 BTA 1286
39	1927	Joslyn Mfg. & Supply Co. v. Comm., 6 BTA 749
40	1927	Kaler v. Comm., 6 BTA 1116
41	1978	Kirven v. Comm., TC Memo 1977-28
42	1941	Kleberg v. Comm., 43 BTA 277[1]
43	1931	Ladew v. Comm., 22 BTA 1213
44	1929	Lee v. Comm., 15 BTA 1213
45	1931	H. Liebes & Co. v. Comm., 23 BTA 787

Number	Year of Decision	Case and Citation
46	1955	Lincoln v. Comm., 24 TC 669
47	1952	Lunsford v. Comm., TC Memo 1952-169
48	1943	Maguire v. Comm., TC Memo 1943-471
49	1976	Malmstedt v. Comm., TC Memo 1976-46
50	1929	Mayer v. Comm., 16 BTA 1239
51	1944	Meissner v. Comm., TC Memo 1944-259
52	1947	Melick v. Comm., 6 BTA 70
53	1946	Anthony P. Miller, Inc. v. Comm., 7 TC 729
54	1942	Moot v. Comm., TC Memo 1942-583
55	1938	Morton v. Comm., 37 BTA 1270
56	1928	Pearsall v. Comm., 10 BTA 467
57	1980	Pomeranz v. Comm., TC Memo 1980-36
58	1979	Post v. Comm., TC Memo 1979-419
59	1976	Reese v. Comm., TC Memo 1976-275
60	1959	Richards v. Comm., TC Memo 1959-74
61	1976	Richards v. Comm., TC Memo 1976-380
62	1930	Robinson v. Comm., 21 BTA 677
63	1969	Ruud v. Comm., TC Memo 1969-252[1]
64	1956	Ryan v. Comm., TC Memo 1956-169
65	1982	Sankary v. Comm., TC Memo 1982-387
66	1977	Scifo v. Comm., 68 TC 714[1]
67	1979	Shvetz v. Comm., TC Memo 1979-298
68	1975	Singer v. Comm., TC Memo 1975-63
69	1941	Spruance v. Comm., 43 BTA 221
70	1950	Estate of I. C. Triplett, Sr. v. Comm., TC Memo 1950-198
71	1961	Universal Consolidated Oil Co. v. Comm., TC Memo 1961-246
72	1938	Watson v. Comm., 38 BTA 1026[1]
73	1970	White v. Comm., TC Memo 1970-132
74	1977	Williams v. Comm., TC Memo 1977-401
75	1976	Windle v. Comm., 65 TC 694
76	1967	Zarnow v. Comm., 48 TC 213

[1]Denotes 2 separate determinations of worthless securities.

[2]Denotes 3 separate determinations of worthless securities.

APPENDIX C

PREDICTED PROBABILITIES OF SUCCESSFUL OUTCOME OF ALL CASES UNDER EACH MODEL--OVERALL MODEL

Case	Actual Outcome of Case	Predicted Probability of Success: Logit	Discriminant	Jackknife Logit
Aagard	Unsuccessful	.1723	.0161	.1786
Adamson	Successful	.9477	.8924	.9559
Adronback	Unsuccessful	.1723	.1061	.1786
Ainsley	Unsuccessful	.9958*	.9877*	.9999*
American	Successful	.9958	.9877	.9958
Austin	Successful	.9958	.9877	.9958
Benton	Unsuccessful	.1723	.1061	.1786
Boyer	Successful	.1723*	.1061*	.1425*
Brandtjen	Unsuccessful	.1723	.1061	.1785
Braun	Unsuccessful	.1723	.1061	.1786
Brown	Unsuccessful	.1723	.1061	.1786
Butler	Unsuccessful	.1723	.1061	.1786
Byrd	Unsuccessful	.1723	.1061	.1786
Byrun	Successful	.7323	.5340	.6983
Camp	Successful	.9477	.8924	.9446
Cornelly	Unsuccessful	.1723	.1061	.1786
Conover	Successful	.9477	.8924	.9446
Drachman	Successful	.9477	.8924	.9446
Eysenbach	Unsuccessful	.1723	.1061	.1786
Funke	Successful	.9958	.9877	.9958
Gahager	Successful	.9994	.9989	.9994
Gilmore	Successful	.7323	.5340	.6983
Ginsburg	Unsuccessful	.1723	.1061	.1786
Goodrich	Unsuccessful	.3656	.5051*	.5162*
Grant	Successful	.9958	.9877	.9958
Gussaw	Successful	.9958	.9877	.9958
Grittman	Successful	.5938	.5717	.5323
Gwynne	Successful	.9958	.9877	.9958
Hankey	Successful	.3656*	.5051	.1412*
Harmon	Successful	.5938	.5717	.5323
Heiss	Successful	.5938	.5717	.5323
Herrick	Unsuccessful	.1723	.1061	.1786
Howe #1	Successful	.9477	.8924	.9446
Howe #2	Successful	.9477	.8924	.9446
Iron Fireman	Successful	.5938	.5717	.5323
Jackling	Successful	.7323	.5340	.6983
Jessups #1	Unsuccessful	.0926	.0999	.1175
Jessups #2	Successful	.1723*	.1061*	.1425*
G. Jones #1	Successful	.9477	.8924	.9446
G. Jones #2	Successful	.1723*	.1061*	.1425*
G. Jones #3	Successful	.7323	.5340	.6983
H. Jones	Successful	.9477	.8924	.9446
Joslyn	Successful	.9477	.8924	.9446
Kaler	Unsuccessful	.1723	.1061	.1786
Kirven	Unsuccessful	.1723	.1061	.1786
Kleberg #1	Unsuccessful	.0066	.0144	.0066
Kleberg #2	Successful	.9477	.8924	.9446
Ladew	Successful	.7323	.5340	.6983

Case	Actual Outcome of Case	Predicted Probability of Success: Logit	Discriminant	Jackknife Logit
Lee	Unsuccessful	.1723	.1061	.1786
H. Liebes	Successful	.9958	.9877	.9958
Lincoln	Unsuccessful	.1723	.1061	.1786
Lunsford	Unsuccessful	.0926	.0888	.1175
Maguire	Successful	.9505	.9280	.9476
Malmsted	Unsuccessful	.1723	.1061	.1786
Mayer	Successful	.9958	.9877	.9958
Meissner	Unsuccessful	.1723	.1061	.1786
Melick	Successful	.3656*	.5051	.1412*
Miller	Unsuccessful	.1723	.1061	.1786
Moot	Unsuccessful	.0066	.0144	.0066
Morton	Unsuccessful	.5938*	.5717*	.6850*
Persall	Successful	.9477	.8924	.9445
Pomerranz	Unsuccessful	.0002	.0012	.0002
Post	Unsuccessful	.1723	.1061	.1786
Reese	Successful	.9477	.8924	.9446
E. Richards	Successful	.4034*	.4133*	.3609*
W. Richards	Unsuccessful	.8834*	.9079*	.9825*
Robinson	Successful	.9922	.9894	.9921
Ruud #1	Unsuccessful	.1723	.1061	.1786
Ruud #2	Successful	.9958	.9894	.9921
Ryan	Unsuccessful	.4034	.4133	.6489*
Sankary	Successful	.7323	.5340	.6983
Scifo #1	Unsuccessful	.0066	.0144	.0066
Scifo #2	Successful	.7323	.5340	.6983
Shvetz	Successful	.9505	.9280	.9476
Singer	Unsuccessful	.1723	.1061	.1785
Spruance	Successful	.9958	.9877	.9958
Triplett	Unsuccessful	.5938*	.5717*	.6851*
Universal	Unsuccessful	.5938*	.5717*	.6851*
Watson #1	Successful	.9477	.8924	.9446
Watson #2	Successful	.9477	.8924	.9446
White	Unsuccessful	.0077	.0100	.0078
Williams	Unsuccessful	.1723	.1061	.1785
Windle	Successful	.9505	.9280	.9476
Zarnow	Unsuccessful	.1723	.1061	.1785

*Misclassified

APPENDIX D

ABSOLUTE ERRORS OF PREDICTION--OVERALL MODEL

Case	Absolute Prediction Error Logit	Discriminant
Aagaard	.1723	.1061
Adamson	.0523	.1076
Adronbach	.1723	.1061
Ainsley	.9958*	.9877*
American	.0042	.0123
Austin	.0042	.0123
Benton	.1723	.1061
Boyer	.8277*	.8939*
Brandtjen	.1723	.1061
Braun	.1723	.1061
Brown	.1723	.1061
Butler	.1723	.1061
Byrd	.1723	.1061
Byrum	.2677	.4660
Camp	.0523	.1076
Connelly	.1723	.1061
Conover	.0523	.1076
Crachman	.0523	.1076
Eysenbach	.1723	.1061
Funke	.0042	.0123
Gahager	.0006	.0011
Gilmore	.2677	.4660
Ginsburg	.1723	.1061
Goodrich	.3656	.5051*
Grant	.0042	.0123
Gussow	.0042	.0123
Grittman	.4062	.4283
Gwynne	.0042	.0123
Hankey	.6344*	.4949
Harmon	.4062	.4283
Heiss	.4062	.4283
Herrick	.1723	.1061
Hoew #1	.0523	.1076
Howe #2	.0523	.1076
Iron Fireman	.4062	.4283
Jackling	.2677	.4660
Jessups #1	.0926	.0888
Jessups #2	.8277*	.8939*
G. Jones #1	.0523	.1076
G. Jones #2	.8277*	.8939*
G. Jones #3	.2677	.4660
H. Jones	.0523	.1076
Joslyn	.0523	.1076
Kaler	.1723	.1061
Kirven	.1723	.1061
Kleberg #1	.0066	.0144
Kleberg #2	.0523	.1076
Ladew	.2677	.4660
Lee	.1723	.1061

Case	Absolute Prediction Error: Logit	Absolute Prediction Error: Discriminant
Liebes	.0042	.0123
Lincoln	.1723	.1061
Lunsford	.0926	.0888
Maguire	.0495	.0720
Malmstedt	.1723	.1061
Mayer	.0042	.0123
Meissner	.1723	.1061
Melick	.6344*	.4949
Miller	.1723	.1061
Moot	.0066	.1061
Morton	.5938*	.5717*
Pearsall	.0523	.1076
Pomeranz	.0002	.0012
Post	.1723	.1061
Reese	.0523	.1076
E. Richards	.5966*	.5867*
W. Richards	.8834*	.9079*
Robinson	.0078	.0106
Ruud #1	.1723	.1061
Ruud #2	.0042	.0123
Ryan	.4034	.4133
Sankary	.2677	.4660
Scifo #1	.0066	.0144
Scifo #2	.2677	.4660
Shvetz	.0495	.0720
Singer	.1723	.1061
Spruance	.0042	.0123
Triplett	.5938*	.5717*
Universal	.5938*	.5717*
Watson #1	.0523	.1076
Watson #2	.0523	.1076
White	.0077	.0100
Williams	.1723	.1061
Windle	.0495	.0720
Zarnow	.1723	.1061

*Misclassified.

APPENDIX E

PREDICTED PROBABILITIES OF SUCCESS IN

POST-1950 CASES UNDER EACH MODEL

Case	Overall Model Logit	Overall Model Discriminant	Post-1950 Model Logit	Post-1950 Model Discriminant
Aagaard	.1723	.1061	.0497	.0262
Ainsley	.9958*	.9877*	.0000	.3946
American	.9958	.9877	.9612	.9684
Austin	.9958	.9877	1.0000	.9999
Benton	.1723	.1061	.0004	.1418
Boyer	.1723*	.1061*	.9996	.8859
Brandtjen	.1723	.1061	.0497	.0262
Butler	.1723	.1061	.0497	.0262
Byrum	.7323	.5340	1.0000	.9979
Camp	.9477	.8924	1.0000	.9979
Drachman	.9477	.8924	1.0000	.9976
Funke	.9958	.9877	.9612	.9784
Gilmore	.7323	.5340	.4310*	.3142*
Ginsburg	.1723	.1061	.0497	.0262
Hankey	.3656*	.5051	.6310	.6428
Herrick	.1723	.1061	.0497	.0252
Howe #1	.9477	.8924	.6310	.6428
Howe #2	.9477	.8924	.9999	.8970
Jessups #1	.0926	.0888	.4310	.3142
Jessups #2	.1723*	.1061*	.9999	.9961
Kirven	.1723	.1061	.0497	.0262
Lincoln	.1723	.0161	.0497	.0262
Lunsford	.0926	.0888	.4310	.3142
Malmstedt	.1723	.1061	.0497	.0262
Pomeranz	.0002	.0012	.0497	.0262
Post	.1723	.0161	.0497	.0262
Reese	.9477	.8924	.6310	.6428
E. Richards	.4034*	.4133*	.6310	.6428
W. Richards	.8834*	.9079*	.9612*	.9684*
Ruud #1	.1723	.1061	.0497	.0262
Ruud #2	.9958	.9877	.9612	.9684
Ryan	.4034	.4133	.6310*	.6428*
Sankary	.7323	.5340	.4310*	.3142*
Scifo #1	.0066	.0144	.0497	.0262
Scifo #2	.7323	.5340	.4310*	.3142*
Shoetz	.9505	.9280	1.0000	.9925
Singer	.1723	.1061	.0497	.0262
Universal	.5938*	.5717*	.0497	.0262
White	.0077	.0100	.0497	.0262
Williams	.1723	.1061	.0497	.0262
Windle	.9505	.9280	.9998	.6892
Zarnow	.1723	.1061	.0497	.0262

*Misclassified.

APPENDIX F

ABSOLUTE ERRORS OF PREDICTION--OVERALL MODELS AND POST-1950 MODELS FOR POST-1950 CASES

Case	Absolute Prediction Error: Overall Model Logit	Overall Model Discriminant	Post-1950 Model Logit	Post-1950 Model Discriminant
Aagaard	.1723	.1061	.0497	.0262
Ainsley	.9958*	.9877*	.0000	.3946
American	.0042	.0123	.0388	.0316
Austin	.0042	.0123	.0000	.0001
Benton	.1723	.1061	.0004	.1418
Boyer	.8277*	.8939*	.0004	.1318
Brandtjen	.1723	.1061	.0497	.0262
Butler	.1723	.1061	.0497	.0262
Byrum	.2677	.4660	.0000	.0021
Camp	.0523	.1076	.0000	.0024
Drachman	.0523	.1076	.0000	.0024
Funke	.0042	.0123	.0388	.0316
Gilmore	.2677	.4660	.5690*	.6858*
Ginsburg	.1723	.1061	.0497	.0262
Hankey	.6344*	.4949	.3690	.3572
Herrick	.1723	.1061	.0497	.0262
Howe #1	.0523	.1076	.3690	.3572
Howe #2	.0523	.1076	.0001	.1030
Jessups #1	.0926	.0888	.4310	.3142
Jessups #2	.8277*	.8939*	.0001	.0339
Kirven	.1723	.1061	.0497	.0262
Lincoln	.1723	.1061	.0497	.0262
Lunsford	.0926	.0888	.4310	.3142
Malmstedt	.1723	.1061	.0497	.0262
Pomeranz	.0002	.0012	.0497	.0262
Post	.1723	.1061	.0497	.0262
Reese	.0523	.1076	.3690	.3572
E. Richards	.5966*	.5867*	.3690	.3572
W. Richards	.8834*	.9079*	.9612*	.9684*
Ruud #1	.1723	.1061	.0497	.0262
Ruud #2	.0042	.0123	.0388	.0316
Ryan	.4034	.4133	.6310*	.6428*
Sankary	.2677	.4660	.5690*	.6858*
Scifo #1	.0066	.0144	.0497	.0262
Scifo #2	.2677	.4660	.5690*	.6858*
Shvetz	.0495	.0720	.0000	.0075
Singer	.1723	.1061	.0497	.0262
Universal	.5938*	.5717*	.0497	.0262
White	.0077	.0100	.0497	.0262
Williams	.1723	.1061	.0497	.0262
Windle	.0495	.0772	.0002	.3108
Zarnow	.1723	.1061	.0497	.0262

*Misclassified.

VITA 2

Bob Grissom Kilpatrick

Candidate for the Degree of

Doctor of Philosophy

Thesis: THE DETERMINATION OF WORTHLESS SECURITIES UNDER INTERNAL REVENUE CODE SEC. 165(g): EMPIRICAL EVIDENCE FROM JUDICIAL DECISIONS

Major Field: Business Administration

Biographical:

Personal Data: Born October 16, 1954, in Tupelo, Mississippi, the son of Mr. and Mrs. S. W. Kilpatrick, Jr.

Education: Received Bachelor of Science degree in Accounting from the University of Southern Mississippi in August, 1975; received Master of Science degree in Accounting from the University of Southern Mississippi in August, 1976; completed the requirements for the Doctor of Philosophy degree at Oklahoma State University in May, 1984.

Professional Experience: Assistant Professor, Department of Business, Belhaven College, August, 1976 to August, 1979; Instructor, School of Accounting, University of Southern Mississippi, August, 1979 to August, 1980; Lecturer, School of Accounting, Oklahoma State University, August, 1980 to May, 1983; Assistant Professor, Texas A & M University, August, 1983 to present.

Professional Memberships: American Accounting Association; American Taxation Association.