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BINARY BRIGHT-LINE DECISION MODELS FOR GOING CONCERN ASSESSMENT: ANALYSIS OF ANALYTICAL TOOLS FOR BANKRUPTCY PREDICTION CONSIDERING SENSITIVITY TO MATERIALITY THRESHOLDS

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DISSERTATION

A dissertation submitted in partial fulfillment of
requirements for the degree of Doctor of Philosophy in the
College of Business and Economics
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ABSTRACT OF DISSERTATION

BINARY BRIGHT-LINE DECISION MODELS FOR GOING CONCERN ASSESSMENT: ANALYSIS OF ANALYTICAL TOOLS FOR BANKRUPTCY PREDICTION CONSIDERING SENSITIVITY TO MATERIALITY THRESHOLDS

In August, 2014, the Financial Accounting Standards Board issued an update concerning the disclosure of uncertainties about an entity's ability to continue as a going concern. The standard requires an entities *management* to evaluate whether there is substantial doubt about the entity's ability to continue as a going concern and to provide related footnote disclosures in certain circumstances. One consequence of this regulation is the need for guidance for audit testing of management's assessments in each phase of the audit.

This research evaluates the usefulness of bankruptcy prediction models as analytical tools in the planning stage of an audit for going concern assertions and questions the use of precision as the only measure of a model's effectiveness. I use simulation to manipulate the fundamental accounting data within five bankruptcy prediction models, explore failure rates in an environment with materiality concerns, and consider the total change in market value due to simulated errors. Given the inherent limitations of the information environment and/or current prediction models, my results indicate auditors' current failure rates are *not* an indication of audit failure. The results suggest that bright-line testing using bankruptcy prediction models are sensitive to materiality and that the cost trade-off between Type I and Type II errors is an important indicator of model choice.

KEYWORDS: going concern, bankruptcy prediction model, materiality, FAS 205-40,
analytical tools

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Date

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What have I learned during the process of this dissertation? That bad news is often a surprise, that timely predictions are difficult to make, that failure can be measured by size and number, and that solid recovery plans often fail. This dissertation took a long road and was a battle at times. I appreciate those who fought with me, those who fought on my behalf, and those that supported me from afar.

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CHAPTER 1: INTRODUCTION

1.1 Introduction and Motivation

A company is a going concern if it has the resources needed to remain in existence long enough for a business to utilize all of its assets. Unless warned otherwise, financial statement users should be able to assume that an entity will not be compelled to liquidate its assets, end operations, or file for bankruptcy protection in the foreseeable future. If a company is likely to be unable to meet its obligations as they become due without extraordinary disposition of assets, debt restructuring, externally-mandated operating revisions, or if management plans to liquidate or cease operations; then certain disclosures are required in current financial statements. Investment decisions about a company facing restructuring or bankruptcy differ greatly from decisions about companies that are going concerns. Providing useful information for economic decision-making is the primary objective of financial reporting; therefore, determining whether a company is a going concern is a fundamental judgment made by financial statement preparers.

Different reporting standards exist for companies with substantial going concern uncertainty. The Generally Accepted Accounting Principles of the United States (GAAP) requires failing firms to include certain disclosures and potentially prepare their financial statements on a liquidation basis. For example, the balance sheet classification of assets and liabilities into current and non-current categories is irrelevant in the liquidation basis. In addition, the periodicity and accrual concepts lose their relevance for distressed firms since the future economic benefit of assets is undefined and the realization of assets for their book value is uncertain for these firms and should be presented differently in financial statements prepared according to the liquidation basis.

Financial Statement information is only valuable to accounting users if it is accurate, relevant, and reliable. When an independent auditor expresses an opinion on whether the financial statements are fairly presented in accordance with GAAP; financial statement users should be able to make decisions with a higher degree of confidence (Geiger, Raghunandan, & Rama, Recent changes in the association between bankruptcies and prior audit opinions, 2005). However, external audit reports only add credibility to financial statements if they consistently express proper opinions (Herbohn, 2007); therefore, a proper assessment of going concern is critical to expressing an opinion on whether the financial statements are presented fairly (Carcello & Neal, 2003). A 2019 study used artificial intelligence techniques and found that the content of the auditors' report contained as much bankruptcy prediction information as the entire financial report (Muñoz-Izquierdo, Camacho-Miñano, Segovia-Vargas, & Pascual-Ezama, 2019). They found that the most significant variables to distinguish between bankrupt and non-bankrupt firms were the audit opinion, the Matter sections disclosed in the audit reports, and the number of comments included in the Matter sections and qualification paragraphs.

An audit opinion containing a going-concern qualification can have economic and legal consequences for both the audited company and the auditor. For example, audit firms face lawsuits if a client files bankruptcy without a warning from audit reports issued within a year of bankruptcy. On the other hand, if an audit firm issues a going-concern opinion and the client remains healthy, the auditor may lose future audit engagements with the client. Although audit fees may motivate auditors to side with clients; when there is a conflict of interests between financial statement users and those of the audit client, the auditor's primary responsibility is to users.

Prior research shows that auditors do not always arrive at an appropriate audit opinion (Herbohn, 2007). Historically, the majority of companies that file bankruptcy neither warned investors through going concern uncertainty disclosures nor prepared the prior financial statements under the liquidation basis of accounting. Given the high rate of errors in this judgment, research questions the information content of and investor's reliance on audit opinions. For decades, improving the accuracy and timeliness of going concern uncertainty disclosures have been at the forefront of discussion within the auditing and accounting profession.

Management and auditors can make two types of errors when issuing an assertion about going concern. Firstly, they could fail to issue a warning for a client that goes on to file bankruptcy in the subsequent two years. Secondly, they could modify the language of their report to issue a warning about substantial doubt for an entity to continue as a going concern and if that entity survived for two years, that would also be an error. Research generally classifies these errors as Type I and Type II. I define error types throughout the text, figures, and tables following the convention for this stream of literature. Figure 1 defines the relationship between audit opinions, bankruptcy, and error types used in this research.

	No Bankruptcy in t+1	Bankruptcy in t+1
Unmodified Audit Opinion in t	No Error: Viable Company	Type I Error: Failed to Issue Warning for Subsequent Bankruptcy
Modified Audit Opinion in t	Type II Error: Warning Issued for Viable Company	No Error: Warning Correctly Issued

Figure 1: Type I and Type II Errors based on Historic Audit Opinions

Due to the predictive nature of going concern assertions, the evaluation of both error types occurs in the subsequent period (t+1). A Type I error is made when a failing company is classified as non-failing (e.g. the financial statements that precede a company's bankruptcy, liquidation, or acquisition fail to include a warning). The economic and social costs for this type of error can be substantial to current investors, creditors, management, and the current audit firm.

A Type II error exists if a modified audit opinion with going concern qualifications was issued for a company that remained viable and existed without bankruptcy a year after the report is issued. A Type II error is incorrectly classifying a healthy company as failed. These "false positives" exist when firms that do not subsequently fail after a going concern warning.

I follow a large body of bankruptcy research in the classification of errors used in this research. This classification may seem to work counter to the convention of standard hypothesis testing where Type I errors are "false positives". The confusion is derived from labeling companies that are failing as GCO companies. Accountants test the assumption that the company will continue to meet its financial obligations. The null hypothesis is that a company is *not* a going concern and is predicted to fail. Issuing a GCO warning is consistent with accepting the null and giving an opinion that a company is *not* a going concern. Therefor in a Type II Error, an auditor has incorrectly accepted the null that a company will not continue. In Type I Errors, an auditor has incorrectly rejected the null that a company will not continue.

Taffler and Citron (1992) show that only 20 percent of UK failed companies received going concern qualifications before a bankruptcy filing. Vanstraelen (2003) found that fewer than 26 percent of bankrupt companies received audit qualifications in Belgium. Van Peusem and Chan (2012) found that only 28 percent of failed companies received appropriate audit qualifications in New Zealand. Approximately half of the companies going bankrupt in the U.S. do not receive a prior GCO. Geiger and Rama (2006) find a Type I misclassification of 88 percent in the period between 1990 and 2000. Myers, Schmidt and Wilkens (2014) find a Type I misclassification of 20 percent in the period between 2000 and 2006 and suggest that increased scrutiny improved performance in large firms, but increased Type II errors in small firms.

Research indicates that auditors are biased against issuing going concern qualifications. From the auditors' perspective, an incorrect audit opinion may result in expensive litigation (Hensher & Jones, 2007), loss of the audit fee, and damage to professional reputation Kaplan and Williams (2013) find that (1) going concern reports deter lawsuits even when auditors are named in lawsuits, (2) an ex ante going concern report reduces the likelihood of large financial settlements. Some research suggests that issuing such a qualification creates a self-fulfilling prophecy (Louwers & Richard, 1999). Research indicates that Type I errors are costliest to auditors, where it would lead to the possible loss of audit fee, professional reputation and litigation from shareholders (Koh, 1991). Grant (1998) reports that approximately 9 percent of auditor revenues in the U.S.A. are spent on defending lawsuits. While this information may encourage auditors to issue more GCOs, auditors appear biased against reporting qualifications because investors react negatively (Menon & Williams, 2010) and auditors may lose the client due to auditor switching.

While individual studies vary, approximately two thirds of companies with a GCO do not subsequently go bankrupt. Lennox (1999) found that U.K. companies that do not go bankrupt in the year subsequent to a GCO is approximately 80 percent. Geiger, et al. (2005) found a Type II misclassification of 46 percent in the period between 2000 and 2003. Geiger and Rama (2006) found a Type II misclassification of 51 percent in the period between 1990 and 2000. Feldmann and Read (2010) found a Type II misclassification of 41 percent in the period between 2000 and 2007. Myers et al. (2014) found a Type II misclassification of 32 percent in the period between 2000 and 2006. In Australia, the proportion of firms with GCOs that do not subsequently go bankrupt was 88 percent, based on first-time GCOs (Carey, Geiger, & O'Connell, 2008). Evidence from Bellovary, Giacomino, & Akers (2006) suggests the issuance of an unqualified audit report for companies that have subsequently filed bankruptcy in the following year reduces the public’s reliance on audit opinions. Further evidence suggests the prevalence of Type II errors during the 2008 financial crisis reduced investor confidence in accounting information and the function of audits.

The costs associated with Type I and Type II errors are likely to be quite different. Prior research on bankruptcy prediction typically focus on (1) searches for statistical models to improve prediction accuracy—defined by precision in count and percentage or (2) probes for new bankruptcy predictors (financial ratios or other explanatory variables) (Mai, 2010). Research has not provided empirical evidence of the trade-off between models that minimize Type I error rates but increase Type II error rates. Currently, bankruptcy prediction studies assess a model's ability to predict by counting total errors and generally correctly classify 95% or more of a sample into bankrupt and non-bankrupt categories. Most models identify fewer Type I errors and the number of Type II errors are consistently higher than the number of Type I errors. The popular press and investors react more strongly to Type I errors; however, Type II errors are not costless. Companies with going concern uncertainty disclosures face higher cost of debt and negative market reactions. Models proposed to reduce Type I errors may increase the number of Type II errors. The overall cost trade-off between Type I and Type II errors should be considered.

The usefulness of a prediction model should consider the total cost trade-off of errors. However, prior research does not evaluate the models based on an estimation of these costs. Altman et al. (1977) use a lender's decision model to argue that a lender could trade-off 35 Type II errors for each Type I error. However, this conclusion naïvely ignores loan size. The size of the loan and the relative cost of errors need to be included in the evaluation of bankruptcy prediction models (hereafter, BPMs). The purpose of this study is to capture the total market cost of bankruptcy errors and evaluate models based on the total cost, not the number of errors.

Since the American Institute of Certified Public Accountants (AICPA) issued SAS No. 2 in 1974, auditors have struggled to assess a firm's going concern status and to develop appropriate predictive models (Akers, Giacomino, & Bellovary, 2007). In a 1987 study, auditors ranked 60 steps that comprised the audit by its level of difficulty. "Determining the validity of the going-concern assumption" ranked fourth in that study (Chow, McNamee, & Plumlee, 1987). A large body of research evaluates the accuracy of auditor's going concern predictions and finds them lacking. Often, this research evaluated the effectiveness of finance models by counting the number of errors as a tool for evaluation.

Australian auditing standards recognize statistical models for assessing going concern uncertainty. The Australian standard on Analytical Procedures (AUS 512) with reference to AUS 708 specifically highlights probit and discriminant analysis models. The1993 *Proceedings of the Expectations Gap Roundtable in the United States* called for continued research into the effectiveness of analytical procedures and identified the use of BPMs for assessing going concern uncertainty (Blocher & Loebbecke, 1993) American standards have historically not provided specific examples or guidance on the selection or timing of procedures using BPMs.

Accounting Standards (SAS) No. 34 and SAS No. 59 did little to improve the accuracy of going concern opinion issuance (Raghunandan & Rama, 1995). Research identifies two problem areas for auditors when making a going concern judgment: auditors have difficulty (1) acquiring or selecting information and (2) processing or combining that information (Ho, 1994), (Rosman, Seol, & Biggs, 1999). Little guidance has been provided to assist auditors in making going concern judgments.

The auditing standards list potential indicators of going concern uncertainty but remain silent about the use of statistical models in assessing going concern uncertainty. AU 341.06 includes four categories indicating going concern uncertainty: (1) negative trends, (2) other indications of possible financial difficulties, (3) internal matters, and (4) external matters. However, the auditing standard does not provide guidance as to how the auditor is to interpret and assess these events. Therefore, auditors must rely on their own judgment when assessing whether a firm's going concern uncertainty meets the "substantial doubt" threshold for disclosure. Research suggests using a decision aid in the process of evaluating going concern uncertainty may be beneficial (Chung, et al., 2012). Research has recognized the potential usefulness of objective statistical models for assessing going concern since the Cohen commission's report (1978) on auditor responsibilities first suggested their use as a means toward reducing the expectations gap. In 1993, the AICPA the USA recognized the public's demand for an early warning system of corporate failure (Loftus & Miller, 2000).

Research shows objective statistical models outperform auditors in assessing company failure (Bellovary, Giacominio, & Akers, 2007). Although recent studies question the notion (Blay, Moon Jr., & Paterson, 2016), research often proxies the propensity to issue GCOs as an indicator of audit quality. A large body of research explores substituting auditor judgment with established BPMs (BPM) as a means to improve audit quality. Such models can help auditors form more objective assessments of a clients' going concern uncertainty and reduce the costs associated with Type I and Type II errors.

Statistical BPMs provide an objective assessment of the probability of the client failing. If a model produces a score indicating a high probability of failure, the auditor can classify the company as high-risk and plan to apply more rigorous audit procedures. Koh (2012) argue that accurate statistical models can help auditors identify high-risk companies in the planning stages of the audit. Identifying high-risk companies at this stage helps the auditor plan specific audit procedures aimed at assessing the appropriateness of the going concern assumption.

However, the audit environment presents a unique challenge due to the materiality assumption. The materiality assumption states that misstatements, including omissions, are material if they, individually or in aggregate, could reasonably be expected to influence the economic decisions of financial statement users. SAS No. 122 addresses the auditor's responsibility to apply the concept of materiality in the planning stage of an audit. The auditor is charged to make judgments about the size of misstatements that will be considered material, thus providing a basis for determining the nature and extent of risk assessment procedures. The standard encourages the use of a percentage applied to a benchmark from the financial statements as a starting point for determining materiality (i.e. performance materiality threshold defined as a percentage of profit before tax from continuing operations). During the planning stage of an audit, unidentified misstatements may impact the accuracy of statistical models that rely on financial statement information. The question of how models perform in this environment has not been explored. This dissertation provides insight to the sensitivity of models to material misstatements present during the planning stage of the audit.

The ability of corporate failure models to provide *objective* evidence for making a going concern judgment is important (Cormier, Magnan, & Morard, 2016). This objectivity in statistical evidence supports BPMs as a substitute for auditor judgment in court (Kuruppu, Laswad, & Oyelere, 2003). Therefore, practitioners can defend the reliance on an established BPM as an objective tool in court cases claiming audit failure. If an objective model minimizes the risk of both Type I and

Type II errors, this defense may help practitioners avoid litigation and minimize costs.

When a company's going concern status becomes uncertain in the period prior to filing bankruptcy, current regulation requires a going concern disclosure. Therefore, many going concern studies assess prediction accuracy using samples of bankrupt and non-bankrupt firms. Research related to BPMs often overlap going concern research. In this literature, bankruptcy is used as a proxy for corporate failure. Despite numerous studies in the area and regulatory updates, bankruptcy prediction rates have not substantially improved (Gissel, Giacomino, & Akers, 2007). Figure 2 lists the ten largest bankruptcies in United States history and highlights that only three firms issued timely going concern warnings.

Rank by Size	Company Name	Date Bankruptcy Filed	Assets	Going Concern Opinion in Prior Year's Audit
1	Lehman Brothers Holdings	September 15, 2008	$691 billion	No
2	Washington Mutual	August 26, 2008	$327.9 billion	No
3	WorldCom	July 21, 2002	$103.9 billion	No
4	General Motors	June 1, 2009	$91 billion	Yes
5	CIT	November 1, 2009	$71 billion	No
6	Enron	December 2, 2001	$65.5 billion	No
7	Conseco	December 17, 2002	$61 billion	No
8	Energy Future Holdings	April 29, 2014	$40.9 billion	Yes
9	MF Global Holdings	October 31, 2011	$40.5 billion	No
10	Chrysler	April 30, 2009	$39 billion	Yes

Figure 2: 10 Largest Bankruptcies in US History

During the 2008 financial crisis, regulators and investors questioned auditors for failing to issue GCOs in the period preceding many bankruptcies. Several hypotheses exist for why Type I errors persist: (1) the current bankruptcy models are not sensitive enough, (2) exogenous subsequent events prediction is beyond the scope of auditors' duties, and (3) auditors purposely fail to issue a GCO due to client retention and because of the "self-fulfilling prophecy" stigma that follows a GCO. However, by not identifying an audit deficiency when Type I errors occurred during the financial crisis, the PCAOB seemed to indicate that Type I errors are beyond the scope of an auditor's responsibility (Gramling, Krishnon & Zhang, 2011).

In the years after the financial crisis, the failure of auditors to issue warnings prior to large bankruptcies continued and both the popular press and investors continued to look toward audit firms for justifications. For example, PwC did not include going concern uncertainty qualifications in the audit report for the financial statements prior to MF Global Holdings declaring bankruptcy in 2011. Forbes, American Banker, and Thomson Reuters all published articles discussing PwC's culpability for investor losses due to MF Global's bankruptcy. PwC ultimately settled lawsuits including a 2015 settlement of $65 million to MF Global investors and an undisclosed amount to the bankruptcy administrator for MF Global.

On August 27, 2014, the Financial Accounting Standards Board (FASB or "the Board") issued *Accounting Standards Update No. 2014-2015* concerning the disclosure of uncertainties about an entity's ability to continue as a going concern. The standard requires an entity's *management* to evaluate whether there is substantial doubt about the entity's ability to continue as a going concern and to provide related footnote disclosures in certain circumstances. The standard clarifies the roles of management and auditors for going concern assertions: management will make an assertion concerning substantial doubt about an entity's ability to continue as a going concern leaving auditors to evaluate the assertion.

One consequence of this regulation is the need for guidance for audit testing of management's assertions in each phase of the audit. My research evaluates the usefulness of BPMs as analytical tools in the planning stage of an audit for going concern assertions. I use simulation to manipulate the fundamental accounting data required by current BPMs, explore failure rates, and the associated net market costs of inaccurate going concern assessments. Given the inherent limitations of the information environment and/or current prediction models, my results indicate auditors' current failure rates are *not* an indication of audit failure. The results suggest that bright-line testing using BPMs are sensitive to materiality and that the cost trade-off between Type I and Type II errors should be considered.

Few studies address whether auditors were capable ex ante of predicting the Type I bankruptcies during the financial crisis. Given the information presented in the financial statements at the time of the audit and the inherent limitations of current BPMs (BPM), auditors may not have been capable of more accurate predictions. Before auditors can implement these models during the planning stage of the audit, several questions concerning their appropriateness and usefulness need to be addressed.

Specifically: (1) Are the models valid and sensitive enough to predict bankruptcies? (2) What thresholds for quantitative planning materiality are appropriate for distressed firms? (3) Are we asking auditors [and managers under IAS No. 1] to assume responsibility for an impossible mission? (4) What is the relative cost of Type I and Type II errors?

My research will address these questions using simulation methods. I will calculate error rates considering common materiality thresholds and estimate the market cost of each type of error. Ultimately, I will inform the discussion about the appropriateness of a BPM as an analytical tool within a risk-based audit setting.

My research will contribute to the research in two important ways. First, my research investigates the role of quantitative planning materiality in going concern risk assessments and examines the sensitivity of BPMs to common thresholds for materiality. My analysis will be useful for regulators as they prepare audit guidance in response to proposed changes to GAAP. Second, my research investigates the relative costs of Type I and Type II errors in going concern opinions as predicted by these models. This information will also inform regulators about the potential costs and benefits of using BPMs as analytical tools in an audit.

1.2 Current Regulation

The FASB issued Accounting Standards Update (ASU) “Disclosure of Uncertainties About an Entity's Ability to Continue as a Going Concern” No. 2014-15 in August 2014. The update includes amendments requiring management to disclose uncertainties about an entity’s ability to continue as a going concern and was effective for annual periods ending after December 15, 2016. Before the amendment, GAAP provided no guidance about management’s responsibility to evaluate substantial doubt for going concern or to provide footnote disclosures. The new standard applies to all entities and requires management (1) to evaluate whether it is probable that within one year after the date of the financial statements are issued for each reporting period (including interim periods) the entity will be unable to meet its obligation as they become due and (2) to disclose substantial doubt with an explicit statement or to explain how substantial doubt is alleviated as a result of management’s plans.

Statement of Auditing Standards No. 122 amended SAS No. 59. This standard’s update aligns GAAP with the current auditing standards: AU-C section 570 and AU-C section 930. AU-C section 570 requires auditors to assess the adequacy of footnote disclosures when auditors conclude that substantial doubt for going concern exists. AU-C 930 requires auditors to consider substantial doubt for going concern in interim financial reports.

The primary objective of Statement of Auditing Standards No. 132 (2017) is to address the provisions of ASU No. 2014-15. Statistical models are often used during the planning stage of an audit. Horizontal and vertical analysis using certain ratios is common and encouraged in audit standards. Research supports the use of analytical procedures to provide quantitative audit evidence and support audit judgment through decision aids.

1.3 Overview of Simulations and Findings

In this research, I use 10 BPM specifications as bright-line tests to predict bankruptcy: (1) Altman's Z-Score with 1.8 score cut-off (1968), (2) Altman's Z-Score (1968) with a calculated 50% probability cut-off, (3) Altman's Z-Score (1993), (4) Hillegeist et al.'s re-estimation of Altman's Z-Score (2004), (5) Ohlson's O-Score(1980), (6) Hillegeist et al.'s re-estimation of Ohlson's O-Score (2004), (7) Shumway's Hazard model at 50% probability (2001), (8) Shumway's Hazard model at 70% probability, (9) Merton's KMV at 50% probability (Bharath & Shumway, 2008) and (9) Merton's KMV at 70% probability. I compare the count and percentages of estimated errors to the errors generated from auditor's historic going concern opinions. I found that bright-line tests derived from Altman's Z-Score and Merton's KMV outperformed auditor's judgment in limiting the count and percentage of Type I errors and a bright-line test derived from Shumway's Hazard model outperformed auditors' judgment in limiting the count and percentage of Type II errors. Only the Shumway Hazard model resulted in fewer total errors than auditors' GCO decisions in any sample.

I propose the use of these models in the planning stage of an audit where risk assessments and testing are subject to materiality thresholds. Applying the models in this unique setting warrants exploration into the sensitivity of the models to materiality thresholds. I investigated the performance of each model under simulated conditions for different definitions of planning materiality thresholds and misstatement classifications. I found that all BMP models were sensitive to misstatements at the level of planning materiality to varying degrees. Consistent with research, my findings suggest that planning materiality thresholds should be lower than "rules-of-thumb" for firms with low or negative income.

Finally, I examine the effectiveness of auditor judgment and bright-line testing using BMPs based on a naïve estimate of total market cost. By estimating the percent change in share price by error type for firms in the historic condition and applying it to the classifications generated by bright-line testing, I quantify an estimate of total market cost for errors predicted by each bright-line test. I find that auditor judgment, the 2004 Altman Z-Score, and the Shumway model outperform other models when evaluated based on this cost trade-off assumption. The evaluation based on market cost is different than a counting of errors approach most often used to support the use of a particular model.

In this dissertation, I provide empirical evidence that while BMPs may be useful in the planning stage of an audit, measuring the effectiveness of a particular model based on precision (count and percentage) does not capture the whole story. I provide evidence of the appropriateness of common materiality thresholds when BPMs are used as bright-line tests for analytical procedures during the planning stage of an audit. Using a naïve model for estimating enterprise value, I measure the market cost trade-off between Type I and Type II errors using changes in cumulative abnormal returns. My study provides evidence that using precision to evaluate Type I and Type II accuracy rather than auditor judgment would result in greater overall negative market reactions. Overall, this research supports the value of auditor judgment and decision making in evaluation going concern uncertainty over reliance on several financial models.

1.4 Organization

The remainder of the dissertation is organized as follows: Chapter 2 provides a review of the research related to the regulation history, reporting trends, bankruptcy prediction in audit testing, and the evolution of BPMs. Chapter 3 develops the hypotheses and motivation of this study. Chapter 4 addresses the research design and methodology. Chapter 5 provides the results and statistical analyses. Chapter 6 discusses the results, limitations, and concludes.

CHAPTER 2: REVIEW OF LITERATURE

2.1 Regulation Stakeholders

The FASB is not the only regulatory body that is taking interest in going concern standards. The International Accounting Standards Board and Auditing Standards Board have a direct interest in the FASB project.

The FASB and International Accounting Standards Board (IASB) have been working closely on a project to converge the accounting standards in the US with those practiced globally. The IASB has a fulltime liaison who monitors the FASB's work and the FASB also serves within the IASB and monitors their discussions and decisions. IAS 1 was originally issued in 1997 and has seen several updates since that time. Currently, IAS 1 (25) specifies for management to make a going concern assessment while preparing the financial statements. The IFRS Interpretations Committee was called to provide more guidance about the timing of and purpose of going concern uncertainty disclosures and monitor FASB's work as they address these concerns (IFRS Interpretations Committee, 2013).

The US Auditing Standards Board's interest in changes to GAAP is obvious. AU Section 341 did not assume that management is responsible for going concern assertions and requires auditors to make predictive assessments for the following twelve months. Despite this regulation, the PCAOB did not seem to hold auditors responsible when going concern assertions turn out to be incorrect. In ex post reviews of audits that fail to accurately predict and warn investors of bankruptcies, the PCAOB has not issued deficiencies (Gramling, Krishnan, & Zhang, 2011). AU-C Section 570 reaffirmed that it was "the auditor's responsibility to evaluate whether there is substantial doubt about the entity's ability to continue as a going concern for a reasonable period of time" (AICPA, 2017).

At a round table at the Center for Audit Quality's Symposium (2012), breakout groups questioned the complexity of disclosures and the overlapping information between the MD&A section and the footnotes. The group concluded that earlier qualitative disclosure by management with specific action plans would mitigate the need and usefulness of going concern opinions issued by the auditor. The International Auditing and Assurance Standards Board (IAASB) issued International Standard on Auditing (ISA) 570, "Going Concern," which established the requirement and guidance for auditors to consider the appropriateness of management's use of the going concern assumption and auditor reporting.

While ASU 2014-15 requires managers to determine whether "substantial doubt" exists concerning a company's ability to continue as a going concern, research questions whether managers are capable of accurately predicting uncertainty 12-months and 24-months beyond the financial statement date given the information available. What tools, if any, can be identified to assisted management in making these assertions and auditors in assessing management's assertions?

2.2 Regulation History

Before the most recent update, the regulation for GCOs was provided in SAS No. 59 with some clarity offered by subsequent amendments. U.S. GAAP required companies to prepare financial statements on a going-concern basis unless (a) a liquidation plan had been approved by the owners or (b) the plan was being imposed by other forces and it was very unlikely that the entity would continue as a going concern. There was considerable debate surrounding liquidation versus going concern presentation of the financial statements, including a call for both presentations for certain distressed firms. However, there was no specific guidance in U.S. GAAP about (1) who was responsible for making going concern assertions, (2) management's role in assessing, or (3) disclosing going concern uncertainties or the timing, nature, and extent of these disclosures. Until the August 2014 Accounting Standards Update, all of the regulation and guidance for making these assertions came from the generally accepted audition standards (GAAS).

Since the AICPA first issued SAS No. 2 in 1974, auditors have struggled to assess a firm's going concern status and to develop appropriate predictive models (Akers, Giacomino, & Bellovary, 2007). SAS No. 2 was the first standard to specifically address the circumstance necessary for a modified "subject to" opinion. When SAS No. 34 replaced SAS No. 2, it provided guidelines for auditors to follow when assessing going concern uncertainty, but fell short of requiring the assessments. To address the "expectation gap" between the role of auditors and the perception of that role, SAS No. 59 made going concern assessments a requirement for auditors but left many thresholds and definitions up to professional judgment. Even though the regulation was tightening and clarifying the role and expectations of auditors, SAS No. 34 and SAS No. 59 did little to improve the usefulness or accuracy of going concern opinion issuance (Carcello, Hermanson, & Huss, 1995).

Statement on Auditing Standards No. 59 (SAS 59), The Auditor's Consideration of an Entity's Ability to Continue as a Going Concern, required auditors to evaluate whether “substantial doubt” exists about an audit client's ability to continue as a going concern. The first stage in making this going concern evaluation required consideration of whether the results of audit procedures performed related to the various audit objectives identify existing conditions and events that indicate “substantial doubt” about the client's ability to continue as a going concern.

Under this standard, when auditors believed that “substantial doubt” existed, they considered management's plans for dealing with the effects of those conditions and events, and then concluded if “substantial doubt” remains. However, regulation fails to provide an exact definition of what constitutes “substantial doubt”. Due to past ambiguity of the definition of “substantial doubt,” much research investigated this threshold in practice. Boritz (1991) concluded that a 50 to 70 percent likelihood would represent substantial doubt. Under SAS 59, if the threshold for “substantial doubt” was met, the auditors were required to include an explanatory paragraph in their report to reflect this uncertainty. For example, if a client company failed to meet a debt covenant but presented evidence that the financial institution waved the requirement and did not consider the client to be in default, then the auditors may choose to issue a modified opinion with certain going concern language instead of a GCO.

In June 2009, General Motors filed the largest bankruptcy in U.S. history preceded by a going concern warning. Deloitte & Touch LLP provide an example of the language used in warnings issued under SAS 59 regulations. On February 17, 2009, General Motors filed a “Viability Plan” detailing management’s intention to continue operating as a going concern after requesting U.S. Government funding totaling $22.5 billion to cover baseline liquidity requests. Subsequent to that filing, Deloitte & Touche LLP’s audit report dated March 4, 2009 included the following explanatory paragraph expressing substantial doubt about General Motor’s ability to continue as a going concern:

> The accompanying consolidated financial statements for the year ended December 31, 2008, have been prepared assuming that the Corporation will continue as a going concern. As discussed in Note 2 to the consolidated financial statements, the Corporation’s recurring losses from operations, stockholders’

> deficit, and inability to generate sufficient cash flow to meet its obligations and sustain its operations raise substantial doubt about its ability to continue as a going concern. Management's plans concerning these matters are also discussed in Note 2 to the consolidated financial statements. The consolidated financial statements do not include any adjustments that might result from the outcome of this uncertainty. (138)

The ambiguous language in standards such as AU section 341 created problems for litigation. In an attempt to clarify the standards, the Auditing Standards Board (ASB) issued Statement on Auditing Standards (SAS) No. 126, *The Auditor's Consideration of an Entity's Ability to Continue as a Going Concern* (Redrafted), to supersede SAS No. 59, *The Auditor's Consideration of an Entity's Ability to Continue as a Going Concern*, as amended. However, SAS No. 126 did not significantly change or expand SAS No. 59 and it did not converge with the IAASB's international auditing standard on going concern.

In 2004, Section-104 of the Sarbanes-Oxley Act of 2002 required audit firms registered with the PCAOB to be assessed on their compliance with professional standards. The publicly available reports from these assessments include identified audit deficiencies. Gramling, Krishnan, and Zhang (2011) studied the audit deficiencies identified during PCAOB Section 104 inspections between 2004 and 2006. The stud indicated no audit deficiencies due to the failure to issue a going concern opinion for firms that subsequently filed bankruptcy. Their analysis did not demonstrate a significant change in the likelihood of issuing a going concern or in Type I and Type II errors. By not issuing deficiencies or requiring additional procedures for evaluating the likelihood of bankruptcy, the PCAOB appear to support the adequacy of audit methods for evaluating going concern assertions.

Since 1973, the FASB has been responsible for issuing standards of financial accounting and reporting for the private sector. Regulators could not agree who was primarily responsible for assessing going concern and issuing opinions: management or external auditors. Throughout this regulatory history, the FASB has remained silent about Going Concern reporting and management has never been required to make a going concern prediction or assertion. As the US GAAP convergence process proceeded, demand for breaking that silence to conform to the IAS 1 (25) grew.

Respondents to FASB's 2008 exposure draft for regulation concerning GCOs expressed concerns over ambiguous language and time horizons as well as the failure of the standard to incorporate current audit research concerning mitigating factors or adequately explain how to prepare the financial statements under the liquidation basis. In 2010 the Board evaluated the issues brought forth in the 2008 exposure draft and modified the project's objectives. In May 2012, the Board began the process of providing guidance to management for assessing going concern uncertainty and making required disclosing. Through the project it is expected that GAAP will provide guidance that is more in line with international standards. IAS 1 (25) currently requires managers to assess going concern during the preparation of the financial statements. IAS 570 requires auditors to consider the appropriateness of management's going concern assumption in both the planning and performing stages of the audit.

On June 26, 2013, the FASB issued an exposure draft for "Presentation of Financial Statements (Topic 205): Disclosure of Uncertainties about an Entity's Going Concern Presumption" (2013) requiring *management* to perform going concern assessments and provide related footnote disclosures in certain circumstances. In an attempt to address some of the concerns from the 2008 Exposure Draft, the new draft carefully defined "substantial doubt" and "probable" and identifies specific time horizons. Two guidelines for disclosing uncertainties were identified according to their time horizon-time: (1) that it is *more likely than not* that the entity will be unable to meet its obligations within 12-months after the financial statement date and (2) it is *known or probable* that the entity will be unable to meets its obligations within 24-months after the financial statement date. In addition, the draft provided seven areas that should be accessed: (1) sources of liquidity, (2) operating funds, (3) conditional and unconditional obligations, (4) adverse conditions and events, (5) mitigating conditions, and (6) the predicted effects of management's plans.

On August 27, 2014, the FASB issued *Accounting Standards Update No. 2014-15, Presentation of Financial Statements – Going Concern (Subtopic 205-40): Disclosures of Uncertainties about an Entity's Ability to Continue as a Going Concern* (the Update). The Update defined managements' responsibility to evaluate whether there is "substantial doubt" about an organization's ability to continue as a going concern and to provide related footnote disclosures. The new standard represents both a move toward convergence with IAS No. 1 (25) and a change in the role of auditors concerning going concern opinions. It also defines the timing and content of disclosures. It applies to all companies and not-for profit organizations with an annual period ending after December 15, 2016.

In periods after 2016, issuing going concern warnings remains a problem even for the largest bankruptcy cases. For example, in its notes to financial statements filed April 12, 2017, Toy's "R" Us included the following going concern disclosure in which it failed to issue a warning for the liquidation that occurred eleven months later:

> In August 2014, the FASB issued ASU No. 2014-15, "Presentation of Financial Statements-Going Concern (Subtopic 205-40): Disclosure of Uncertainties about an Entity's Ability to Continue as a Going Concern" ("ASU 2014-15"). ASU 2014-15 is intended to define management's responsibility to evaluate whether there is substantial doubt about an organization's ability to continue as a going concern and to provide related footnote disclosures, if substantial doubt exists. The amendments in this ASU are effective for reporting periods ending after December 15, 2016, with early adoption permitted. The Company adopted the amendments of ASU 2014-15 as of January 28, 2017. The adoption did not have an impact on our Consolidated Financial Statements. (2017)

In January 2015, the IAASB revised ISA 570 to expand the descriptions of auditors' and managements' roles and responsibilities regarding going concern for annual periods ending after December 15, 2016.

In response, in February 2017, the ASB issued *SAS No. 132, The Auditor's Consideration of an Entity's Ability to Continue as a Going Concern* to supersede SAS No. 126. SAS No 132 clarifies the auditor's objectives and provides guidance related to audit scope, timing, and explanatory language within the audit report. This standard takes effect beginning after fiscal years ending on or after December 15, 2017. The standard requires auditors to make determinations and conclusions based on audit evidence on whether substantial doubt exists about an entity's ability to continue as a going concern for a reasonable amount of time. It also includes a list of examples of adverse conditions and events that may raise substantial doubt about an entity's ability to continue as a going concern. That list includes "negative financial trends," "other indicators of possible financial difficulties," and other adverse key financial and liquidity ratios. Financial and accounting researchers have long studied BPMs and other “negative financial trends” that are more predictive than simple trends in ratios. Because these models are widely accepted and supported publicly in research, the results from these models may better fulfill the evidence requirements of SAS No. 132 than simple ratios.

2.3 Reporting Trends

Because auditors are charged to evaluate management’s assertion for a business’ likelihood of being able to meet future obligation; investors, creditors, shareholders, and other financial statement users expect to be warned by a going concern disclosure of an impending bankruptcy. Audit Analytics reported that between 14.1% and 21.1% of audit opinions included going concern uncertainty language each year between 2000 and 2016 (Whalen, Esq. & McKeon, 2018), yet investors are only warned about 43% of bankruptcies through GCO. Compared to the accuracy of auditors’ predictions, a case for removing auditor judgment and defaulting to BPM in making GCOs may exist.

In response to the collapses of Carillion and BHS, the British Financial Reporting Council (FRC) issued a statement that existing going concern requirements need to be strengthen. On March 4, 2019 the FRC unveiled proposals to make auditors apply more robust checks and through tests when reviewing whether a company was likely to continue as a going concern and to include an explanation for how they came to their conclusion (Financial Reporting Council, 2019). The proposed changes to the International Auditing Standard on Auditing (UK) 570 was available for comments as an exposure draft until June 14, 2019. The draft did not include specific guidelines for identifying appropriate testing. At the time of this defense, deliberations on the proposal were ongoing.

In their review of going concern prediction studies, Gissel, Giacomino and Akers (2007) report the model accuracy of 27 BPMs. Overall, they found that predictive abilities from multiple discriminate analysis models achieved 78-94% accuracy, logit models achieved 60-100% accuracy, probit models achieved 83-86% accuracy, and neural network models achieved 77-92% accuracy. According to their research “over time, the range of model accuracies remained consistent.” However, accuracy rates fail to consider the trade-off of costs between both types of errors. While auditor judgment seems less likely to predict a subsequent bankruptcy, they are also less likely to issue a qualified opinion for a non-bankrupt firm.

The Gissel et. al (2007) study also notes that adding explanatory variables did not necessarily improve accuracy. This seems to support the debate that academic conclusions based solely on statistical tests may include models that suffer from overfitting. In the 2019 edition of The American Statistician, 43 articles are presented that encourage researchers to consider the reliance on p-values for drawing conclusions about associations.

Although other forms of liquidation risk exist, bankruptcy is a common proxy throughout the research for “business failure” or identification as a “non-going-concern”. It is important to note that going-concern assessments are a prediction about an uncertain future and not all conditions or circumstances are knowable by the auditors at the financial statement date. Therefore, a Type I or Type II error does not necessarily indicate an audit failure. The PCAOB does not routinely issue audit deficiencies based on the failure of an audit firm to issue a GCO for a company that subsequently filed for bankruptcy[1]. Current auditing standards prevent auditors from considering circumstances, events, and risks that have not yet occurred, thus constraining an auditor’s ability to issue a GCO due to worsening market conditions.

The Cohen Commission (1978) and other research (Altman, 1993; Asare, 1990; Louwers & Richard, 1999; Loftus and Miller, 2000) suggest that auditors' opinions were inferior indicators of bankruptcy relative to the predictions of statistical models. However, Hopwood, McKeown, and Mutchler (1994) reexamined the question and found that auditors are not substantially worse. They found two research design choices to be particularly important: partitioning the sample into stressed and non-stressed observations and adjusting the forecast errors to reflect the proportion of bankrupt firms’ auditors face. One implication of my research is to provide information about the efficacy of using BPMs as an analytical review tool.

My research may have further implications for documenting objective measure criteria used during ligation. In the final stages of the audit, BPMs may verify that a client’s overall going concern assessment is appropriate (Chen & Church, 1996). In the event that an adverse or qualified opinion is rendered, an objective statistical model can more readily help the auditor in justifying the decision

[1] Although PCAOB inspection reports do not find material weaknesses for Type I failures, research suggests that PCAOB inspections are associated with GCO rates. Audit firms with recent audit deficiencies are more likely to issue a GCO for their clients (Gramling, Krishnan, & Zhang, 2011).

to interested parties (Chen and Church, 1992) and avoid litigation (Kaplan & Williams, 2013).

2.4 Decision Aids

Statistical BPMs consistently outperform auditors' going concern judgment in discriminating between bankrupt and non-bankrupt companies. Due to the perceived expectations gap between auditors and financial statement users, statistical models may assist auditors in making more accurate going concern judgments if used as a decision aid during audit planning.

The Audit Standards Board issued SAS No. 56 in 1988. The standard formally required auditors to use analytical procedures in all financial audits. The purpose of analytical procedures varies across different phases of the audit (i.e. planning phase, testing phase, and completion phase). In the planning phase, analytical procedures are employed as attention–directing devices to inform the nature, timing, and extent of substantive procedures performed in the testing phase. Simple quantitative techniques involving ratio and trend analysis were the most commonly used analytical procedures (Putra, 2010). Researchers have suggested analytical procedures be used in the planning phase of going concern assessments (Koskivaara, 2004). Auditing standards are silent about the use of specific statistical models in assessing going concern uncertainty. AU 341.06 includes four categories of events that may indicate substantial doubt about the continuation as a going concern: (1) negative trends, (2) other indications of possible financial difficulties, (3) internal matters, and (4) external matters. Nevertheless, the auditing standard is unclear as to how the auditor is to interpret and assess these events.

Accounting practitioners and researchers recognize the need for reliable audit tools to assist auditors in evaluating the going concern assertion. Kuruppu et. al. (2012) surveyed 152 New Zealand auditors and found that auditors perceive corporate failure models as beneficial in the planning stage of an audit. They concluded that these models could help identify high-risk clients and alert them to expand the scope of testing. In order to evaluate the existence of substantial doubt a company will continue as a going-concern, the auditor must know what information to acquire as well as how to combine that information. The auditor's going concern assessment is a complex process that can benefit from the use of a decision aid (Putra, 2010).

The use of decision aids has many uses improving judgments and decision making. Bonner, Libby and Nelson (1996) suggest that decision aids could help auditors weight causal explanations relevant to determining a client's ability to continue as a going concern. Discriminate analysis common in BPMs includes a mechanical weighting of identified variables. However, Davis (1998) finds that decision makers prefer descriptive phrases over mechanical aggregation aids. Davis notes that decision makers follow aid recommendations to a greater extent when aid type matches their personal style. Analytical individuals rely more heavily on quantitative information and concrete data (Davis & Elnicki, 1984). It follows that the use of a quantitative models (such as BPMs) as part of the analytical procedures performed during an audit may match the analytical decision aid with the task and personal style of auditors.

2.5 Materiality in Audit Testing

Furthermore, SAS No. 122 (AU-C Section 320) provides guidance for auditor's responsibility to apply the concept of materiality in planning and performing and audit of financial statements. Auditing materiality provides a framework for the scope of the audit and risk assessment--how much the auditor needs to look for misstatements. AU-C Section 320 discusses materiality determinations and "tolerable misstatement." Per the standards, "performance materiality" should be applied to various classes of transactions, account balances, or disclosures based on the auditor's judgment. "Performance materiality" is defined in AU-C Section 320 as an amount set by the auditor "to reduce to an appropriately low level the probability that the aggregate of uncorrected and undetected misstatements exceeds materiality for the financial statements as a whole." Performance materiality is used in planning to (1) determine the scope of the audit (e.g. which financial statement areas and accounts the auditor will focus their attention on); (2) calculate statistical sample sizes; (3) determine whether analytical review variances should be investigated; and (4) assess the risk of material misstatement. The auditing standards preclude the sole use of analytical procedures as a source of audit evidence to support a significant assertion unless supported by tests of details or controls.

AU-C Section 320 describe a basis for setting a "benchmark" to determine planning materiality from among key financial statement items or other metrics. Auditor judgment is required in the selection of an appropriate benchmark. Certain benchmarks based on accounting measures may be too volatile, thus creating impractical audit scope and sample sizes. Benchmarks can also create comparability issues when evaluating year-to-year waived adjustments. Levy & Jacoby recommend that auditors use relatively stable benchmarks for determining planning materiality, such as the larger of assets or revenues, or a measure of entity value (2016).

Research consistently finds that large accounting firms have higher materiality thresholds than smaller firms and are less likely to issue going-concern qualifications (Eilifsen & Messier Jr, 2015). Research examining auditors' materiality judgments on financial ratios such as the ratio of misstatement to current net income, inventory write-downs, and changes in accounting principles find that an item's percentage effect on income is the single most important factor in materiality judgments (Chewning, Pany, & Wheeler, 1989). Results also indicate large national CPA firms have larger materiality thresholds than smaller firms (Messier, Jr., 1983). Ryu and Roh (2007) find that firms defining higher materiality thresholds were less likely to issue going-concern opinions to their clients with financial problems. We would expect larger firms to have higher rates of bankruptcy prediction error; however, Geiger and Rama (2006) investigated both types of errors for Big Four and non-Big Four audit firms and found that both Type I and II error rates for Big Four audit firms are significantly lower than the error rates for non-Big Four firms.

Eilfesen and Messier (2015) examine the proprietary materiality guidance of the eight largest U.S. accounting firms and find a high level of consistence across firms in terms of quantitative benchmarks. They identify ten accounting measures used for benchmarking by the largest eight firms. They report that percentages from these fundamental accounting measurements are applied to determine overall materiality for determining tolerable misstatement. Their results suggest that small firms set a lower quantitative materiality threshold; however, that doesn't translate into lower error rates. Because the levels of materiality set by large national CPA firms in prior research did not seem to negatively impact error rates, I use *Table 3: Percentages Used for Setting Quantitative Benchmarks* from their research to select the materiality benchmarks used in the simulations in this dissertation.

2.6 BPMs in Audit Testing

Auditing standards do not require an auditor to design specific audit procedures to identify conditions and events that might raise questions about the validity of the going-concern assumption. SAS No 132 requires auditors consider key financial ratios and adverse financial trends. In addition, auditors are required to consider whether certain conditions or events discovered during the course of the audit contradict the going-concern assumption. Such evidence would include information about the company's ability to meet its maturing obligations without selling operating assets, restructuring debt, revising operations based on outside pressures, or similar strategies.

SAS No. 56 did not mandate specific analytical procedures for auditors to use in their evaluation of the going concern issue; however, research often associates BPMs with this evaluation (Hopwood, McKeown, and Mutchler 1994; Blocher and Loebbecke 1993; and Altman 1993).

SAS No. 59 does not specify audit procedures that auditors should use to evaluate the going concern assumption. However, the standard highlights analytical procedures as an *example* of audit procedures that may identify conditions that would create doubt about a company's ability to continue as a going concern. Adding a requirement for BPMs to be performed as part of the analytical procedures of all audits may prove useful. Research suggests, however, that auditors do not apply BPMs as part of the analytical procedures in the planning or final stages of an audit even when the use of analytical procedures is prescribed by the standards of that country[2] (Vida & Roghayyeh, 2011).

Similarly, SAS No. 132 provides examples of risk assessment procedures and related activities, but falls short of recommending any specific tests, ratios, or models to evaluate liquidity or financial distress. The standard directs auditors to base their risk assessments on negative financial trends including "other adverse key financial ratios." I argue that existing BPMs would provide a stronger basis of risk assessment than general ratio analysis.

The Proceedings of the Expectations Gap Roundtable called for continued research on the effectiveness of analytical procedures in various contexts, including the going concern evaluation (Blocher & Loebbecke, 1993). The Cohen Commission indicated that statistical failure models might be considered by auditors in their overall assessments of companies (Cohen, 1978).

BPMs may alert auditors to certain problems that are difficult to detect with traditional auditing procedures. Altman and McGough (1974) suggested that BPMs may help auditors' judge companies' abilities to continue as a going concern by alerting

[2] Data from a survey of 153 Iranian auditors. Regulatory differences may impact the implementation of similar standards within the United States.

auditors to certain problems that may be difficult to detect using traditional auditing procedures. Other early research presented evidence that BPMs may be useful to auditors in making going concern judgments (Lasalle, Anandrarajan, & Kleinmann, 1996) (Mutchler, Hopwood, & McKeown, 1997). If models are useful audit tools for evaluating a firm's going concern potential, then they may be helpful for making GCO assessments, particularly as analytical procedures during the require risk assessment stage of the audit.

2.7 Bankruptcy Prediction Models

Academic researchers and financial institutions have long used BPMs to assess financial distress. As a suggestion for future research, Beaver (1966) introduced the possibility that considering multiple ratios simultaneously might have higher predictive value than a single ratio. From there, Altman's (1968) study identified five financial ratios out of 22 studied to form a score from discriminate analysis using data from 33 industrial firms. Sinkey's (1975) study examined 110 banks using a matched sample to identify five significant indicators out of over 100 studied. Trieschmann and Pinches' (1974) model classifies insurance firms as distressed or solvent using a combination of six variables. This study advanced the models by including a systematic factor analysis to evaluate the usefulness of the proposed ratios.

The seminal work by Altman (1968) and McGough (1974) first suggested the usefulness of BPMs for assessing company going concern status. They compared their model's 82-percent accuracy in predicting bankruptcy filings to auditors' going concern assessment of 46-percent accuracy. These results gave rise to a stream of research in which researchers developed BPMs to predict company failure and examined the usefulness of a model for assessing going concern by comparing the accuracy of developed models to auditors' going concern qualifications issued prior to bankruptcy. Chen and Shimerda (1981) reviewed 27 early discriminate analysis studies from 1932 to 1975 and tabulated which of 66 distinct financial ratios were mentioned or found to be useful for predicting distress in each study. Since these seminal studies, numerous models and modifications to models have been proposed and tested. The research concerning BPMs is vast and replete with examples of models being evaluated by count and percentage accuracy. Bellovary et al. (2007) reviewed 165 BPM journal articles published between 1930 and 2007 and determined that multivariate discriminate analysis and neural networks offer the most promise. Altman et al. (2014) finds over thirty publications between 2000 and 2014 using and expanding upon the Z-Score model alone. Alaka (2018) reviewed 49 BPM journal articles published between 2010 and 2015 and classified BPMs into eight categories: multiple discriminate analysis, logistic regression, artificial neutral network, support vector machines, rough sets, case-based reasoning, decision tree and genetic algorithm. Emerging models using artificial intelligence are criticized for operating in a "black box" and lacking explanations for predictions. They concluded that bankruptcy prediction should be informed by an integration of tools (Alaka, 2018).

Mulcher (1985), Hopwood, McKeown, & Mutchler (1994), Cormier et al. (2016), and Lennox (1999) measured the number of errors identified by various financial models and found the models to be more accurate than auditors' prior audit opinions. This evidence in aggregate suggests that financial models could assist auditors in forming more accurate going concern judgments. Applying these models could assist the accounting profession to reduce the public's expectation gap of the profession, and to increase the public's confidence in the audit function.

Lennox (1999) went further to study whether stakeholders should rely on five BPMs for decision-making rather than auditor issued GCOs: (1) Altman's Z-Score (1968), (2) Merton's model (1974) (3) Ohlson's O-Score (1980), (4) Shumway's distance to default model (2001), and (5) Campbell et al.'s CHS Model (2008). Default prediction models and the auditors' institutional environment have evolved since the 1990's, however research continues to question the accuracy of GCOs as predictors of default. BPMs cannot incorporate auditors' professional judgment and access to private information, so a large body of research focuses on the value and quality of this incremental information in issuing GCOs. Recently, a study (Gutierrez, Krupa, Minutti-Meza, & Vulcheva, 2016) combining GCOs and default probability models resulted in small, although statistically significant, incremental predictive accuracy, suggesting that the incorporation of a statistical model in the GCO assessment may be beneficial. They also compare GCOs against changes in public credit ratings and find that GCOs have statistically greater predictive power, which suggest that auditors compound changes in credit ratings in their GCO assessment. A 2017 study found that private information, including business strategy, influenced the decision of auditors to issue GCOs. Specifically, they found that auditors commit more Type II errors when a troubled firm exhibits a prospector business strategy (Chen, Eshleman, & Soileau, 2017).

For the purpose of scope and clarity, this research examines four seminal models categorizing trends in research: discriminate analysis, logistical regression, hazard model, and distance to default. By evaluating these four seminal models, this research limits the scope while providing insight into four classifications of models from the extant literature.

Zmijewski (1984), Ohlson (1980), and Altman (1968) developed early BPMs. Ohlson and Altman employed multiple discriminate analysis (MDA). Discriminate analysis models can be used as a decision aid to mechanically combine several variables into a single measure, which is then used to classify a company as either bankrupt or non-bankrupt. Many of the BPMs using MDA, however, rely heavily on assumptions that do not hold in going-concern reporting. Logit uses maximum likelihood estimation that does not impose the same statistical requirements on the distributional properties of the predictors. Ohlson's (1980) and Shumay's (1981) model incorporated a more complex estimation model: a logit regression. While the MDA used in Gissel et al. (2007) reports that including more variables does not necessarily increase a model's accuracy. Still more bankruptcy prediction studies use logistic regression models (Chen and Church 1992; Hopwood et al. 1994; and Mutchler et al. 1997). However, logit and probit BPMs are criticized due to small samples sometimes used in GCO studies that may not be statistically appropriate.

Researchers have used structural equation modeling to explore financial dimensions and financial ratios (Ziebart, 1987). Bankruptcy prediction using structural equation models was first introduced as distance to default which builds upon the Black Scholes (1973) option pricing model and Moody's structural default probability model (hereafter, KMV) (Merton, 1974). Where other models are based on factor analysis, distance to default is mathematically based on the assumption that a company will default on financial obligations when its liabilities are greater than its assets.

In 2001, Shumway introduced a new way to think about bankruptcy prediction by arguing that hazard models are more appropriate than single-models in forecasting the outcomes of ailing firms. His research finds that a simple hazard model using both accounting ratios and market-driven data produces consistent estimates using fewer explanatory variables.

2.7.1 Discriminate Model: Z-Score

The use of discriminate models in credit analysis applies financial ratios to help lenders quantify a potential borrower's default risk and serve as an early warning device for changes in a borrower's credit risk. Discriminate models consider the effects of many key financial ratios simultaneously. One popular model used extensively in financial and accounting research is the Altman Z-Score. Altman's Z-score BPM is a frequently used benchmark for the performance of newly developed BPMs. Altman's Z-Score has been used in a number of different countries across various industry settings, and has been found to outperform country-specific corporate failure models (Eidleman, 1995).

In 1968, Edward Altman introduced the Zeta Model for predicting bankruptcy. Rather than search for a single best ratio, Altman built a discriminate analysis model that estimates the chance of a public company going bankrupt by combining five key performance ratios into a single score—the Z-score. To develop the Z-Score formula, Altman (1968) compiled a list of twenty-two financial ratios and classified each into one of five categories (liquidity, profitability, leverage, solvency, and activity). Altman selected the ratios on the basis of their popularity in the research and his belief about their potential relevancy to bankruptcy. Altman derived his original coefficients from a sample of 66 bankrupt manufacturing firms from 1946 to 1965. Ultimately, the model combines information about the company's current profitability, long-term profitability, liquidity, solvency, and asset efficiency into a single measure of bankruptcy risk. The Z-score's famous calculation gives insight on corporate financial health. While the model has been updated and evaluated several times throughout the literature, the original model is generalizable to publicly traded companies.

Accounting researchers, practitioners, and educators cite the Z-Score model than any other BPM (Altman 1993), therefore I select it as my discriminate analysis model for simulation. For sensitivity, I calculate Z-Scores for each firm-year using the 1968, 1983, and 2004 weightings for the defined variables. I limit the pool of Z-Score derivatives due to practical considerations[3].

The five determinants of the Z-Score model and associate weightings for each model follow. The original 1968 Z-Score formula follows:

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[3] For example, in 1977 Altman published a re-estimation of his model using 1969-1975 bankruptcies. In that study, he trademarked the ZETA™ score. I do not test the ZETA™ due to issues related to the sensitivity of the cut-off.

$$\text{Z-Score} = 1.2\,(X1) + 1.4\,(X2) + 3.3\,(X3) + 0.6\,(X4) + 1.0\,(X5) \qquad (1)$$

Where:

X1= Working Capital/Total Assets,

X2=Retained Earnings / Total Assets,

X3=Earnings Before Interest and Tax / Total Assets,

X4=Market Value of Equity / Total Liabilities, and

X5=Sales / Total Assets

Z-scores are interpreted using a system of established rankings and ratings. In general, the lower the Z-score, the more likely a company will subsequently file bankruptcy. Certain cut-offs are commonly seen in the literature. A Z-Score lower than 1.8 indicates severe financial distress; a Z-Score above 2.99 suggests that a company is a Going Concern (or a “prompt payer”); and a Z-Score between 1.81 and 2.7 predicts that a company has an increased probability of insolvency. Altman classified anything less than 1.81 as clearly fell into a “deadbeat” category and predicted to go bankrupt. Z-scores have since been converted to credit ratings using conventional cutoffs: 4 – AAA, 3.5 – AA, 2.9 – A, 2.5 – BBB, 2.25 - BB, 2 – B, 1.8 – C, and less than 1.8 D. I apply these definitions as a bright-line test, where a Z-Score less than 1.8 would predict a going concern modification.

Studies suggest that bankruptcy model predictions are more accurate than auditor opinions in signaling impending failure (Koh 1991; Altman 1982; and Altman and McGough 1974). The accuracy of auditors signaling impending failure ranged from 40% to 54% in pre-SAS No. 59 studies, while the accuracy of the models ranged from 82% to 93%. Altman and McGough (1974) provided a link between BPMs and auditors’ opinion decisions by comparing the accuracy of Altman’s (1968) BPM to auditors’ opinions prior to the bankruptcy event. They analyzed the model’s predictions and auditors’ opinions for 34 firms that filed bankruptcy during the 1970-1973 period. The results indicated that the Z-Score model correctly signaled impending failure prior to bankruptcy in 82% of the cases. They reported that auditors’ opinions signaled impending failure in only 46% of the cases.

Altman (1982) extended the evaluation of Altman’s original Z-Score model in the auditors’ opinion context using two additional samples: (1) 37 bankrupt firms from 1974-1978 and (2) 44 bankrupt firms from 1978-1982. The Z-Score model correctly signaled impending failure for 81.1% (93%) of the 1974-1978 (1978-1982) companies; additionally, he reported that auditors issued GCOs to 59.5% (40%) of the 1974-1978 (1978-1982) companies. These results suggest Z-Score model (auditors) provided early warning signals of subsequent failure in 86.2% (48.1%) of the cases.

Over the last half century, many researches have studied and updated the coefficients to reflect larger samples, more recent samples, and samples of firms from both more diverse and more specialized industries. Hillegeist et al. (2004) conclude that several of the coefficients in accounting-based bankruptcy models have changed possibly due to the Bankruptcy Reform Act of 1978 and asbestos-related bankruptcies in the manufacturing industry. For robustness, I examine the error rates using two subsequent versions of Altman's Z-Score: the Altman et al.(1983) coefficients expand beyond manufacturing firms and the Hillegeist et al. (2004) coefficients that update using 756 bankrupt firms from 1980-2000.

$$\text{Z-Score83} = 6.56\,(X1) + 3.26\,(X2) + 6.72\,(X3) + 1.05\,(X4) \qquad (2)$$

$$\text{Z-Score04} = 4.34 + 0.08\,(X1) - 0.04\,(X2) + 0.1\,(X3) + 0.22\,(X4) - 0.06\,(X5) \qquad (3)$$

I also examine a subset of firms from the financial industry. These firms face a unique regulatory environment. The Gramm-Leach-Billey Act and the more recent financial crisis were particularly important among financial firms. The probability of bankruptcy of financial firms and performance of statistical models may be distorted in my sample because of the Emergency Stabilization Act of 2008 and the American Recovery and Reinvestment Act of 2009. I remove these firms for sensitivity analysis.

Following Hillegeist et al. (2004), I estimate the probability of bankruptcy as ($e^{Score}/1+e^{Score}$) for Z-Score, Z-Score93 and Z-Score04. I evaluate the score using a bright-line test that predicts a going concern modification when the predicted probability of bankruptcy is greater than fifty percent.

Studies using multiple discriminant analysis often use a matched-sample or equal-group-size sample approach. Because discriminant analysis optimally classifies between the two given sample groups, a matched sample is not necessary. George and Mallery (2003) explain that because prior probabilities can be computed from the individual samples by weighing, discriminant analysis does not require equal group sizes.

2.7.2 Logit Model: Ohlson

Created by James Ohlson in the 1980's, the Ohlson Score model (O-Score) introduced a bankruptcy prediction indicator generated from a set of balance sheet ratios. Ohlson's model was derived from a much larger sample (2,058 public companies including 105 bankruptcies) than the Z-Score model (66 companies including 33 bankruptcies). The O-Score used a sample of bankrupt firms from 1970 to 1976 to identify a 9-factor linear combination of coefficient-weighted business ratios which are available in standard annual reports provided by publicly traded corporations. The O-Score Model estimates the probability of failure using a logit regression. He found that using the probability cut-off point of 3.8% minimized Type I and Type II errors and correctly classified 87.6% of his bankrupt sample and 82.6% of his non-bankrupt sample. One of the advantages of this model as an analytical tool at the planning stage of an audit is that it is entirely an accounting-based model and that it is relatively simple and the results are intuitive. The most current BPMs that employ machine learning methods are criticized for the lack of explainability in the results. The O-Score produced by Ohlson's model is readily interpreted as the probability of bankruptcy.

Ohlson ultimately identified six variables from previous approaches and added three dummy control variables to create his predictive model of nine weighted variables:

$$\text{O-Score} = 1.32 + 0.41(X1) - 6.03(X2) + 1.43(X3) - 0.08(X4) + 2.37(X5) + 1.83(X6) - 0.285(X7) + 1.72(X8) + 0.52(X9) \quad (4)$$

Where:

X1 = Adjusted Size (AS): Ohlson measures a company's size as its total assets adjusted for inflation. Smaller companies are deemed to be more at risk for failure. AS = log(Total assets/GNP price-level index).

X2 = Leverage Measure (LM): Designed to capture the indebtedness of a company, the more leveraged the more risk the company is to shocks. LM = Total liabilities/Total assets.

X3 = Working Capital Measure(WCM): Even if a company is endowed with assets and profitability, it must have sufficient liquidity to service short-term debt and upcoming operational expenses to avoid going bust. WCM = Working capital/Total Assets.

X4 = Inverse Current Ratio (ICR): This is another measure of a company's liquidity. ICR = log(Current liabilities/Current assets).

X5 = Discontinuity Correction for Leverage Measure (X): Dummy variable equaling one if total liabilities exceeds total assets, zero otherwise. Negative book value in a corporation is a very special case and hence Ohlson felt the extreme leverage position needed to be corrected through this additional variable.

X6 = Return on Assets (ROA): An indicator of how profitable a company is, assumed to be negative for a close to default company. ROA = Net income/Total Assets.

X7 = Funds to Debt Ratio: A measure of a company's ability to finance its debt using its operational income alone, a conservative ratio because it does not include other sources of cash. If the ratio of funds from operations to short-term debt is less than one the company may have an immediate problem. FTDR = Funds from operations/Total liabilities; where Funds from operations = pretax income + depreciation.

X8 = Discontinuity Correction for Return on Assets: Dummy variable equaling one if income was negative for the last two years, zero otherwise.

X9 = Change in Net Income (Y): Designed to take into account any potential progressive losses over the two most recent periods in a company's history. CINI = (Net income $_{t}$ - Net $_{\text{income } t-1}$) / (Net income $_{t}$ + Net income $_{t-1}$)

Like Altman's original model, the original O-Score has been extensively followed and updated through literature. Begley et al. (1996) replicated the methodology on a new sample and didn't find Ohlson's original precision rates to hold. For robustness, I also examine the model using the updated coefficients from Hillegeist et al. (2004):

$$\text{O-Score} = 5.91 - 0.04(X1) - 0.08(X2) - 0.011.43(X3) + 0.01(X4) - 1.20(X5) - 0.18(X6) - 0.01(X7) - 1.59(X8) + 1.10(X9) \quad (5)$$

Following Hillegeist et al. (2004) I convert each O-Score into a probability using the formula Probability = ($e^{Score}/1+e^{Score}$). This model allows for a bright-line test where a probability of bankruptcy of greater than 0.5 indicates a company is “more likely than not” to fail the going concern assumption.

Studies have generally found the O-Score to be a better forecaster of bankruptcy than the 1968 Altman’s Z-Score. The O-Score even outperforms updated variations of the Z-Score model. However, past research is mixed. Studies found no significant difference in accuracy between MDA models and logit analyses (Collins and Green, 1982; Cormier *et al.*, 1995; Allen and Chung, 1998). Neither model has been able to regularly beat the predictive accuracy Merton’s Distance to Default. Therefor I move away from discriminate analysis and BPMs that use only accounting-based numbers.

2.7.3 Distance to Default Model: Merton’s KMV

Introduced as the “Kealhofer-Merton-Vasicek” model (hereafter, Merton’s KMV) in 1974, the distance-to-default estimates the probability a firm will default by comparing the firm’s value to the face value of the firm’s debt. The model uses simultaneous equations to measure the distance between the expected value of the assets (drawing from assumptions in the Black-Scholes option pricing theory) and the default point to calculate the probability of default. To calculate the probability, the model subtracts the face value of the firm’s existing debt from an estimate of the future market value of the firm and then divides this difference by an estimate of the volatility of the firm (scaled to reflect the horizon of the forecast). The ratio is substituted into a cumulative density function to calculate the probability that the value of the firm will be less than the face value of debt. The resulting score is referred to as the expected default frequency (hereafter, EDF).

Merton’s KMV uses a two-step process to set the default point as somewhere between short-term debt (LCT) and the total debt (LT). The first step to calculate the EDF is to derive parameters needed in estimation:

1. Returns and volatility of equity over the previous year;
2. Market rate of equity: total number of stocks times the closing stock price (S);
3. Risk-free interest rate (r);
4. Liabilities maturing in one year (LCT); and
5. And short-term liabilities plus one half of long-term liabilities (TD).

The second step simultaneously solves two linear equations to derive value (μ) and volatility (σ) of the firm’s assets. And, finally, distance-to-default and probability to default are calculated. I interpret EDF as the percentage likelihood of bankruptcy.

Research suggests that regulation requires an uncertainty disclosure for uncertainty assessed at somewhere between 50% and 70%. Therefore, I set bright-line testing thresholds for GCO judgments at EDF greater than 0.5 and EDF greater than 0.7.

The major disadvantage of Merton's model lies in its complexity and its need for market-based data. Not all audit firms have access to the market-based information needed to run the model and not all audit clients are publicly traded, which makes it impractical as a potential analytical tool for private companies and small audit firms. In order to use the Black-Shoal's bond pricing model, distance to default makes two important assumptions. First, that the total firm value follows a Brownian motion. The second is that the firm has only one discount bond maturing in the time-period.

2.7.4 Hazard Model: Shumway

For decades, accountants and economists employed static, single-period models to predict bankruptcies. In his 2001 study, Shumway argues that the use of a discrete hazard model for forecasting bankruptcy is more appropriate than single–period models because it recognizes that companies change over time. Hazard functions (often used in survival analysis) determine the probability that an entity will experience an event (e.g. bankruptcy) within a defined time-period, given the risk that the event might occur. In the bankruptcy setting, hazard models measure a firm's "health" as a function of its latest financial condition. Unlike static models, hazard models utilize panel data to control for how long a firm is at risk of failure and impound information. Shumway's model is essentially a multi-period dynamic logit model.

Shumway's bankruptcy forecasting technique estimates a discrete-time hazard model with a logit program consisting of several accounting ratios and market-driven variables (Shumway, 2001). In his re-estimation of Altman (1968) and Zmijewski (1984), Shumway found that many of the determinants from these models were unrelated to bankruptcy after market driven variables were introduced and he explicitly controlled for each firm's period at risk (Shumway, 2001). He also incorporated market variables such as market size, past stock returns, and idiosyncratic returns variability as bankruptcy predictors. He found that a multi-period logit outperformed traditional MDA for his sample including 300 bankrupt firms.

$$\text{Shumway\_Score} = -13.03 - 1.982(X1) + 3.593(X2) - 0.467(X3) - 1.809(X4) + 5.791(X5) \quad (6)$$

Where:

X1 = Return on Assets (ROA): The ratio of net income to total assets measures profitability of a firm.

X2 = Leverage Measure (LM): Designed to capture the indebtedness of a company, the more leveraged the more risk the company is to shocks. LM = Total liabilities/Total assets.

X3 = Average Relative Size: The logarithm of each firm's size relative to the total size of the NYSE and AMEX market.

X4 = Abnormal Returns: Each firm's past excess return in year t as the return of the firm in year t-1 minus the value-weighted CRSP NYSE/AMEX index return in year t-1; where each firm's annual returns are calculates by cumulating monthly returns.

X5 = Sigma: The idiosyncratic standard deviation of each firm's stock returns. Sigma is related to variable cash flows and may measure something like operating leverage.

Again, this model is more complex than the discriminate analysis and scores produced by the Z-Score and O-Score models. The need for market-based data limits the practical application and usefulness of this model during audit planning for private clients and small audit firms.

2.8 Proprietary Models

Large audit firms have developed and used internally developed BPMs for years. PricewaterhouseCoopers, LLP (PwC) designed an econometric model to quantify the relationship between observed business conditions and the incidence of bankruptcy filings (Pate, 2003). Similar to discriminate analysis, PwC's measure focuses on five factors that influence the level of bankruptcy filings: degree of corporate leverage, cost of borrowing, prevalence of excess production capacity, change in high-yield debt issuance, and aggregate economic activity. Deloitte utilizes a "data analytics" tool specifically to identify first-time defaulters (Deloitte Center for Financial Services, 2011). Anecdotal evidence suggests that large audit firms use a combination of ratio analysis and proprietary models to analyze the likelihood of bankruptcy. These models, however, are not publicly available or vetted in the academic literature.

Mai's (2010) dissertation also examines these four models. Her empirical results show that combining Shumway's model with accounting ratios and market-driven variables improves bankruptcy forecasting accuracy and precision. She also ranks the precision of these models with the best results from Shumway (2001), Altman (1993), Ohlson (1980), and Zmijewski (1984). My dissertation adds to this discussion by evaluating the models based on market cost in addition to precision.

2.9 Cost Estimation

Many market participants view the auditor's report as a critical component for warning of imminent going-concern problems (Venuti, 2009). Auditors are charged with warning stakeholders through issuing going concern opinions to decrease investor surprise. While companies do not always enter liquidation through bankruptcy, investors tend to equate going concern opinions as a prelude to bankruptcy. The expectation is that auditors' going concern qualifications will minimize losses at the time of bankruptcy by providing investors with an ex ante signal. Given the frequency of bankruptcies that occur with no warning, there is a great deal of uncertainty about the role of GCOs as a warning system. Some research defines "audit failure" as only those situations where clients become bankrupt within the next financial reporting period when auditors failed to issue a going-concern.

Evidence suggests that there is a large gap between the warnings that investors expect auditors to provide, and the actual warnings issued (Carson, et al., 2013). Investors, legislatures, the popular press, and the public at large expect auditors to issue a warning before each bankruptcy. From January 2001 to December 2017, audit firms issued 48,053 going concern warnings. During the same period, 2,698 corporations filed bankruptcy. However, a warning preceded only 43% of the actual bankruptcies. Not only did they fail to issue a warning 1,994 times (Type I error); they issued 46,539 false warnings. The top 10 largest bankruptcy filings in U.S. history occurred between April, 2001 and December, 2016 (see Figure 2). Only three of those companies included qualifying language to warn investors of substantial doubt for the company's ability to continue as a going concern in their annual report prior to the filing. Each of these large, unwarned bankruptcies caught international media attention and investors questioned auditor reliance.

The FASB issued an update in August 2014 to provide guidance in U.S. GAAP about management's responsibilities in evaluating going concern uncertainty and disclosure requirement for an entity's financial statement footnotes. While the role is technically different, the ability of auditors' to evaluate these disclosures and to predict financial distress and impending bankruptcy is paramount in improving the reputation and value of the audit report to stakeholders. Therefore, there is continued interest in improving the accuracy rate of GCO reporting and reducing the associated costs of both Type I and Type II errors.

As noted, research assesses the value of a prediction model by comparing the percentage of firms, bankrupt and non-bankrupt, predicted correctly by the model. We argue this fails to capture the impact of the nature of the costs of errors.

Altman et al. (1977) estimate the relative cost of errors using the bank loan function and argue that a representative approximate cost for Type I errors is “in the vicinity of” 70% of the amount of the loan, and the cost for Type II errors is equal to between 2-4% of the amount that could have been lent, The cost of Type II errors for this study was an estimate of the opportunity cost of not earning the spread on the loan. They conclude that the cost trade-off is approximately 35 Type II errors have the equivalent cost to lenders as one defaulted loan. They use this trade-off when determining the optimum cut-off for ZETA™. However, this proposed trade-off does not consider loan size. The size of the firm (or loan amount) and the relative cost of errors should be included in the evaluation of BPMs. Their model also studies the costs from a lender perspective and fails to consider other market participants.

The purpose of this study is to demonstrate the necessity of incorporating the costs of errors to properly assess the models’ trade-off between errors as well as in evaluating one model against another. I use changes in total market capitalization to show how incorporating both Type I and Type II error costs impact the evaluation of models. It may seem obvious to some that the usefulness of a prediction model cannot be fully assessed without considering these costs; however, the extensive body of research examining and using the ability of financial statement information to predict bankruptcy does not yet include this assessment. This study attempts to fill this void.

The second piece of this research is to quantify the costs of both Type I and Type II errors. Although, quantifying the total cost of errors in going concern assertions is difficult, limited attempts at estimating the trade off in costs have been made. Carson et al. (2013) calls for more research in the cost of errors. My research attempts to answer this call. I define a Type I error cost as the total change in market capitalization to a bankrupt firm, and a Type II error cost as the opportunity loss from not lending to a non-bankrupt firm (or a gain from lending to a non-bankrupt firm). The market capitalization of a company represents the value that the market places on the entire company. Market capitalization represents total enterprise value of all the company’s outstanding stock:

the share price multiplied by the number of shares outstanding. I evaluate bankruptcy models by calculating the overall market cost for errors produced by each model.

Krishnan and Krishnan (1993) research the cost trade-off that arises when auditors issue qualified opinions. They conclude that auditor's litigation risk and client retention are important factors influencing an auditor's decision to issue a qualified opinion. Audit firms often lose audit fees as a result of auditor-switching when going concern opinions are issued (Carey, Geiger, & O'Connell, 2008). There is a large stream of research that follows the impact of client retention on independence and the issuance of qualified opinions, including going concern opinions. In addition, the implementation of new models within analytical procedures would not be costless, because the level of testing required for a given engagement affect audit fees. My work, however, ignores these costs. Instead, I focus on the cost of bankruptcy surprise for investors in the stock market.

Kausar, Kumar and Taffler's (2009) study provides insight on the type of investors trading based on GCOs information and describes these trades in terms of a lottery system. According to their work, GC investors are similar to retail investors who have a greater propensity to gamble and have specific socioeconomic and regional characteristics. They conclude that this gambling activity may add noise to the market and cloud investors' ability to respond rationally to the unambiguous bad news signal conveyed by a GCO. Winchel, Vanervelde, and Tuttle's experimental work, however, suggests that the reliability of the GCO signal would contribute to market pricing (2017). They conclude that GCOs will meet their objectives of informing investors of impending bankruptcies and stabilizing the stock prices of viable companies only when GCOs are highly reliable. This would suggest that research and models that improve the accuracy rates of bankruptcy prediction and GCO issuance are necessary to improve the usefulness of GCOs. However, it also demonstrates the difficulty of calculating the total impact of changes in Type I and Type II errors.

Davydenko, Strebuaev and Zhao (2012) use a large sample of firms with observed prices of debt and equity that defaulted over fourteen years to estimate the cost of default for an average defaulting firm. They find the average cost of default to be 21.7% of the market value of assets. The costs vary from 14.7% for bond renegotiations to 30.5% for bankruptcies, and are substantially higher for investment-grade firms (28.8%) than for highly levered bond issuers (20.2%).

In their ex post study of Belgium firms, Carcello, Vanstrael, and Willenborg (2009) provide evidence that after Belgian auditing standards were introduced that required compliance to two specific criteria, there was a decrease in Type II errors and an increase in Type I errors. The research goes on to estimate the net cost of this trade-off in errors for creditors, auditors, companies, and employees. Earlier work by Carcello, Hermanon, and Huss provides guidance for estimating the net market cost of changes in Type I and Type II failures (1995).

I use a simple model that captures cumulative abnormal returns (hereafter, CAR) within the three-day or five-day window surrounding a bankruptcy announcement to estimate the trade-off of costs between Type I and Type II errors. Prior research finds that GCOs provide some explanatory power and should therefor reduce market surprise surrounding the bankruptcy announcement period. CAR should be less negative for firms with GCO warnings than those without (Type I error). However, distressed firms that survive (Type II errors) would also experience unusually negative CAR when GCOs are announced. I acknowledge that this approach fails to capture litigation and other costs of bankruptcy directly. I loosely replicate Carcello et al. (1995), Chen and Church (1996), and Davydenko, Strebuaev and Zhao (2012) to investigate the trade-off in cost associated with lowering Type II errors using the various models. I use ex post data to simulate the effect of using BPMs as criteria for going concern assessments.

CHAPTER 3: RESEARCH QUESTIONS AND HYPOTHESIS

A vast research explores BPMs (Bellovary, Giacominio, & Akers, 2007). Most of this research focuses on improving the efficacy of a particular model or comparing the efficacy of one or more models as tools for prediction. While some researchers conclude that the existing models are not useful for prediction, others find that using these models as decision tools for determining going concern risk results in higher accuracy rates than current auditor judgment.

The literature, however, fails to consider the materiality qualification in auditors' assertion. In the audit opinion, the scope of the audit is limited and auditors explain that "they have reasonable assurance about whether the financial statements are free of *material* misstatement" (emphasis added). This means that accounting numbers and estimates may differ from actual firm performance within a predetermined threshold for materiality. When testing the sensitivity of bankruptcy models, prior research has not explored the possibility that "immaterial" changes in accounting fundamentals may create material differences in the outcome of bankruptcy models that are driven by these amounts.

Although there is no set standard for the quantity of materiality, SAS No. 2 (1985) states that an amount is material if "its omission or misstatement could influence the economic decision of users taken on the basis of the financial statements." The level of materiality depends on the size of the item or error judged within particular circumstances. Thus, the concept of materiality provides a threshold or cut-off point rather than providing a primary qualitative characteristic for useful information.

3.1 Research Question 1: Model Sensitivity

A few "rule-of-thumb" levels for quantitative materiality (e.g. five percent of net income, 0.5 percent of total assets, one percent of total equity) exist in practice (U.S. Securities and Exchange Commission, 1999). AU Section 312.34 specifically warns that quantities deemed immaterial according to rules-of-thumb would be considered material if they trigger loan-covenant default. The sensitivity of BPMs (and thus economic decisions predicted by them) to these rule-of-thumb levels for quantitative materiality has not been tested empirically. Moreover, prior research does not provide evidence about whether assuming unreported "bad news" within these materiality levels would improve the predictability and accuracy rate of existing bankruptcy models. My research examines this question.

RQ1: Ex post, how sensitive are current bankruptcy models to small changes in the accounting fundamentals within the prior year's annual report?

Using accounting fundamentals and existing bankruptcy models, I will calculate the likelihood of default for firms and compare the results to known bankruptcies. Through simulation, I will manipulate the accounting fundamentals of each firm assuming negative outcomes within rule-of-thumb materiality thresholds and document the changes in prediction and accuracy rates. I predict that the accuracy of current bankruptcy models will not significantly improve through simple mathematical manipulations of accounting fundamentals at magnitudes less than the materiality thresholds used by the auditing profession as rules-of-thumb.

H1a: Bankruptcy models predict all bankruptcies.

H1b: BPMs are robust within rule-of-thumb materiality changes in accounting fundamentals.

3.2 Research Question 2: Decision Sensitivity

I recognize that any amount which would cause a change in investor decisions should be considered material by definition. If a change in accounting fundamentals changes the outcome of a bankruptcy model, then the change in the underlying accounting, regardless of size, would be material. Misstatements typically impact one or two accounts, while BPMs weigh information about the overall company. It is not obvious if a particular BPM will be sensitive to relatively small misstatements. However, the appropriateness and magnitude of materiality as they apply to bankruptcy decisions using models has not been explored directly through research. Therefore, I question the sensitivity of bankruptcy models to materiality thresholds.

RQ2: How often would an event within the level auditors consider “standard materiality” trigger a failure in the model?

Through simulation I will manipulate the accounting fundamentals of each firm as with H1 and identify firms whose bankruptcy prediction score from a given model changes due to “immaterial” fluctuations. After identifying these firms, I will consider if the change in prediction from the model reflects the ex post outcomes of the firm (i.e. bankruptcies reported in the following two years). I predict that current bankruptcy models are not sensitive enough for “immaterial” changes to improve predictive accuracy rates. In other words, I predict that BPM accuracy rates will not change if fundamental accounting inputs change by an immaterial amount.

H2: Bright-line decisions based on BPMs are robust within rule-of-thumb materiality changes in accounting fundamentals.

3.3 Research Question 3: Cost of Investor Surprise

Historically, more than half of the bankruptcies filed for public companies in a given year were preceded by a going concern warning. Given the failure rates of going concern predictions and the availability of other—often more timely--information, stakeholders question the usefulness of going concern disclosures. The failure to warn investors of impending bankruptcies has caught the attention of investors, media, and regulators. Research related to the "self-fulfilling prophecy" nature of going concern opinions cautions any attempt to quantify the costs of either failing to issue a going concern qualification or issuing one for a company that continues to operate. However, investor surprise is not costless. Some attempt has been made to estimate the cost trade-off from a lender perspective, but the overall economic impact has been ignored. While the absence of comprehensive cost models make it difficult to address the economic impact of inaccurate predictions, estimating the cost of investor surprise does provide some insight into the trade-off between issuing too many going concern opinions and issuing too few.

RQ3: What is the cost of investor surprise for bankruptcies when auditors failed to issue going concern opinions?

Bankruptcy is costly to investors. While the total cost of bankruptcy is difficult to quantify, I measure the cost by examining the market reaction around the date a bankruptcy was announced (i.e. the bankruptcy filing date). I predict a negative market reaction on that date. Chen and Church (1996) find that investors do respond to going concern opinions and provide evidence of a significantly stronger negative reaction to bankruptcy news for firms who file bankruptcy in the absence of a going concern warning. I apply their methods to my sample and predict similar outcomes.

H3: The estimated market cost due to "surprise" from Type II errors is zero.

3.4 Research Question 4: Cost Trade-off

Further, I continue to question the expanded use of BPMs and their sensitivity to auditors' materiality. I explore the trade-off in costs for using bankruptcy models for going concern assertions.

> RQ4: What is the cost trade-off for using BPMs as a decision-aid for going concern assertions?

Managers and auditors have access to private information that may mitigate the risk identified by BPMs. However, some research suggests that using these models provides a more accurate basis for making this determination. I question the cost trade-off when bankruptcy models are used as a bright-line test for issuing going concern opinions. Altman et al. (1977) defines a 1:35 ratio between Type I and Type II error costs based commercial bank loan analysis framework. I measure the overall market cost of errors by applying CAR to the total market capitalization for firms. I evaluate and rank BMPs based on their total market cost of errors.

H4a: The cost of Type I Errors is more than 35 times the cost of the average Type II Error.

I then apply the average CAR to the simulated errors to measure the cost of changes in predictions due to immaterial misstatements.

> H4b: The change in total cost of errors due to simulated misstatements is zero.
>
> H4c: A 1% decrease in Type I error costs results in a greater than 35% increase in Type II error costs.

After considering the results from testing the hypotheses above, my research should address whether or not BPMs are an appropriate analytical tool for managers or auditors to use in making and testing going concern assertions. The results also provide information about the sensitivity of bankruptcy models to "standard materiality" assumptions within accounting fundamentals and provide insight about the appropriateness of these models within an audit.

CHAPTER 4: RESEARCH METHODOLOGY AND DESIGN

This study is designed as an *ex post* analysis using archival data for a sample of 688 firms that filed bankruptcy between 2002 and 2017. I conduct analyses using BPMs and going concern prediction models from the current literature. Going Concern Opinions are available on Audit Analytics beginning in 2002. Access to fundamental accounting data and market data required to calculate the probability score for bankruptcy generated by various models from prior research (Altman's Z, Zmijewski's score, distance to default, etc) or a probability score generated through current going concern prediction models are available through Compustat and CRSP. Materiality thresholds are manipulated through simulation (5% of net income, 1% of total sales, 0.3% of total assets, 0.5% of total assets, and 1% of retained earnings). I will manipulate the size (materiality) of an event required by each model to reduce Type II error to the level predicted by FASB's exposure draft. I will follow prior research to form a conservative estimate of the reduction in market cost (from increased Type I error) of accepting each model. I will also explore a long-window trend for these models to determine if long-term downward trends resulted in higher prediction accuracy than one-time shocks.

4.1 Data and Sample Selection

Data available from Audit Analytics – Bankruptcy Notifications identifies 2,698 bankrupt filings from January 1, 2000 through December 31, 2017. Of this original sample, two filings were unclassified, 572 filed Chapter 7, and 2,124 filed Chapter 11. Data available from Audit Analytics – Audit Opinions identifies 283,219 audit opinions from January 1, 1999 through December 31, 20016. I matched the bankruptcy data from audit analytics to the audit opinion from prior fiscal years' filings using the date range beginning 730 days prior to the bankruptcy filing date. Using this definition, if an auditor predicted a bankruptcy up to two years prior to the filing date, my results would not reflect a Type II error. Some firms had more than one audit report filed within this range. 620 firms with bankruptcies were not matched to an audit report within 730 days of the filing date. My final matched sample includes 279,761 observations with 3,458 bankruptcies and 48,053 going concern opinions.

Current accounting and auditing standards explicitly allow for some Type II errors. ASU No. 2014-2015 uses "probable" in the standard to define when an auditor should include language about “substantial doubt” for going concern. The standard states:

> Substantial doubt about an entity’s ability to continue as a going concern exists when relevant conditions and events, considered in the aggregate, indicate that it is *probable* that the entity will be unable to meet its obligations as they become due within one year after the date that the financial statements are issued (or available to be issued). The term *probable* is used consistently with its use in Topic 450, Contingencies. [emphasis added]

This language is important because it identifies a specific threshold for testing. In the early 1990s, the General Accounting Office urged FASB to clarify the continuum in SFAS 5 because it had found that, in practice, “probable” meant as high as 95%. A GASB survey of CPA firms defined “probably” as 75-80 percent. The Federal Accounting Standards Advisory Board discussed the definition of probably in their January 17-18, 2007 meeting and came up with ambiguity and uncertainty around identifying a specific percentage. In general, “probable” has a higher threshold than “more-likely-than-not”. In practice, the "probable" threshold is generally understood to mean a 70 to 75 percent confidence level while the "more likely than not" threshold generally equates to 50 percent or less. Since “more-likely-then-not” is 50 percent, and the low end of firm estimates “probable” at 70 percent, I test at each of these endpoints. Because ASU No. 2014-2015 requires auditors to issue GCO when a company has 50-70% likelihood of filing bankruptcy, when the standard is perfectly applied 30-50% of GCO’s issued should be false positives and result in Type II errors. Figure 3 shows the error rates expected by the standards given a sample size of 279,761 with 3,458 bankruptcies.

The 2x2 matrix follows the same structure as Figure 1. This matrix shows that Type II errors are prescribed by the standards. The error rates expected by the standards given the sample size and subsequent bankruptcies for this study. My sample includes 3,458 bankruptcies. According to the standard, auditors should issue a warning within one year of every firm that is more likely than not to file bankruptcy within one year. If I follow auditors’ definition of “more likely than not” as a 50% probability, the standards suggest that 6,916 GCOs would be issued and 50% would be correct (3,458) with 3,458 Type II errors expected. They would correctly predict a bankruptcy half for half of the GCOs issued. If auditors used a 70% threshold for firms that will file bankruptcy within two years, then 1,482 Type II Errors would be still be expected. The figure highlights that the standard prescribes Type II Errors, but not Type I Errors.

	No Bankruptcy in t+1	Bankruptcy in t+1
Unmodified Audit Opinion in t	No Error: 272,845 – 274,821	Type I Error: 0
Modified Audit Opinion in t	Type II Error: 1,482 - 3,458	No Error: 3,458

Figure 3: Diagram of Expected GCOs, Type II Errors, and Type II Errors given Sample Size

Figure 4 shows the number of historical errors observed in the sample based on GCOs issued and bankruptcies filed within 730 subsequent days. Note that both Type I and Type II errors are significantly higher than the standards prescribe for this sample (p>0.0001). Figure 4 highlights the actual errors and error rates contained in the sample from Audit Analytics. The sample includes the 283,219 firm-year observations available in Audit Analytics. For the majority of surviving firms, auditors did not issue GCO warnings. 82.35% of the firms in the overall sample were healthy firms with no error. In addition, auditors correctly identified 1,514 firms as having uncertainty with respect to going concern. 0.53% of the sample declared bankruptcy with warning. Although these firms failed, this is not defined as an error because auditors appropriately warned investors. In this study, firms failing after warnings are classified as Type III.

The sample includes 1,994 Type I errors where firms filed bankruptcy without warning. For these firm-year observations, the audit firm failed to warn investors in the audit of the annual report prior to a bankruptcy filing. Type I errors represent 0.69% of the sample of all firms. The standard expects 100% of bankruptcies to be preceded by a warning; however, out of 3,508 bankruptcies filed, 56.84% were not preceded by a GCO warning.

The sample includes 46,539 Type II errors. For these firm-year observations, the audit firm issued a GCO warning, but the firm did not file bankruptcy within one year. Type II errors represent 16.43% of the sample.

	No Bankruptcy in t+1	Bankruptcy in t+1
Unmodified Audit Opinion in t	No Error: 233,222	Type I Error: 1,994
Modified Audit Opinion in t	Type II Error: 46,539	No Error: 1,514

Figure 4: Diagram of Actual GCOs, Type II Errors, and Type II Errors for Sample

Table 4.1 Panel A reports the sample of all firms by audit opinion indicators reported in Audit Analytics by year from 1999 through 2016 with column 1 reporting the number and percentage of firms with a clean GCO during the year, column 2 including the number and percentage of firms with a GCO warning during the year, and column 3 reporting the total number of firms with audit opinions for each year. The sample for period t includes 283,219 firm-year observations with 48,053 going concern warnings issued.

Table 4.1 Panel B reports the sample by all firms with bankruptcy indicators reported in Audit Analytics by year from 1999 through 2016 with column 1 reporting the number and percentage of firms without a bankruptcy during year t+1, column 2 including the number and percentage of firms with a bankruptcies filing during year t+1, and column 3 reporting the total number of firms with audit reports for each year. The sample for period t includes 283,219 firm-year observations with 3,458 bankruptcies filed from 2000 to 2017. I tested the relation between historic auditor's judgement and actual bankruptcies (untabulated). In each Pearson's Chi-Square test, the relation between historical auditors' judgment and actual bankruptcies is statistically significant (at P<0.001).

Table 4.1 Number of Firms in Sample by Year

	Panel A: Number of Firms with GCO Opinions by Year		Panel B: Number of Firms with Bankruptcies Filed by Year		
Year	No GCO Issued	GCO Issued	No Bankruptcy	Bankruptcy Filed in t+1	Total
1999	7,536	1,574	8,875	325	9,110
2000	17,382	2,844	19,709	517	20,226
2001	15,925	3,018	18,571	372	18,943
2002	14,355	2,863	16,986	232	17,218
2003	15,137	2,590	17,573	154	17,727
2004	14,199	2,579	16,650	128	16,778
2005	14,252	2,738	16,843	147	16,990
2006	13,760	2,896	16,421	235	16,656
2007	13,378	3,328	16,391	315	16,706
2008	13,487	3,392	15,682	197	15,879
2009	12,542	3,137	15,546	133	15,679
2010	12,811	3,007	15,703	115	15,818
2011	12,518	2,581	15,096	101	15,199
2012	12,245	2,592	14,761	76	14,837
2013	12,136	2,436	14,470	102	14,572
2014	11,952	2,285	14,103	134	14,237
2015	11,452	2,141	13,472	121	13,593
2016	11,099	1,952	12,997	54	13,051
Total	235,166	48,053	279,761	3,458	283,219
Percentage	83.03%	16.97%	98.78%	1.22%	100%

Table 4.2 explores these errors by year. The significant Pearson's Chi-Square ($p<0.001$) indicates that there is a strong dependence between GCO opinions in t and Bankruptcies in t+1. Bankruptcies are distributed throughout the sample period as expected with a higher rate of bankruptcy in 2008-2010 as expected due to the 2008 recession.

Table 4.2 Error Count by Error Type and Sample Year

Year	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
1999	7,314	79	1,471	246	9,110
2000	17,083	139	2,626	378	20,226
2001	15,725	64	2,845	308	18,943
2002	14,251	48	2,735	154	17,218
2003	15,057	23	2,516	131	17,727
2004	14,140	25	2,510	103	16,778
2005	14,174	21	2,669	126	16,990
2006	13,619	31	2,602	204	16,656
2007	13,179	66	3,212	248	16,706
2008	12,145	32	3,267	145	15,879
2009	12,484	11	3,062	122	15,679
2010	12,753	23	2,950	92	15,818
2011	12,465	23	2,633	78	15,199
2012	12,202	11	2,559	65	14,837
2013	12,071	12	2,399	89	14,572
2014	11,849	29	2,254	105	14,237
2015	11,360	47	2,104	74	13,593
2016	11,072	16	1,925	38	13,051
Total Percentage	233,222 82.35%	699 0.25%	46,539 16.43%	2,759 0.98%	283,219 100%

Where Year is the fiscal year end. Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing.

There are several types of bankruptcy protection available to companies under the current US Bankruptcy law. Chapter 7 is a straight liquidation, while Chapter 11 allows a firm to “reorganize” and continue operations. Some argue Chapter 11 bankruptcies do not require a GCO, as a Chapter 11 bankruptcy may be strategic. Chapter 15 covers cases in which firms with US assets file bankruptcy internationally. Table 4.3 examines the error rates among the type of bankruptcy filed. The relationship between Type I errors and the type of bankruptcy filed is significant ($p<0.001$) using Fisher’s exact testing. Auditors issued GCO warnings within the two years prior to 75.24% of the Chapter 7 bankruptcies and 65.73% of the Chapter II bankruptcies. By far, the most common form of bankruptcy in my sample was Chapter 11. Type I and errors were more likely for Chapter 11 firms than Chapter 7 firms. This may indicate that auditors are making the distinction between strategic bankruptcies and straight liquidations. However, Chapter 7 firms may also be characterized by greater financial distress and thus more accurate predictions can be made in advance. The source of this discrepancy is beyond the scope of my study, but it could be addressed in future research. The sample includes only twelve Chapter 15 bankruptcies. This subsample is too small for further analysis.

Table 4.3 Comparison of Error Rates Based on the Type of Bankruptcy Filed

US Bankruptcy Filing Type	Type I:	Type III: No Error	Total
Chapter 7	86	612	718
Chapter 11	608	2,119	2,727
Chapter 15	4	8	12
Unclassified	1	0	1
Total	699	2,759	3,458
Percentage	20.21%	79.79%	100%

Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing.

Other descriptive statistics about the sample highlight systematic differences between firms with GCOs and/or subsequent bankruptcies. Table 4.4 reports the number of days between the audit opinion and a subsequent bankruptcy by error type. Firms with no bankruptcies report 365 by design. The mean number of days between the firms with each kind of error is significantly different. On average bankruptcies that were preceded by a warning were filed 171 after the date of the auditor's report. Bankruptcies filed without warning were, on average, filed 60 days later (mean 231 days after the audit report). Bankruptcies that weren't preceded by a warning occurred after a longer delay from the previous audit report. This may indicate that GCOs expedite a firms' bankruptcy under the "self-fulfilling prophecy" hypothesis, or it could indicate that predictive accuracy decreases due to the information environment over time. Or, this relationship may indicate that factors influencing a later bankruptcy may not have been available at the time of an audit.

Table 4.4 Mean Number of Days Between Auditor Report and Bankruptcy Filing

Panel A: Number of Days between Date of Audit Report and Bankruptcy Filing Date

Error Type	Number of Firms	Number of Days until Bankruptcy Filing			
		Mean	Standard Deviation	Minimum	Maximum
Type I	699	231.07	90.13	1	355
Type III: No Error (bankruptcy in t+1)	961	171.05	103.81	0	355
Type III: No Error (bankruptcy in t+2)	1,798	543.15	107.58	356.00	730

Panel B: Number of Days between Year End and Bankruptcy Filing Date

Error Type	Number of Firms	Number of Days until Bankruptcy Filing			
		Mean	Standard Deviation	Minimum	Maximum
Type I	699	346.77	134.54	70	355
Type III: No Error (bankruptcy in t+1)	961	267.36	129.52	77	355
Type III: No Error (bankruptcy in t+2)	1,798	554.52	136.65	426	730

Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing.

I divided the sample by CIK industry classification to analyze the potential impact from a concentration of firms in the financial industry. Tables 4.5 provides descriptive statistics comparing the sample of financial firms to non-financial firms. This table highlights that both Type I and Type II errors are less likely for financial firms. There are 39,728 financial firms in the sample with 312 bankruptcies and 5,905 GCOs. I identify 65 Type I errors and 5,788 Type II errors. The Pearson's Chi Square test is significant ($p<0.001$) for firm type and both going concern opinions and bankruptcies, so sensitive testing is planned. This analysis is necessary to highlight any concentration during the 2008 financial crisis particularly due to "Too Big to Fail" policies at that time. I conclude that removing financial firms from my sample is not necessary.

Table 4.5 Comparison of Error Types within a Subsample of Firms in the Financial Industry

	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
Financial Firms	39,726	65	5,788	247	45,826
Non-Financial Firms	194,114	634	40,751	2,512	238,011
Total	233,842	699	46,539	2,759	283,839
Percentage	82.39%	0.25%	16.40%	0.97%	100.00%

Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing.

When setting the level for planning materiality, auditors use several rules-of-thumb. Common thresholds for planning materiality include: five percent of earnings before taxes (EBIT), one percent of EBIT, 0.3 percent of total assets, 0.5 percent of total assets, or one percent of retained earnings. Table 4.6 describes the mean of each of these five thresholds for the historical sample. Panel A highlights the mean difference between the quantitative thresholds for surviving entities versus entities with subsequent bankruptcies. Note that the mean RE for bankrupt firms is negative and all planned quantitative materiality thresholds for firms with subsequent bankruptcies are less than that planned for firms without subsequent bankruptcies. In Panel B, note that firms with Chapter 7 bankruptcies have lower quantitative thresholds than those with Chapter 11 bankruptcies when determined based on EBI or Total Assets. These differences in underlying fundamentals may drive the performance of certain bankruptcy models in the audit environment.

Table 4.6 Descriptive Statistics for Common Materiality Thresholds by Bankruptcy Indicator and Type

Panel A: Descriptive Statistics for Materiality Thresholds by Bankruptcy Indicator

Bankruptcy Indicator	Number of Firms	Materiality Threshold	Mean	Lowers 95% CL for Mean	Upper 95% CL of Mean	Standard Deviation
0	51,976	5% of EBIT	11.96	11.72	12.20	25.82
		1% of EBIT	2.39	2.34	2.44	5.16
		0.3% of Total Assets	14.73	14.47	15.00	30.35
		0.5% of Total Assets	24.56	24.12	24.99	50.59
		1% of Retained Earnings	5.05	4.91	5.18	15.32
1	493	5% of EBIT	1.41	0.58	2.24	9.16
		1% of EBIT	0.28	0.12	0.45	1.83
		0.3% of Total Assets	6.73	5.27	8.19	16.51
		0.5% of Total Assets	11.22	8.78	13.65	27.52
		1% of Retained Earnings	-2.07	-2.63	-1.50	6.29

Table 4.6 (continued)

Panel B: Descriptive Statistics for Materiality Thresholds by Bankruptcy Type

Bankruptcy Type	Number of Firms	Materiality Threshold	Mean	Lowers 95% CL for Mean	Upper 95% CL of Mean	Standard Deviation
Chapter 7	74	5% of EBIT	-0.45	-0.74	-0.15	1.23
		1% of EBIT	-0.09	-0.15	-0.03	0.25
		0.3% of Total Assets	0.40	0.11	0.68	1.24
		0.5% of Total Assets	0.66	0.18	1.14	2.06
		1% of Retained Earnings	-1.16	-1.84	-0.47	2.98
Chapter 11	472	5% of EBIT	1.29	0.48	2.10	8.73
		1% of EBIT	0.26	0.10	0.42	1.75
		0.3% of Total Assets	6.89	5.50	8.28	15.37
		0.5% of Total Assets	11.48	9.17	13.80	25.62
		1% of Retained Earnings	-2.06	-2.66	-1.46	6.47
Chapter 15	6	5% of EBIT	20.19	-6.07	46.45	25.03
		1% of EBIT	4.04	-1.21	9.29	5.01
		0.3% of Total Assets	50.24	-2.42	102.9	50.19
		0.5% of Total Assets	83.74	4.04	171.5	83.64
		1% of Retained Earnings	-3.40	-6.48	-0.32	2.93

Where the Bankruptcy Indicator equals 1 for firms with a bankruptcy filed within 730 days of the audit report filing date.

4.2 Part 1. Model Simulations

I collect all accounting variables required for Z-Score, O-Score, Shumway Score, and the Merton KMV's Distance to Default calculation from the Compustat annual file. Audit Analytics identified the issuance of a going concern opinion as a “1” in the indicator variable “GCO”. After matching on the Central Index Key (CIK), my sample includes 45,828 financial firm-year observations from Audit Analytics. I identify 5,905 companies with a modified audit report for going concern (GCO) in t and 312 companies with bankruptcies in t+1. The pattern of bankruptcies by year was similar to that of the overall sample, with higher filing rates near 2001 and 2008.

4.2.1 Z-Score Testing.

I collect the variables needed to calculate each determinant of Altman's Z-Score from Compustat North America Daily - Fundamentals Annual dataset from 1999 through 2016. I match the variable to my sample from Audit Analytics. The matched sample includes 89,755 firm-year observations with adequate data availability that include 2,456 bankruptcies and 15,950 modified going concern opinions. Table 4.7 includes descriptive statistics for the determinant variables of Altmans Z-Score, Winsorized at 1% to limit the effect of outliers in the Compustat data. The descriptive statistics highlight the absence of data for some observations. Observations with incomplete data for each model are dropped from the sample when testing that model only.

Table 4.7 Descriptive Statistics for Determinant Variables of Z-Score Model

Variable	N	Mean	Standard Deviation	Minimum	Median	Maximum
AT	142,386	7,306.55	30,282.76	0.02	440.30	248,437.00
ACT	101,937	831.62	2,563.05	0.00	86.84	19,023.00
LT	142,386	5,613.93	24,913.83	0.08	249.33	209,886.00
LCT	102,394	621.54	2,067.37	0.04	38.52	15,347.82
WCAP	101,073	197.17	719.33	-1,489.72	21.93	4,939.46
CSHO	142,386	90.80	249.69	0.00	21.20	1,884.31
SALE	123,456	2,144.72	6,845.84	0.00	145.07	49,964.80
OIADP	123,454	283.97	1,034.22	-209.00	9.84	7,876.94
EBIT	122,810	284.39	1,034.83	-209.78	9.83	7,877.00
RE	138,988	635.06	2,980.63	-2,803.46	3.96	22,632.00
PRCC_F	130,202	36.01	1,199.49	0.00	11.86	141,600.00

Where possible, firm-level variables are consistent with Compustat labels. Where AT indicating total assets, ACT indicating total current assets, LT is total liabilities, WCAP is working capital, CSHO is the number of common shares outstanding, SALE is total revenue, OIADP is operating income before amortization and depreciation, EBIT is earnings before interest and taxes, RE is retained earnings, and PRCC_F is the price per share of common stock at the end of the fiscal year. N is the number of firm-level observations.

Following literature, I use three models of the Altman Z-Score to estimate the probability of bankruptcy. I calculate the Z-Score according to the specifications in Altman (1968), Altman et al. (1993), and Hillegeist et al. (2004). Table 4.8 reports the means of Altman's Z-Score for each model. Panel A compares the sample of firms with bankruptcies in t+1 to all other firms. As expected, for each model, the mean Z-Scores for firms with bankruptcies is significantly smaller than the Z-Score for surviving firms. Panel B compares the sample of firms with going concern opinions in t to firms all other firms. Note the mean Z-Score for the going concern sub-sample using equation 1 and 2 are significantly lower than the “healthy” firms, as expected. However, the mean Z-Score for GCO firms using the Hillegeist (2004) model in equation 3 is higher than the non-GCO firms. Testing the reason behind this surprising result is beyond the scope of my dissertation, but it could indicate that auditors’ predictions fail to incorporate changes in bankruptcy regulation in the 2004 model.

Table 4.8 Descriptive Means of Z-Score Models - Equations 1-3

Panel A: Descriptive Statistics for Z-Scores for all Firms in Sample

Variable	N	Mean	Standard Deviation	Minimum	Median	Maximum
Altz	88,955	-6.18	65.45	-533.25	2.53	107.56
Altz93	88,955	-21.38	162.83	-1,346.52	3.33	185.38
Altz04	88,955	7.06	8.27	4.16	4.89	70.31

Panel B: Descriptive Statistics for Z-Scores by Bankruptcy Indicator

Bankruptcy Indicator	Variable	N	Mean	Standard Deviation	Minimum	Median	Maximum
0	Altz	86,980	-6.10	65.75	-533.25	2.59	107.56
	Altz93	86,980	-21.22	163.56	-1,346.52	3.45	185.38
	Altz04	86,980	7.10	8.33	4.16	4.91	70.31
1	Altz	1,975	-9.86	50.36	-533.25	-0.12	107.56
	Altz93	1,975	-28.20	126.68	-1,346.52	-3.07	185.38
	Altz04	1,975	5.35	4.25	4.16	4.41	70.31

Panel C: Descriptive Statistics for Z-Scores by GCO Indicator

GCO Indicator	Variable	N	Mean	Standard Deviation	Minimum	Median	Maximum
0	Altz	75,465	4.48	21.04	-533.25	2.96	107.56
	Altz93	75,465	5.91	47.67	-1,346.52	4.17	185.38
	Altz04	75,465	6.41	6.23	4.16	4.86	70.31
1	Altz	13,490	-65.82	146.89	-533.25	-9.48	107.56
	Altz93	13,490	-174.02	366.97	-1,346.52	-27.16	185.38
	Altz04	13,490	10.73	14.74	4.16	5.33	70.31

Where the Bankruptcy Indicator equals 1 for firms with a bankruptcy filed within 730 days of the audit report filing date. GCO Indicator equals 1 for firms with going concern qualifications in the audit report.

I test the appropriateness of using a bright-line test based on BPMs as a substitute for auditors’ judgment to identify firms with going concern uncertainty during the planning stages of an audit. I again use three models of the Altman Z-Score to estimate the probability of bankruptcy. The results of testing are summarized in Table 4.9. A sample of 142,386 firms had sufficient data to calculate Z-Scores. A classifies sample firms based on historic GCO warnings and bankruptcies filed. Auditor judgment resulted in appropriate predictions for 88.47% of firm observations with 1,466 (1.03%) Type I errors and 14,946 (10.50%) Type II errors reported.

Table 4.9 Panel B reports the error rates that would result if equations 1-3 had been used in place of auditor judgment. For the classic model (equation 1) the bright-line test is defined by any score less than 1.8 substitutes for auditor judgment as a predicted bankruptcy in period t+1. Using the classic cut-off definition of Z-Score<1.8 as a bright-line test resulted in the greatest number of GCO warnings issued prior to a bankruptcy (2,456, 84.25%) which is significantly better than auditor's predictions (987, 40.19%). Therefore, Type I error rates were 3.8 times higher for bankrupt firms based on auditor judgments. If the only goal of auditors was to predict bankruptcies, a bright-line test based on the classic Z-Score appears to outperform auditor judgment; however, there were significantly more Type II errors using the bright-line test in Panel A (87,726) compared to historical errors (14,963).

For robustness I also tested the original model and two re-estimated models (equation 2 and 3) and use probability of bankruptcy > 50% and 70% as a bright-line tests to substitute for auditor judgment. Each model resulted in a similar tradeoff between Type I and Type II errors when evaluated by count and rate. Because the cost of each type of error and each bankruptcy is not equal to stakeholders, evaluating the usefulness of each model requires cost trade-off analysis between Type I and Type II errors. The results based on count do not address whether the costliest bankruptcies were predicted by auditor judgment for a specified model.

Table 4.9 Results from Bright-Line Testing of Z-Score Models

Panel A: Historical Error Count based on Auditor Judgment

Auditor Judgment	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
Going Concern Opinions	124,989	1,466	14,946	985	142,386
Percentage	87.78%	1.03%	10.50%	0.69%	100.00%

Panel B: Simulated Error Count Where Bright-Line Testing Replaces Auditor Judgment

Bright-Line Test	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
1968 Z-Score with Classic Threshold	53,066	386	86,869	2,065	142,386
	37.27%	0.27%	61.01%	1.45%	100.00%
1968 Z-Score with Probability (p>0.5)	71,309	1,497	68,626	954	142,386
	50.08%	1.05%	48.20%	0.67%	100.00%
1993 Z-Score with Probability (p>0.5)	76,015	1,847	63,920	604	142,386
	53.39%	1.30%	44.89%	0.42%	100.00%
1993 Z-Score with Probability (p>0.7)	75,547	1,830	64,388	621	142,386
	53.06%	1.29%	45.22%	0.44%	100.00%
2004 Z-Score with Probability (p>0.5)	52,955	476	86,980	1,975	142,386
	37.19%	0.33%	61.09%	1.39%	100.00%
2004 Z-Score with Probability (p>0.7)	71,309	1,497	66,626	954	142,386
	50.08%	1.05%	48.20%	0.67%	100.00%

Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing.

Because many of the Chapter 11 bankruptcies in the overall sample may be strategic, these types of bankruptcies might not be prewarned in financial fundamentals and some have argued that strategic bankruptcy filings do not represent going concern uncertainty. Chapter 7 bankruptcies, however, do meet the standard definition of going concern uncertainty. Table 4.10 examines the use of bright line testing to limit Type I errors by bankruptcy type. Auditors issued GCOs before 259 of the Chapter 7 bankruptcies (untabulated). The bright-line test using the classic 1.8 threshold would have predicted 382. The difference between the Type I error count for auditor judgment versus (195) the classic Z-Score model (72) for Chapter 7 bankruptcies is significant ($p<0.001$), but doesn't address the relative market cost given firm characteristics.

Table 4.10 Simulated Error Count Using Z-Score Classic Model for Bright-Line Test by Bankruptcy Type

Bankruptcy Type	Type I:	Type III: No Error	Total
Chapter 7	72 15.86%	382 84.14%	454 100.00%
Chapter 11	314 15.81%	1,672 84.19%	1,986 100.00%
Chapter 15	0 0%	10 100%	10 100.00%

Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing.

I include a Pearson's Correlation matrix in Table 4.11 for each BPM specification against actual bankruptcies in t+1. As expected, each model is significantly predictive. The correlation coefficient between Bankruptcy Indicator and GCO Indicator (0.1218) is larger than between Bankruptcy Indicator and any of the tested Z-Score models. This suggests that auditor judgment outperforms the scores for bankruptcy prediction.

Table 4.11 Pearson's Correlation Matrix for BPM Predictions compared to Historical Going Concern Opinions and Bankruptcy Filings

Variable	Bankruptcy Indicator	GCO Indicator	1968 Z-Score Classic Indicator	1968 Z-Score (p>0.5) Indicator	1993 Z-Score (p>0.5) Indicator	2004 Z-Score (p>0.5) Indicator
Bankruptcy Indicator	1.0000					
GCO Indicator	0.1218 <0.0001	1.0000				
1968 Z-Score Classic Indicator	0.0596 <0.0001	0.1810 <0.0001	1.0000			
1968 Z-Score (p>0.5) Indicator	-0.0263 <0.0001	-0.2061 <0.0001	-0.7930 <0.0001	1.0000		
1993 Z-Score (p>0.5) Indicator	-0.0550 <0.0001	-0.2264 <0.0001	-0.8252 <0.0001	0.92724 <0.0001	1.0000	
2004 Z-Score (p>0.5) Indicator	0.0495 <0.0001	0.1628 <0.0001	-0.6008 <0.0001	0.7577 <0.0001	0.7055 <0.0001	1.0000

Where the Bankruptcy Indicator equals 1 for firms with a bankruptcy filed within 730 days of the audit report filing date. GCO Indicator equals 1 for firms with going concern qualifications in the audit report. Model specifications and variable definitions are provided in equations 1-3.

This dissertation questions whether it is appropriate to use bright-line tests in the planning stage of an audit. This is a unique environment because auditors must consider the impact of planning materiality when performing analytical procedures. I simulate the risk-based auditing environment by transforming the accounting fundamentals for individual companies to reflect negative news at common materiality thresholds[4].

I test five alternatives for quantitative materiality thresholds that could be used during audit planning. I manipulate the accounting fundamentals of each company to reflect negative news within five common materiality thresholds. The five levels of planning materiality simulated or each type of misstatement include (1) five percent of earnings before taxes (hereafter, EBIT), (2) one percent of EBIT, (3) 0.3 percent of total assets, (4) 0.5 percent of total assets, and (5) one percent of retained earnings. In analyzing the results, I am aware that different thresholds for planning materiality are used to evaluate balance sheet and income statement items. A percentage of EBIT (1 and 2) is used to evaluate misstated sales (A), where a percentage of total assets (3 and 4) is used to evaluate misstated assets and liabilities (B through E). Furthermore, quantitative materiality thresholds are often set at 5% of net income as a rule-of-thumb in practice; however, research suggests that this threshold is set lower for companies that show weak earnings.

I simulated the performance of bright-line testing using (1) the Altman's (1968) Z-Score model and the classic threshold of Z-Score < 1.8 as a proxy for default and (2) the Hillegeist et al. (2004) Z-Score with the threshold probability of default at 50%. For each model, I simulated twenty-five errors: the combination of errors at five levels of planning materiality and five types of misstatements tested include simulations where (A) net sales are overstated, (B) long-term assets are overstated, (C) current assets are overstated, (D) long-term liabilities are understated, and (E) current liabilities are understated. Table 4.12 presents the results of the simulations. Panel A includes the simulation results using the 1968 classic definition of Z-Score. Panel B reports the results from the 2004 re-estimation.

[4] Preliminary analysis of $1 less than the materiality threshold or 99.99% of the materiality threshold indicated that BPM analysis is not sensitive to this cut off.

Table 4.12 Simulated Error Count from Bright-Line Tests using Z-Score Model in a Simulated Audit Planning Environment

Panel A: Bright-Line Tests of 1968 Z-Score Classic Model Given Simulated Overstatements in Sales

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
5% of EBIT	87,028 61.12%	2,057 1.44%	52,907 37.16%	394 0.28%	142,386 100.00%
1% of EBIT	87,072 61.15%	2,064 1.45%	52,863 37.13%	387 0.27%	142,386 100.00%
0.3% of TA	87,312 61.32%	2,072 379%	52,623 36.96%	379 0.27%	142,386 100.00%
0.5% of TA	87,457 61.42%	2,073 1.46%	52,478 36.86%	378 0.27%	142,386 100.00%
1% of RE	86,950 61.07%	2,062 1.45%	52,985 37.21%	389 0.27%	142,386 100.00%

Panel B: Bright-Line Tests of 1968 Z-Score Classic Model Given Simulated Overstatement in Long-term Assets

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
5% of EBIT	96,951 68.09%	1,528 1.07%	42,984 30.19%	923 0.65%	142,386 100.00%
1% of EBIT	9,943 65.28%	1,829 1.28%	46,992 33.00%	622 0.44%	142,386 100.00%
0.3% of TA	106,182 74.57%	2,186 1.54%	33,753 23.71%	265 0.19%	142,386 100.00%
0.5% of TA	109,583 76.96%	2,214 1.55%	30,652 21.32%	237 0.17%	142,386 100.00%
1% of RE	139,935 98.28%	2,451 1.72%	0 0.00%	0 0.00%	142,386 100.00%

Panel C: Bright-Line Tests of 1968 Z-Score Classic Model Given Simulated Overstatement in Current Assets

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
5% of EBIT	96,939 68.08%	1,524 1.07%	42,996 30.20%	927 0.65%	142,386 100.00%
1% of EBIT	92,947 65.28%	1,829 1.28%	46,988 33.00%	622 0.44%	142,386 100.00%
0.3% of TA	106,212 74.59%	2,186 1.54%	33,723 23.68%	265 0.19%	142,386 100.00%
0.5% of TA	109,623 76.99%	2,215 1.56%	30,312 21.29%	236 0.17%	142,386 100.00%
1% of RE	94,515 66.38%	1,702 1.20%	45,420 31.90%	749 0.53%	142,386 100.00%

Table 4.12 (continued)

Panel D: Bright-Line Tests of 1968 Z-Score Classic Model Given Simulated Understatement in Long-Term Liabilities

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
5% of EBIT	86,843 60.99%	2,050 1.44%	53,092 37.29%	401 0.28%	142,386 100.00%
1% of EBIT	87,003 61.10%	2,066 1.45%	52,932 37.18%	385 0.27%	142,386 100.00%
0.3% of TA	87,196 61.24%	2,066 1.45%	52,739 37.04%	385 0.27%	142,386 100.00%
0.5% of TA	87,259 61.28%	2,066 1.45%	52,676 37.00%	385 0.27%	142,386 100.00%
1% of RE	86,805 60.96%	2,059 1.45%	53,130 37.31%	392 0.28%	142,386 100.00%

Panel E: Bright-Line Tests of 1968 Z-Score Classic Model Given Simulated Understatement in Current Liabilities

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
5% of EBIT	86,834 60.98%	2,048 1.44%	53,101 37.29%	403 0.28%	142,386 100.00%
1% of EBIT	87,004 61.10%	2,066 1.45%	52,931 37.17%	385 0.27%	142,386 100.00%
0.3% of TA	87,245 61.27%	2,068 1.45%	52,690 37.01%	383 0.27%	142,386 100.00%
0.5% of TA	87,337 61.34%	2,068 1.45%	52,598 36.94%	383 0.27%	142,386 100.00%
1% of RE	86,793 60.96%	2,060 1.45%	53,142 37.32%	391 0.27%	142,386 100.00%

Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing. Where possible, firm-level variables are consistent with Compustat labels. Where AT is total assets, EBIT is earnings before interest and taxes, and RE is retained earnings.

Informed by the performance of bright-line testing in Table 4.9. I selected the 2004 Z-Score Model as a sensitivity test for discriminate analysis models. I repeated the test simulations from Table 4.12 with the 2004 specification (equation 3) of the Z-Score model. The results appear in Table 4.13. The pattern suggests that this model fails to correctly predict bankruptcies given relatively small changes in accounting fundamentals. Auditors using this model as an analytical procedure in the planning stage of the audit would identify fewer Type II errors, but would also fail to identify almost all bankruptcies.

Table 4.13 Simulated Error Count from Bright-Line Testing using the 2004 Z-Score Model in a Simulated Audit Planning Environment

Panel A: Bright-Line Tests of 2004 Z-Score Model Given Simulated Overstatements in Sales

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
5% of EBIT	86,879 97.67%	1,975 2.22%	101 0.11%	0 0.00%	88,955 100.00%
1% of EBIT	86,879 97.67%	1,975 2.22%	101 0.11%	0 0.00%	88,955 100.00%
0.3% of TA	86,879 97.67%	1,975 2.22%	101 0.11%	0 0.00%	88,955 100.00%
0.5% of TA	86,879 97.67%	1,975 2.22%	101 0.11%	0 0.00%	88,955 100.00%
1% of RE	86,879 97.67%	1,975 2.22%	101 0.11%	0 0.00%	88,955 100.00%

Panel B: Bright-Line Tests of 2004 Z-Score Model Given Simulated Overstatement in Long-term Assets

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
5% of EBIT	86,929 97.72%	1,975 2.22%	51 0.06%	0 0.00%	88,955 100.00%
1% of EBIT	86,917 97.71%	1,975 2.22%	63 0.07%	0 0.00%	88,955 100.00%
0.3% of TA	86,879 97.67%	1,975 2.22%	101 0.11%	0 0.00%	88,955 100.00%
0.5% of TA	86,879 97.67%	1,975 2.22%	101 0.11%	0 0.00%	88,955 100.00%
1% of RE	86,924 97.72%	1,975 2.22%	56 0.06%	0 0.00%	88,955 100.00%

Panel C: Bright-Line Tests of 2004 Z-Score Model Given Simulated Overstatement in Current Assets

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
5% of EBIT	86,930 97.72%	1,975 2.22%	50 0.06%	0 0.00%	88,955 100.00%
1% of EBIT	86,917 97.71%	1,975 2.22%	63 0.07%	0 0.00%	88,955 100.00%
0.3% of TA	86,879 97.67%	1,975 2.22%	101 0.11%	0 0.00%	88,955 100.00%
0.5% of TA	86,879 97.67%	1,975 2.22%	101 0.11%	0 0.00%	88,955 100.00%
1% of RE	86,924 97.72%	1,975 2.22%	56 0.06%	0 0.00%	88,955 100.00%

Table 4.13 (continued)

Panel D: Bright-Line Tests of 2004 Z-Score Model Given Simulated Understatement in Long-Term Liabilities

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
5% of EBIT	86,558 97.31%	1,972 2.22%	422 0.47%	3 0.00%	88,955 100.00%
1% of EBIT	86,862 97,65%	1,975 2.22%	118 0.13%	0 0.00%	88,955 100.00%
0.3% of TA	86,883 97.67%	1,975 2.22%	97 0.11%	0 0.00%	88,955 100.00%
0.5% of TA	85,883 97.67%	1,975 2.22%	97 0.11%	0 0.00%	88,955 100.00%
1% of RE	86,217 95.92%	1,965 2.21%	763 0.86%	10 0.01%	88,955 100.00%

Panel E: Bright-Line Tests of 2004 Z-Score Model Given Simulated Understatement in Current Liabilities

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
5% of EBIT	86,562 97.31%	1,972 2.22%	418 0.47%	3 0.00%	88,955 100.00%
1% of EBIT	86,863 97.65%	1,975 2.22%	117 0.13%	0 0.00%	88,955 100.00%
0.3% of TA	86,883 97.67%	1,975 2.22%	97 0.11%	0 0.00%	88,955 100.00%
0.5% of TA	86,883 97.67%	1,975 2.22%	97 0.11%	0 0.00%	88,955 100.00%
1% of RE	86,221 96.93%	1,965 2.21%	759 0.85%	10 0.01%	88,955 100.00%

Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing. Where possible, firm-level variables are consistent with Compustat labels. Where AT is total assets, EBIT is earnings before interest and taxes, and RE is retained earnings.

Note that the classic Z-Score model appears more sensitive to misstated assets. Overall, the 2004 model and the probability>0.5 test appear less sensitive to misstatements at the level of planning materiality and more stable in the audit environment. However, this bright-line test also results in substantially more Type II errors, as noted previously. The 2004 Z-Score model appears to be sensitive to errors that auditors may consider immaterial during the planning stage of the audit. Table 5.3-Panel D reports 474 Type I errors with the 2004 O-Score model used as a bright-line test in audit planning. The simulations demonstrate that a misstatement at the level of planning materiality could result in between 474 and 2,456 Type I errors using this model as a bright-line test. Type II errors would decrease from 87,743 to between 54,468 and 87,244. This may indicate that these levels for planning materiality are inappropriately large if the O-Score is used a bright-line test for going concern.

4.2.2 O-ScoreTesting.

I collect the variables needed to calculate each determinant of Ohlson's O-Score specified in equation 5 and 6 from Compustat North America Daily - Fundamentals Annual dataset from 1999 through 2016. I match the variable to my sample from Audit Analytics. I define X6 as an indicator variable when the cumulative net income over the previous two years is negative and X8 as an indicator variable equal to one if owners' equity is negative. The matched sample includes 142,784 firm-year observations with adequate data availability that include 2,098 bankruptcies and 14,417 modified going concern opinions. Table 4.14 includes descriptive statistics for the determinant variables of Ohlson's O-Score, Winsorized at 1% to limit the effect of outliers in the Compustat data.

Table 4.14 Descriptive Statistics for Determinant Variables in O-Score Models – Equations 4-5

Panel A: Descriptive Statistics for Variables in O-Scores for all Firms in Sample

Variable	N	Mean	Standard Deviation	Minimum	Median	Maximum
AT	142,784	13,516.45	112,235.96	0.00	441.52	3,771,199.85
ACT	102,232	1,029.53	4,797.65	-0.17	86.84	161,978.00
LT	142,784	11,618.56	105,587.11	0.00	249.90	3,589,783.24
LCT	102,687	813.47	4,521.89	-43,132.55	38.57	329,795.00
WCAP	101,368	224.30	1,713.09	-99,289.00	21.87	88,652.00
NI	123,796	163.98	1,446.50	-80,053.00	2.63	104,821.00
EBIT	123,150	381.12	2,382.41	-9.35	4.59	130,622
Oscore	29,206	-5.61	26.51	-182.98	0.47	9.53
Oscore04	29,206	6.32	2.57	0.33	6.54	19.74

Where possible, firm-level variables are consistent with Compustat labels. Where AT is total assets, ACT indicating total current assets, LT is total liabilities, LCT is total current liabilities, WCAP is working capital, NI is net income, EBIT is earnings before interest and taxes, Oscore is the result of equation 5, and Oscore04 is the result of equation 6. N is the number of firm-level observations.

Table 4.15 reports the mean of Ohlson's O-Score for each model. Panel A compares the sample of firms with bankruptcies in t+1 to all other firms. Panel B compares the sample of firms with going concern opinions in t to firms all other firms. Note that, as expected, the mean O-Score for both bankrupt and going concern samples is lower than the mean for surviving firms and those with unmodified opinions. However, using the 2004 re-estimated model shows that the average O-Score for firms with GCOs is higher than the non-GCO firms. In all cases, the standard deviation of the means for bankrupt or GCO firms is larger.

Table 4.15 Decriptve Means of O-Score Models - Equations 4-5Panel A: Descriptive Statistics for O-Scores by Bankruptcy Indicator

Bankruptcy Indicator	Variable	N	Mean	Standard Deviation	Minimum	Median	Maximum
0	Oscore	28,581	-5.61	26.70	-182.98	0.53	9.53
	Oscore04	28,581	6.35	2.57	0.33	6.55	19.74
1	Oscore	625	-5.26	15.53	-182.98	-2.22	9.53
	Oscore04	625	5.24	2.42	0.33	4.71	19.74

Panel B: Descriptive Statistics for O-Scores by GCO Indicator

GCO Indicator	Variable	N	Mean	Standard Deviation	Minimum	Median	Maximum
0	Oscore	24,789	0.15	8.45	-182.98	1.12	9.53
	Oscore04	24,789	6.11	1.84	0.33	6.55	19.74
1	Oscore	4,417	-37.89	54.96	-182.98	-13.13	9.53
	Oscore04	4,417	7.54	4.80	0.33	5.86	19.74

Where the Bankruptcy Indicator equals 1 for firms with a bankruptcy filed within 730 days of the audit report filing date. GCO Indicator equals 1 for firms with going concern qualifications in the audit report. Oscore is the result of equation 5, and Oscore04 is the result of equation 6. N is the number of firm-level observations.

I test the appropriateness of using a bright-line test based on BPMs as a substitute for auditors' judgment to identify firms with going concern uncertainty during the planning stages of an audit. Following Hillegeist et al. 2004, I test two O-Score models to estimate the probability of bankruptcy. I test the original model (equation 4) and the 2004 re-estimated model (equation 5) and use probability of bankruptcy > 50% and 70% as a bright-line tests to substitute for auditor judgment.

Table 4.16 reports the error rates of each model. Using the more-likely-than-not definition (where the probability of default is estimated to be greater than 50%) as a bright-line test or the 2004 O-Score model resulted in the greatest number of GCO warnings issued prior to a bankruptcy (2,093, 85.22%) which is significantly better than auditor's predictions (987, 40.19%). Type I error rates were 3.8 times higher for bankrupt firms based on auditor judgments. If the only goal of auditors was to predict bankruptcies, the bright-line test in Panels B and D would appear to be a clear winner; however, there were significantly more Type II errors using the bright-line test in for O-Score in Panel B (93,393) compared to historical errors (14,981). Overall, auditors predicted 15,968 bankruptcies and were correct 6.18% of the time. The Bright-line test in Panel B predicted 95,486 bankruptcies and was correct 2.19% of the time. The Bright-line test in Panel D predicted 95,466 bankruptcies and was correct 2.19% of the time. Evaluating the usefulness of each test requires cost trade-off analysis between Type I and Type II errors.

Table 4.16 Results of Bright-Line Testing of O-Score Models

Panel A: Historical Error Count based on Auditor Judgment

Auditor Judgment	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
Going Concern Opinions	125,347	1,469	14,981	987	142,784
Percentage	87.79%	1.03%	10.49%	0.69%	100.00%

Panel B: Simulated Error Count Where Bright-Line Testing Replaces Auditor Judgment

Bright-Line Test	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
1980 O-Score with Probability	124,530	2,307	15,798	149	142,784
(p>0.5)	87.22%	1.62%	11.06%	0.10%	100.00%
1980 O-Score with Probability	127,011	2,348	13,317	108	142,784
(p>0.7)	88.95%	1.64%	9.33%	0.05%	100.00%
2004 O-Score with Probability	111,747	1,831	28,581	625	142,784
(p>0.5)	78.26%	1.28%	20.02%	0.44%	100.00%
2004 O-Score with Probability	112,085	1,837	28,243	819	142,784
(p>0.7)	78.50%	1.29%	19.78%	0.43%	100.00%

Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing.

The sample contains 1,991 Chapter 11 bankruptcies that may be strategic and not proxy for a failing firm. Table 4.17 examines the use of bright line testing for the 454 Chapter 7 bankruptcies included in the sample. Auditors using the bright-line test with the 2004 O-Score Model (Equation 5) would have identified 370 (81.50%) of these bankruptcies prior to filing. Using the bright-line test limited Type I errors to 18.50% for Chapter 7 bankruptcies. This is significantly fewer Type I errors than using historic GCO (195, 42.95%).

Table 4.17 Simulated Error Count Using O-Score Classic Model for Bright-Line Test by Bankruptcy Type

Bankruptcy Type	Type I:	Type III: No Error	Total
Chapter 7	195 42.95%	259 57.05%	454 100.00%
Chapter 11	1,254 63.49%	727 35.51%	1991 100.00%
Chapter 15	9 90.00%	1 10.00%	10 100.00%

Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing.

I include a Pearson's Correlation matrix in Table 4.17 of each BPM against actual bankruptcies in t+1. As expected, each model is significantly predictive. The correlation coefficient is higher between the bankruptcy indicator and auditors going concern opinions than the tested O-Score models. This suggests that auditor judgment outperforms the scores for bankruptcy prediction.

Table 4.18 Pearson's Correlation Matrix for BPM Predictions compared to Historical Going Concern Opinions and Bankruptcy Filings

Variable	Bankruptcy Indicator	GCO Indicator	1980 O-Score(p>0.5) Indicator	2004 O-Score(p>0.5) Indicator
Bankruptcy Indicator	1.00000			
GCO Indicator	0.12175 <0.0001	1.00000		
1980 O-Score(p>0.5) Indicator	-0.02269 <0.0001	-0.10114 <0.0001	1.00000	
2004 O-Score(p>0.5) Indicator	0.01644 <0.0001	0.05382 <0.0001	0.63949 <0.0001	1.00000

Where the Bankruptcy Indicator equals 1 for firms with a bankruptcy filed within 730 days of the audit report filing date. GCO Indicator equals 1 for firms with going concern qualifications in the audit report. Model specifications and variable definitions are provided in equations 4-5.

Next, I simulated the risk-based auditing environment by transforming the accounting fundamentals for individual companies to reflect negative news at common materiality thresholds.

I simulated the performance of bright-line testing using the 2004 O-Score model with the threshold probability of default at 50%. The five types of misstatements tested include simulations where (A) net sales are overstated, (B) long-term assets are overstated, (C) current assets are overstated, (D) long-term liabilities are understated, and (E) current liabilities are understated. I manipulate the accounting fundamentals of the companies to reflect negative news within five common materiality thresholds. The five levels of planning materiality simulated or each type of misstatement include (1) five percent of earnings before taxes (EBIT), (2) one percent of EBIT, (3) 0.3 percent of total assets, (4) 0.5% of total assets, and (5) one percent of retained earnings. I simulated five errors at five levels of planning materiality. In analyzing the results, I limited inclusion based on the general use of EBIT-based materiality thresholds to audit income statement items and asset-based thresholds to audit balance sheet items. The fifteen most relevant simulations follow in Table 4.18.

Table 4.19 Simulated Error Count from Bright-Line Tests using O-Score Models in a Simulated Audit Planning Environment

Panel A: Bright-Line Tests of 1980 O-Score Model Given Simulated Overstatements in Sales

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
5% of EBIT	112,250 78.62%	1,835 1.29%	28,058 19.66%	621 0.43%	142,784 100.00%
1% of EBIT	112,236 78.61%	1,837 1.29%	28,092 19.67%	619 0.43%	142,784 100.00%
1% of RE	112,957 79.13%	1,842 1.29%	27,341 19.15%	614 0.43%	142,784 100.00%

Panel B: Bright-Line Tests of 1980 O-Score Classic Model Given Simulated Overstatement in Long-term Assets

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
0.3% of TA	113,005 79.14%	1,842 1.29%	27,323 19.14%	614 0.43%	142,784 100.00%
0.5% of TA	113,036 79.14%	1,842 1.29%	27,322 19.14%	614 0.43%	142,784 100.00%
1% of RE	112,950 79.13%	1,842 1.29%	27,348 19.15%	614 0.43%	142,784 100.00%

Table 4.19 (continued)

Panel C: Bright-Line Tests of 1980 O-Score Model Given Simulated Overstatement in Current Assets

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
0.3% of TA	112,942 79.10%	1,841 1.29%	27,386 19.18%	615 0.43%	142,784 100.00%
0.5% of TA	112,971 79.12%	1,841 1.29%	27,357 19.16%	615 0.43%	142,784 100.00%
1% of RE	112,405 78.72%	1,840 1.29%	27,923 19.56%	616 0.43%	142,784 100.00%

Panel D: Bright-Line Tests of 1980 O-Score Classic I Given Simulated Understatement in Long-Term Liabilities

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
0.3% of TA	112,876 79.05%	1,841 1.29%	27,452 19.23%	615 0.43%	142,784 100.00%
0.5% of TA	112,876 79.05%	1,841 1.29%	27,452 19.23%	615 0.43%	142,784 100.00%
1% of RE	112,942 79.10%	1,842 1.29%	27,356 19.18%	614 0.43%	142,784 100.00%

Panel E: Bright-Line Tests of 1980 O-Score Model Given Simulated Understatement in Current Liabilities

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
0.3% of TA	112,851 79.06%	1,841 1.29%	27,447 19.22%	615 0.43%	142,784 100.00%
0.5% of TA	112,822 79.02%	1,841 1.29%	27,506 19.26%	615 0.43%	142,784 100.00%
1% of RE	113,445 79.45%	1,847 1.29%	26,883 18.83%	609 0.43%	142,784 100.00%

Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing. Where possible, firm-level variables are consistent with Compustat labels. Where AT indicates total assets, EBIT is earnings before interest and taxes, and RE is retained earnings.

The 2004 O-Score model appears to be sensitive to errors that auditors may consider immaterial during the planning stage of the audit. Table 4.19-Panel B reports 363 Type I errors with the 2004 O-Score model used as a bright-line test in audit planning. The simulations demonstrate that a misstatement at the level of planning materiality would result in 375-433 Type I errors using this bright-line test. Type II errors would decrease from 93,393 to between 84,909 and 88,337. This may indicate that these levels for planning materiality are inappropriately large if the O-Score is used a bright-line test for going concern.

4.2.3 Hazard Model Testing.

The Shumway Hazard model required data from Compustat North American Daily – Fundamentals Annual dataset and the Center for Research in Security Prices (CRSP) Stock/Security Files. I calculated all scores then matched the scores to my sample from Audit Analytics. The matched sample includes 53,043 firm-year observations with adequate data availability that include 963 bankruptcies and 2,046 modified going concern opinions. Table 4.20 includes descriptive statistics for the determinant variables for Shumway's Hazard model (Windsorized at 1%). Panel A highlights the difference in variable means by error type. Firms with going concern indicators were smaller with a mean net loss. Note that the probability of default is higher for bankrupt and GCO firms, as expected. The mean probability of default for bankrupt firms with GCO warnings is 43%. Bankrupt firms with GCO warnings had the smallest mean assets and the largest mean loss of any group, as expected.

Table 4.20 Descriptive Statistics for Determinant Variables of Shumway Model – Equation 6

Panel A: Descriptive Statistics for Variables in Shumway for all Firms in Sample

Variable	N	Mean	Standard Deviation	Minimum	Median	Maximum
AT	50,043	4,752.86	18,632.88	5.02	398.61	161,165.00
LT	50,043	3,185.14	12,905.69	0.89	191.24	111,881.00
NI	50,043	135.66	578.07	-642.37	6.25	4295.30
PRCC_F	50,043	19.24	18.94	0.27	13.62	94.00
CSHO	50,043	100.88	260.74	1.47	27.30	1,884.31
sigma	50,043	0.04	0.03	0.00	0.03	1.21
shumway	50,043	0.03	0.14	0.00	0.00	1.00

Panel B: Descriptive Statistics Shumway by Bankruptcy Indicator

Bankruptcy Indicator	Variable	N	Mean	Standard Deviation	Minimum	Median	Maximum
0	Shumway	52,080	0.03	0.13	0.03	0.00	1.00
1	Shumway	963	0.24	0.36	0.00	0.04	1.00

Table 4.20 (continued)

Panel C: Descriptive Statistics for Shumway by GCO Indicator

GCO Indicator	Variable	N	Mean	Standard Deviation	Minimum	Median	Maximum
0	Shumway	50,997	0.02	0.11	0.00	0.00	1.00
1	Shumway	2,045	0.29	0.36	0.00	0.10	1.00

Where possible, firm-level variables are consistent with Compustat labels. Where AT indicating total assets, ACT indicating total current assets, LT is total liabilities, NI is net income, CSHO is the number of common shares outstanding, and PRCC_F is the price per share of common stock at the end of the fiscal year. Sigma and Shumway are outputs of the model specified in equation 6; where Shumway represents the likelihood of default. N is the number of firm-level observations.

Table 4.21 reports the mean Shumway score (3%). Panel A compares the mean Shumway score for the sample of firms with bankruptcies in t+1 (0.24) to all other firms (0.03). Panel B compares the mean Shumway score for the sample of firms with going concern opinions in t (0.29) to firms all other firms (0.02). These results highlight that auditors capture the information contained in Shumway scores to some degree during their going concern judgments.

Table 4.21 Results of Bright-Line Testing of Shumway Models

Panel A: Historical Error Count based on Auditor Judgment

Auditor Judgment	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
Going Concern Opinions	50,356	641	1,724	322	53,043
Percentage	94.93%	1.21%	3.25%	0.51%	100.00%

Panel B: Simulated Error Count Where Bright-Line Testing Replaces Auditor Judgment

Bright-Line Test	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
Shumway with Probability (p>0.5)	51,070 96.28%	765 1.44%	1,010 1.92%	198 0.37%	53,043 100.00%
Shumway with Probability (p>0.7)	51,252 96.62%	793 1.50%	826 1.56%	170 0.32%	53,043 100.00%

Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing. Where possible, firm-level variables are consistent with Compustat labels.

To test the appropriateness of using Shumway default probability scores as a substitute for auditors' judgment in the identification of going concern uncertainty during the planning stages of an audit, I define a bright-line test of Shumway probability at greater than 50% and 70%. Table 4.22 contains the results of this test. Panel A reports the errors using $p > 0.50$. Using this bright-line test resulted in the correct identification of 198 bankruptcies (20.6%) with 765 (79.4%) misidentified of the 963 in the sample. This test recommends the issuance in 1,208 GCOs, of which 1,010 would be on firms that did not go bankrupt in the following period (83.6%). Panel B reports the errors using $p > 0.70$. The 70% bright-line test would predict 998 bankruptcies. Using this definition correctly identified 170 bankruptcies with 793 (82.3%) Type I errors and 828 (83.0%) Type II errors. Defining the appropriate threshold for the bright-line testing highlighted a trade-off between Type I and Type II errors. While the 50% probability bright-line test identified more bankruptcies (as would be expected), ranking the appropriateness of these tests cannot be determined without comparing the cost of each error type.

Table 4.22 Simulated Error Count Using Shumway Model for Bright-Line Test by Bankruptcy Type

Bankruptcy Type	Type I:	Type III: No Error	Total
Chapter 7	134 76.57%	41 23.43%	175 100.00%
Chapter 11	657 83.69%	128 16.31%	785 100.00%
Chapter 15	2 100.00%	0 0.00%	2 100.00%

Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing.

The sample contains 785 Chapter 11 bankruptcies that may be strategic and not proxy for a failing firm. This represents the bulk of the sample with sufficient data availability for the Shumway model. Table 4.24 examines the use of bright line testing for the 175 Chapter 7 bankruptcies included in the sample. Reported in Panel A, auditors using the bright-line test with the 70% threshold with the Shumway default probability score would have identified 41 (23.4%) of these bankruptcies in the period prior to filing. Type I errors for Chapter 7 bankruptcies (134) represented 76.6% of the Chapter 7 bankruptcies remaining in the sample. Panel B reports that 82 of the 175 received a GCO in the prior period. This indicates a significantly higher rate of Type I errors using the bright-line test (134, 76.6%) than using historic GCO (93, 53.1%) for the sub-sample of Chapter 7 firms.

Table 4.23 tests the significance of resulting predictions using a Pearson's Correlation Matrix. It reports that Shumway's model is significantly predictive at $p < 0.001$. The correlation statistic for the model (0.20048) is slightly lower for the Shumway score than for GCO Indicator (0.20687). This suggests that auditor judgment is a better predictor of bankruptcy than the Shumway model.

Table 4.23 Pearson's Correlation Matrix for BPM Predictions compared to Historical Going Concern Opinions and Bankruptcy Filings

Variable	Bankruptcy Indicator	GCO Indicator	Shumway (p>0.5) Indicator
Bankruptcy Indicator	1.0000		
GCO Indicator	0.20687 <0.0001	1.0000	
Shumway (p>0.5) Indicator	0.20048 <0.0001	0.37705 <0.0001	1.0000

Where the Bankruptcy Indicator equals 1 for firms with a bankruptcy filed within 730 days of the audit report filing date. GCO Indicator equals 1 for firms with going concern qualifications in the audit report. Model specifications and variable definitions are provided in equations 6.

Next, I simulated the risk-based auditing environment by transforming the accounting fundamentals for individual companies to reflect negative news at common materiality thresholds. Because the Shumway model relies less heavily on accounting fundamentals, changes in materiality in several scenarios does not affect model results. For example, total current assets and total current liabilities aren't variables in the Shumway model, so the simulations for overstated current assets and understated current liabilities have been omitted. The panels in Table 4.24 display only those scenarios where my planned manipulations affected Shumway scores. The number of correctly predicted bankruptcies range from 188 to 198. The number of Type I and Type II errors range from 765 to 775 and 931 to 1,013, respectively. It appeared that the performance of this model was most sensitive to non-material overstatements of assets.

Table 4.24 Simulated Error Count from Bright-Line Tests using Shumway Model in a Simulated Audit Planning Environment

Panel A: Bright-Line Tests of Shumway Model Given Simulated Overstatements in Sales

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
5% of EBIT	51,088 96.31%	766 1.44%	992 1.67%	197 0.37%	53,043 100.00%
1% of EBIT	51,076 96.29%	766 1.44%	1,004 1.89%	197 0.37%	53,043 100.00%
1% of RE	51,098 95.33%	767 1.45%	982 1.85%	196 0.37%	53,043 100.00%

Panel B: Bright-Line Tests of Shumway Model Given Simulated Overstatement in Long-term Assets

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
0.3% of TA	51,067 96.27%	765 1.44%	1,013 1.91%	198 0.37%	53,043 100.00%
0.5% of TA	51,067 95.27%	765 1.44%	1,013 1.91%	198 0.37%	53,043 100.00%
1% of RE	51,149 96.43%	775 1.46%	931 1.76%	188 0.35%	53,043 100.00%

Panel C: Bright-Line Tests of Shumway Model Given Simulated Understatement in Long-Term Liabilities

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
0.3% of TA	51,066 95.28%	765 1.44%	1,012 1.91%	198 0.37%	53,043 100.00%
0.5% of TA	51,067 96.27%	765 1.44%	1,013 1.91%	198 0.37%	53,043 100.00%
1% of RE	51,118 95.37%	769 1.45%	962 1.61%	194 0.37%	53,043 100.00%

Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing. Where possible, firm-level variables are consistent with Compustat labels. Where AT indicates total assets and RE is retained earnings.

4.2.4 Distance-to-Default Testing.

I followed the framework established by Bharath and Shumway (2008) to estimate the Merton-KMV Distance-to-Default model using Compustat and CRSP to obtain the financial variables needed for the analysis. From Compustat, I obtained the total value of long-term debt (DLTTQ) and the value of debt in current liabilities (DLCQ) on a quarterly basis. From CRSP, I acquired daily stock prices (PRC) and total shares outstanding (SHROUT) on a daily basis. I obtain the monthly risk-free rate for three-month treasury bills from the Board of Governors of the Federal Reserve System. I used the SAS code provided by Bharath and Shumway (2008) to fit the Merton Distance-to-Default model and calculated the EDF.

I began by calculating the EDF for all firms with adequate data availability. This resulted in 297,095 firm-quarter observations. I matched these observations to my sample of firms from Audit Analytics and isolated the largest quarterly EDF per firm-year. The matched sample includes 90,746 firm-year observations with adequate data availability that include 1,199 bankruptcies and 2,859 modified going concern opinions. Table 4.25 includes descriptive statistics for the determinant variables for Merton's KMV model. Panel A highlights the difference in variable means by error type. Firms with going concern indicators were smaller with a mean net loss. Note that the expected default frequency is higher for bankrupt and GCO firms, as expected. The mean EDF for bankrupt firms with GCO warnings is 95%. Bankrupt firms with GCO warnings had the smallest total firm value of any group, as expected.

Table 4.25 Descriptive Statistics for Determinant Variables of Merton's Distance-to-Default Model – Equation 7

Panel A: Descriptive Statistics for Variables in Distance-to-Default for all Firms in Sample

Variable	N	Mean	Standard Deviation	Minimum	Median	Maximum
AT	63,987	156,033.55	525,167.70	0.06	12,560.22	30,121,763.83
MU	63,987	-0.63	1.75	-25.29	-0.39	32.23
assetvol	63,987	0.90	0.66	0.02	0.72	17.25
F	63,987	39,410.35	660,725.18	0.02	2,209.00	72,701,942.00
EDF	63,987	0.39	0.41	0.00	0.19	1.00

Panel B: Descriptive Statistics Distance-to-Default by Bankruptcy Indicator

Bankruptcy Indicator	Variable	N	Mean	Standard Deviation	Minimum	Median	Maximum
0	EDF	62,788	0.38	0.41	0.00	0.17	1.00
1	EDF	1,199	0.85	0.28	0.00	0.99	1.00

Panel C: Descriptive Statistics for Distance-to-Default by GCO Indicator

GCO Indicator	Variable	N	Mean	Standard Deviation	Minimum	Median	Maximum
0	EDF	61,128	0.37	0.40	0.00	0.16	1.00
1	EDF	2,859	0.78	0.34	0.00	0.98	1.00

Where AT is the total value of assets, MU is the expected asset return, assetvol is the volatility of AT and F is total current liabilities plus one half of the long-term debt.

Table 4.25 reports the mean EDF of 0.39. Panel A compares the mean Merton Distance-to-Default score (EDF) for the sample of firms with bankruptcies in t+1 (0.85) to all other firms (0.38). As expected, firms with subsequent bankruptcies have a mean EDF that is higher than both bright-line testing thresholds (50% and 70%). Panel B compares the mean EDF for the sample of firms with going concern opinions in t (0.78) to firms all other firms (0.37). These results highlight that auditors capture the information contained in EDF scores to some degree during their going concern judgments.

To test the appropriateness of using Merton's Distance-to-Default scores as a substitute for auditors' judgment in the identification of going concern uncertainty during the planning stages of an audit, I define a bright-line test of Merton's Distance-to-Default probability at greater than 50% and 70%. Table 4.26 contains the results of this test at the 50% threshold. Panel A reports the errors using $p > 0.50$. Using this bright-line test resulted in the prediction of 24,759 bankruptcies--correctly identifying 1,058 bankruptcies (88.24%) with 141 Type I errors (11.76%). This test would also result in 23,701 predicted bankruptcies on firms that did not go bankrupt in the following period (Type II errors).

Panel B reports the errors using p > 0.70. The 70% bright-line test would predict 20,423 bankruptcies. Using this definition correctly identified 993 (82.82%) bankruptcies with 206 (17.19%) Type I errors and 19,430 Type II errors. Defining the appropriate threshold for the bright-line testing highlighted a trade-off between Type I and Type II errors. While it is tempting to disqualify Distance-to-Default as a useful test for auditors, the relative cost between Type I and Type II errors must be considered. While the 50% probability bright-line test identified more bankruptcies (as would be expected), ranking the appropriateness of the thresholds also cannot be determined without comparing the cost of each error type.

Table 4.26 Results of Bright-Line Testing of Distance-to-Default Models

Auditor Judgment	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
Going Concern Opinions	60,341	787	2,447	412	63,987
Percentage	94.30%	1.23%	3.82%	0.64%	100.00%

Panel A: Historical Error Count based on Auditor Judgment

Panel B: Simulated Error Count Where Bright-Line Testing Replaces Auditor Judgment

Bright-Line Test	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
D2D with Probability (p>0.5)	39,087	141	23,701	1,058	63,987
	61.09%	0.22%	37.04%	1.65%	100.00%
D2D with Probability (p>0.7)	43,358	206	19,430	933	63,987
	67.76%	0.32%	30.37%	1.55%	100.00%

Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing. Where possible, firm-level variables are consistent with Compustat labels.

The data requirements for the Distance–to-Default model limit the sample. The sample of firms with sufficient data for the model contains 986 Chapter 11 bankruptcies that may be strategic and not proxy for a failing firm. Table 4.27 examines the use of bright line testing for the 206 Chapter 7 bankruptcies included in the sample. Reported in Panel A, auditors using the bright-line test with the 50% and 70% thresholds the EDF score would have identified 108 (52.4%) and 162 (78.64%) respectively of Chapter 7 bankruptcies in the period prior to filing. Type I errors for Chapter 7 bankruptcies represented 47.6% (21.36%) of the Chapter 7 bankruptcies remaining in the sample. Panel B reports that 108 of the 206 Chapter 7 received a GCO in the prior period. These results indicate a significantly lower rate of Type I errors using the bright-line test than using historic GCO for the sub-sample of Chapter 7 firms.

The test also provides empirical evidence that the threshold for a bright-line test using the Distance–to-Default model is sensitive to bankruptcy type. The model was more successful in predicting Chapter 7 bankruptcies (47.6%) than Chapter 11 bankruptcies (30.8%) using the 50% threshold (when accuracy is measured by count). However, the model is less successful in predicting Chapter 7 bankruptcies (78.6%) than Chapter 11 bankruptcies (83.6%) using the 70% threshold.

Table 4.27 Bright-Line Testing of Merton's Distance-to-Default Model by Type of Bankruptcy

Bankruptcy Type	Type I:	Type III: No Error	Total
Chapter 7	33 16.02%	173 83.95%	206 100.00%
Chapter 11	108 10.95%	878 89.05%	986 100.00%
Chapter 15	0 0.00%	6 100.00%	6 100.00%

Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing.

Table 4.28 tests the significance of resulting predictions using a Pearson's Correlation Matrix. It reports that Distance-to-Default model is significantly predictive at $p < 0.01$. The correlation coefficient is higher for GCO Indicator (0.19995) than for EDF (0.15698). This suggests that auditor judgment outperforms a bright-line test based on the Distance-to-Default model.

Table 4.28 Pearson's Correlation Matrix for BPM Predictions compared to Historical Going Concern Opinions and Bankruptcy Filings

Variable	Bankruptcy Indicator	GCO Indicator	D2D (p>0.5) Indicator
Bankruptcy Indicator	1.00000		
GCO Indicator	0.19995 <0.0001	1.00000	
EDF (p>0.5) Indicator	0.15698 <0.0001	0.20500 <0.0001	1.00000

Where the Bankruptcy Indicator equals 1 for firms with a bankruptcy filed within 730 days of the audit report filing date. GCO Indicator equals 1 for firms with going concern qualifications in the audit report. EDF is the expected frequency of default from the distance to default model specified in equation 7.

Next, I simulated the risk-based auditing environment by transforming the accounting fundamentals for individual companies to reflect negative news at common materiality thresholds. Because the Distance-to-Default model does not rely heavily on accounting fundamentals, changes in materiality in several scenarios does not affect model results. The model only considers current and long-term liabilities. Therefore, the simulations for overstated current assets, total assets, and sales have been omitted. The panels in Table 4.29 display only those scenarios where my planned manipulations affected Distance-to-Default bright-line tests at the 50% and 70% thresholds. It appears that this model is not sensitive to relatively small overstatements of liabilities.

Table 4.29 Simulated Error Count from Bright-Line Tests using Distance-to-Default Model in a Simulated Audit Planning Environment

Panel A: Bright-Line Tests of Distance to Default Model with a 50% threshold for Expected Default Given Simulated Understatement in Long-Term Liabilities

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
5% of EBIT	25,289	111	17,714	854	43,968
	57.52%	0.25%	40.29%	1.94%	100.00%
1% of EBIT	25,120	111	17,543	852	43,968
	57.58%	0.25%	40.21%	1.95%	100.00%
0.3% of TA	17,083	48	11,562	354	29,047
	58.81%	0.17%	39.80%	1.22%	100.00%
0.5% of TA	17,059	48	11,586	354	29,047
	58.73%	0.17%	39.89%	1.22%	100.00%
1% of RE	10,892	41	8,490	288	19,711
	55.26%	0.21%	43.07%	1.46%	100.00%

Panel B: Bright-Line Tests of Distance to Default Model with a 70% threshold for Expected Default Given Simulated Understatement in Long-Term Liabilities

Materiality Threshold	Type 0: No Error	Type I:	Type II:	Type III: No Error	Total
5% of EBIT	28,377	152	14,626	813	43,968
	64.54%	0.35%	33.27%	1.85%	100.00%
1% of EBIT	19,142	66	9,503	336	43,968
	65.90%	0.23%	32.73%	1.16%	100.00%
0.3% of TA	19,142	66	9,503	336	29,047
	65.90%	0.23%	32.72%	1.16%	100.00%
0.5% of TA	19,135	66	9,510	336	29,047
	65.88%	0.23%	32.74%	1.16%	100.00%
1% of RE	12,309	58	7,073	271	19,711
	62.45%	0.29%	35.88%	1.37%	100.00%

Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing. Where possible, firm-level variables are consistent with Compustat labels. Where AT is total assets, EBIT is earnings before interest and taxes, and RE is retained earnings.

4.2.5 Summary of Bright-line Testing.

The majority of bankruptcy prediction research evaluates the success and effectiveness of a particular model using count or percentages to comparing predictive between models. Table 4.30 provides a summary of count and percentage of accuracy of bright line testing to historic accuracy rates without considering sensitivity to materiality thresholds. The sample size of each model differs due to data limitations. Note that the Z-Score and Distance to Default models outperform historical auditor judgment (GCOs) by limiting Type I errors. Auditor's GCO predictions result in fewer Type II errors than Z-score, O-score, and Distance-to-Default models.

Table 4.30 Summary of Results from Bright-Line Tests

Panel A: Count of Errors by Type for Each Model Compared to Auditor Judgment

Bright-Line Test	No Error: Correctly Predicted Surviving Firm	Type I Error: Bankrupt Firms with No Warnings	Type II Error: Surviving Firms with Predicted Bankruptcies	No Error: Correctly Predicted Bankruptcy	Total
Historical Auditor Judgment	233,222	1,944	46,539	1,514	283,219
1968 Z-Score <1.8 Auditor Judgment	52,568 125,331	387 1,469	87,726 14,963	2,069 987	142,750 142.750
1968 Z-Score Prob >0.5 Auditor Judgment	71,050 125,331	1,471 1,469	69,244 14,963	985 987	142,750 142.750
1993 Z-Score Prob >0.5 Auditor Judgment	75,706 125,331	1,831 1,469	64,588 14,963	625 987	142,750 142.750
2004 Z-Score Prob >0.5 Auditor Judgment	52,551 125,331	474 1,469	87,743 14,963	1,982 987	142,750 142.750
1974 O-Score Prob >0.5 Auditor Judgment	246,638 251,410	3,909 2,017	51,468 46,696	277 1,549	302,292 301,672
2004 O-Score Prob >0.5 Auditor Judgment	204,709 251,410	2,092 2,017	93,397 46,696	2,094 1,549	302,292 301,672
Shumway's Score – 50% Auditor Judgment	79,483 77,734	1,171 908	962 2,711	195 458	81,811 81,811
Shumway's Score – 70% Auditor Judgment	79,784 77,734	1,232 908	661 2,711	134 458	81,811 81,811
Merton's EDF – 50% Auditor Judgment	39,087 60,341	141 787	23,701 2,447	1,058 412	63,987 63,987
Merton's EDF – 70% Auditor Judgment	43,358 60,341	206 787	19,430 2,447	993 412	63,987 63,987

Table 4.30 (continued)

Panel B: Percentage of Historic Bankruptcies Identified

Bright-Line Test	No Error: Correctly Predicted Bankruptcy	Type I Error: Bankrupt Firms with No Warnings	Total Bankruptcies
Historical Auditor Judgment	1,514 43.8%	1,944 56.2%	3,458
1968 Z-Score <1.8	2,069 84.2%	387 15.8%	2,456
1968 Z-Score Prob >0.5	985 40.1%	1,471 59.9%	2,456
1993 Z-Score Prob >0.5	625 25.4%	1,831 74.5%	2,456
2004 Z-Score Prob >0.5	1,982 80.7%	474 19.3%	2,456
Auditor Judgment	987 40.2%	1,469 59.8%	2,456
1974 O-Score Prob >0.5	277 6.6%	3,909 93.4%	4,186
2004 O-Score Prob >0.5	2,094 50.0%	2,092 50.0%	4,186
Auditor Judgment	2,169 51.8%	2,017 48.2%	4,186
Shumway's Score – 50%	198 20.6%	765 79.4%	963
Shumway's Score – 70%	170 17.7%	793 82.7%	963
Auditor Judgment	332 34.5%	641 66.6%	963
Merton's EDF – 50%	1,058 88.2%	141 11.8%	1,199
Merton's EDF – 70%	993 82.8%	206 17.2%	1,199
Auditor Judgment	412 34.4%	787 65.6%	1,199

Table 4.30 (continued)

Panel C: Percentage of GCOs Correctly Predicted

Bright-Line Test	No Error: Correctly Predicted Bankruptcy	Type II Error: Surviving Firms with Predicted Bankruptcies	Total Predicted GCOs
Historical Auditor Judgment	1,514 3.2%	46,539 96.8%	48,053
1968 Z-Score <1.8	2,069 2.3%	87,726 97.7%	89,795
1968 Z-Score Prob >0.5	985 1.4%	69,244 98.6%	70,229
1993 Z-Score Prob >0.5	625 1.0%	64,588 99.0%	65,213
2004 Z-Score Prob >0.5	1,982 2.2%	87,743 97.8%	89,725
Auditor Judgment	987 6.2%	14,963 93.8%	15,950
1974 O-Score Prob >0.5	277 0.5%	51,468 99.5%	51,745
2004 O-Score Prob >0.5	2,094 2.2%	93,397 97.8%	95,491
Auditor Judgment	1,549 3.2%	46,696 96.8%	48,245
Shumway's Score – 50%	195 16.9%	962 83.1%	1,157
Shumway's Score – 70%	134 16.9%	661 83.1%	795
Auditor Judgment	458 14.5%	2,711 87.4%	3,169
Merton's EDF – 50%	1,058 4.3%	23,701 95.7%	24,759
Merton's EDF – 70%	993 4.9%	19,430 78.5%	20,423
Auditor Judgment	412 14.4%	2,447 85.6%	2,859

Table 4.30 (continued)

Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing.

Table 4.30 Panel B presents Type I errors as a percentage of total bankruptcy. This panel shows the percentage of bankruptcies that would be preceded by a warning under each condition. The 1968 Z-Score and Distance to Default models result in the lowest percentage of Type I errors. Of the ten primary models tested, six outperformed auditor judgment for percentage of predicted bankruptcies.

Table 4.30 Panel C presents Type II errors as a percentage of total GCO predictions. This panel addresses the false positive result. The reported counts may be misleading because sample size varies across models due to data limitations. For example, auditors issued 15,950, GCOs for the Altman Z-Score sample firms. A bright-line test using the 1968 Z-Score model specification would have resulted in over 5 times more warnings. In general, number of warnings issued would be significantly higher using BMP bright-line testing based on O-Score and Z-Score models. Seven models produce a higher percentage of correctly predicted bankruptcies. Shumway's Hazard Model outperformed auditor judgment in both count and percentage.

4.3 Part 2. Cost Trade-off Between Type I and Type II Errors

During a review of literature, I noted that most studies regarding BPMs evaluate the efficacy of models by calculating the count of percentage of accurate predictions. Count and percentages are not the only way to evaluate the effectiveness of a BPM. For Example, when a firm with a large market value prior to bankruptcy files bankruptcy without warning, the cost to stakeholders is higher than when a small firm with smaller enterprise value files. Chava and Jarrow (2004) evaluate models using size deciles, arguing that different models are more appropriate for different sized firms. They also classify BMP results by count and percentages after controlling for industry effects across models (Chava & Jarrow, 2004). However, I argue that count and percentages ignore market value and the cost trade-off between Type I and Type II errors. In the following analysis, I attempt to capture the cost trade-off by estimating the cost of bankruptcy prediction errors and applying the estimated market cost to a simulated environment.

I calculate CAR for each firm during my sample period around various windows surrounding (1) the date or the auditors' predictive opinion and (2) the date a bankruptcy was declared or, for surviving firms, one year past the date of the original report. I used the Eventus tool available to graduate students at the University of Kentucky through the WRDS portal. Eventus pulls data directly from CRSP stock database, calculates the CAR or standardized CAR (hereafter, SCAR) according to the parameters set by the user. To calculate CAR for this research I loaded the entire sample twice. First, I calculated CAR and SCAR on windows based on the date of the auditors' report (time t). I ran the program for CAR and SCAR windows defined as windows at (-2, +2), (-1,+1), (0,0) (-1, +3) (-1,+30) and (-30, +1). Next, I calculated CAR and SCAR on windows based on the earlier of a bankruptcy filing date or 365 after time t (t+1). I ran the program for the same CAR and SCAR windows. I reviewed the resulting tables for anomalies. General patterns emerged that appeared consistent with expectations. At time t, the mean CAR and SCAR for companies with GCO modifications or subsequent bankruptcy were negative. The CAR for firms with Type I and Type II errors were negative across almost all windows surrounding time t. Standard deviations were higher for firms with errors, going concern modifications, and bankruptcies. Standard deviations were larger for longer windows. At time t+1, CAR estimates were near zero or positive for firms without prior GCO modifications. They were significantly negative for firms with GCO modifications. At time t+1, The CAR for firms with Type I and Type II errors were negative across all windows. Standard deviations at time t+1 followed a pattern similar to time t.

In the next step, I added the effect from both windows and compared average change in enterprise value (EV) for firms in each of the following conditions: (0) a surviving firm with no GCO warning, (1) a firm with a Type I Error, (2) a firm with a Type II Error, (3) a firm with a GCO warning that filed bankruptcy in t+1, and (4) a firm with a GCO warning that filed bankruptcy in t+2. I note the distributions for combined CAR were non-normal with high kurtosis and skewed. I found empirical evidence that for firms with historic errors, the percent change in stock price estimated by CAR was negative with a high kurtosis and negative skewness. A scatter plot confirmed the distributions were non-normal with the scatter and histograms of the CAR for Type I error, Type II error, and correctly predict bankrupt firms all having leptokurtic density functions with thicker left-hand tails.

I estimate the change in market capitalization for each firm, using the following formula:

$$\Delta MRKTCAP = (CAR \times CHSO \times PRCC\_F) \qquad (7)$$

Where ΔMKTCAP is the change in total market capitalization for each firm, CAR is the mean combined buy/hold CAR calculated as a percentage of stock price over the five day window (-2, 2) at time t and t+1, CHSO is the net number common shares outstanding at year end for t, and PRCC_F is firm closing stock price at time t.

Table 4.31 compares the CAR and change in market capitalization between firms with and without a GCO in period t. The results are as expected. The CAR of firms with a GCO is negative with a relatively large standard deviation. Firms that didn’t have a going concern warning achieved higher abnormal returns across all windows. Panels A through C report that the estimated mean abnormal change in total market capitalization is 6-7 times higher for firms without a GCO.

Table 4.31 Descriptive Statistics of Changes in Market Capitalization based on Going Concern Indicator

Panel A: Estimated Change in Market Capitalization over a 3-Day Window (-1,+1)

GCO Indicator	CAR (-1,+1)									
	N	Mean	Standard Deviation	Kurtosis	Skew	Standard Error	Min	P5	P95	Max
0	37,039	0.00	0.07	90.92	3.73	0.00	-0.84	-0.08	0.08	1.96
1	963	-0.02	0.18	57.80	5.31	0.01	-0.82	-0.22	0.17	2.38
Total	38,002	0.00	0.07	124.87	4.96	0.00	-0.84	-0.09	0.09	2.38

GCO Indicator	Change in Market Capitalization Over a 3-Day Window (-1,+1)								
	N	Sum	Mean	Standard Deviation	Kurtosis	Skew	Standard Error	P5	P95
0	21,247	-$232	0	26.22	1,676.26	21.27	0.18	-10.56	10.82
1	505	-904	-2	24.62	84.25	5.06	1.10	-26.37	12.88
Total	21,752	-1,227	0	26.19	1,647.77	4.96	0.18	-11.00	10.85

Table 4.31 (continued)

Panel B: Estimated Change in Market Capitalization over a 5-Day Window (-2,+2)

GCO Indicator	CAR (-2,+2)									
	N	Mean	Standard Deviation	Kurtosis	Skew	Standard Error	Min	P5	P95	Max
0	37,039	0.00	0.08	273.61	6.41	0.00	-0.79	-0.00	0.11	4.41
1	963	-0.02	0.21	30.63	3.64	0.01	-0.27	-0.02	0.23	2.30
Total	38,002	0.00	0.09	231.27	6.31	0.00	-0.11	-0.00	0.11	4.41

GCO Indicator	Change in Market Capitalization Over a 3-Day Window (-2,+2)										
	N	Sum	Mean	Standard Deviation	Kurtosis	Skew	Standard Error	Min	P5	P95	Max
0	21,247	$2,594	$0	30.29	2,400.44	33.65	0.21	-$573	0.01	13.28	$2,130
1	505	-1,202	-2	26.07	36.13	2.00	1.16	-192	-0.68	17.24	233
Total	21,752	1,392	0	30.20	2,373.31	33.19	0.20	-573	0.00	13.37	2,130

Panel C: Estimated Change in Market Capitalization over a 367-Day Window (-1,+365)

GCO Indicator	CAR (-1,+365)									
	N	Mean	Standard Deviation	Kurtosis	Skew	Standard Error	Min	P5	P95	Max
0	37,051	-0.02	0.08	440.06	-7.50	0.01	-73.30	-1.55	1.57	23.46
1	967	0.10	0.21	8.37	-1.26	0.08	-16.29	-3.54	3.80	9.77
Total	38,018	-0.01	0.09	361.78	-6.63	0.01	-73.30	-1.61	1.64	23.46

Table 4.31 (continued)

GCO	Change in Market Capitalization Over a 367-Day Window (-1,+365)										
Indicator	N	Sum	Mean	Standard Deviation	Kurtosis	Skew	Standard Error	Min	P5	P95	Max
0	31,193	$2,142	$0	335.39	790.24	-6.36	1.90	-$15,094	-147.42	-147.87	$13,773
1	844	-3,867	5	225.50	196.15	-10.15	7.76	-4,504	-180.43	-180.98	1,350
Total	32,037	-1,724	0	332.96	793.23	-6.41	1.86	-15,094	-147.99	-149.18	13,773

GCO Indicator equals 1 for firms with going concern qualifications in the audit report.
Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing. Where possible, firm-level variables are consistent with Compustat labels.

Table 4.32 reports the descriptive statistics for CAR and ΔMRKTCAP for each condition. Following prior research, RQ4 predicted that the cost of Type I Errors were 35 times costlier than Type II Errors. The results from my sample suggest that total change in enterprise value for Type I Errors is between 3.24 and 3.41 times less costly than Type II Errors. I find that the estimated costs do not have a normal distribution. The distribution is marked by high positive kurtosis which indicates that the distribution has heavier tails than a normal distribution and that maximum and minimum estimates may be misleading. An abnormal distribution of CAR could mean CAR a larger number of outliers than would be predicted in a normal distribution. I examined the plots of the distribution for each error classification to verify that outliers are not responsible for this result. I tabulate the CAR at the 95% confidence interval and include ranges in my estimates to provide a more complete explanation of the estimates.

For sensitivity, I estimate the change in MRKTCAP for each firm over 3-day, 5-day and 367-day windows from the date of the auditor's report. The beginning of each window is based on the date the 10-K was filed (t). One year past the filing date for surviving firms or the date a bankruptcy was filed is defined as t+1. The three-day window includes the abnormal returns of six days: t, the active trading days before and after the filing at t, t+1 and the active trading days before and after t+1. The five-day window includes the abnormal returns of 10 days: t, the active trading days two days before and two days after the filing at t, t+1 and the two active trading days before and after t+1. The 365-day window begins on day t and extends through the shorter of two trading after the next scheduled 10-K filing or two days after a filed bankruptcy.

I estimated CAR over defined windows and observed similar patterns and results with each window. The five-day window (tabulated) captures any fluctuation or effects due to timing yet is less noisy and eliminates confounds that might be included the CAR calculated over an entire trading year. Although the 3-day window showed similar results, it might be too short and include an initial market reaction to bankruptcy news without subsequent correction. I report the results of in Table 4.34. The change in market capitalization for firms with Type I errors over the five-day window had a mean loss of 30.96 (-739.92 to 22.52 at the 95% confidence interval). The change in market capitalization for firms with Type II errors over the five-day window had a mean loss of 1.07 (-62.26 to 33.13 at the 95% confidence interval). The mean estimate market cost for Type I errors was almost 29 times higher than Type II errors. This generally supports prior findings on minimizing Type I errors at the expense of increasing Type II errors.

Table 4.32 Descriptive Statistic of Changes in Market Capitalization based on Bankruptcy Indicator

Panel A: Estimated Change in Market Capitalization over a 3-Day Window (-1, +1)

Bankruptcy Indicator	CAR (-1, +1)									
	N	Mean	Standard Deviation	Kurtosis	Skew	Standard Error	Min	P5	P95	Max
0	37,742	0.00	0.07	130.77	5.10	0.00	-0.84	-0.09	0.09	2.38
1	260	-0.01	0.16	10.52	1.45	0.01	-0.52	-0.23	0.17	1.02
Total	38,002	0.00	0.07	124.87	4.96	0.00	-0.84	-0.09	0.09	2.38

Bankruptcy Indicator	Change in Market Capitalization Over a 3-Day Window (-1, +1)										
	N	Sum	Mean	Standard Deviation	Kurtosis	Skew	Standard Error	Min	P5	P95	Max
0	21,641	$1.219	$0	26.05	1,690.75	21.45	0.18	-$764	-10.43	10.82	$1,650
1	111	-2,446	-22	40.16	5.14	-1.61	3.81	-219	-108.11	43.51	52
Total	21,752	-1.277	-0	26.19	1,647.77	20.96	0.18	-764	-11.00	10.85	1,650

Panel B: Estimated Change in Market Capitalization over a 5-Day Window (-2, +2)

Bankruptcy Indicator	CAR (-2,+2)									
	N	Mean	Standard Deviation	Kurtosis	Skew	Standard Error	Min	P5	P95	Max
0	37,742	0.00	0.09	245.79	6.60	0.00	-0.79	-0.10	0.11	4.41
1	260	-0.02	0.20	5.42	0.74	0.01	-0.78	-0.30	0.29	0.90
Total	38,002	0.00	0.09	231.27	6.31	0.00	-0.79	-0.11	0.11	4.41

Bankruptcy Indicator	Change in Market Capitalization Over a 3-Day Window (-2, +2)										
	N	Sum	Mean	Standard Deviation	Kurtosis	Skew	Standard Error	Min	P5	P95	Max
0	21,641	$4,230	$0	30.09	2,421.89	33.78	0.20	-0.79	-0.10	0.11	4.41
1	111	-2,838	-26	40.45	5.26	-1.78	3.84	-0.78	-0.30	0.29	0.90
Total	21,752	1,392	0	30.20	2,373.31	33.19	0.20	-0.79	-0.11	0.11	4.41

Table 4.32 (continued)

Panel C: Estimated Change in Market Capitalization over a 367-Day Window (-1, +365)

Bankruptcy Indicator	CAR (-1, +365)									
	N	Mean	Standard Deviation	Kurtosis	Skew	Standard Error	Min	P5	P95	Max
0	37,758	-0.01	1.22	371.94	-6.76	0.01	-73.30	-1.58	1.64	23.46
1	260	-0.69	1.82	2.75	-0.36	0.11	9.59	-3.37	2.39	4.50
Total	38,018	-0.01	1.22	361.78	-6.63	0.01	-73.30	-1.61	1.64	23.46

Bankruptcy Indicator	Change in Market Capitalization Over a 367-Day Window (-1, +365)										
	N	Sum	Mean	Standard Deviation	Kurtosis	Skew	Standard Error	Min	P5	P95	Max
0	31,795	$11,109	$0	333.76	791.56	-6.41	1.87	-$15,094	-145.01	149.15	$13,773
1	242	-12,833	-53	193.30	15.90	-1.92	12.43	-1,485	-333.44	151.08	832
Total	32,037	-1,724	-0	332.96	793.23	-6.41	1.86	-15,094	-147.99	149.18	13,773

Where Bankruptcy Indicator equals 1 for firms with a bankruptcy filed within 730 days of the audit report filing date. GCO Indicator equals 1 for firms with going concern qualifications in the audit report. CAR is the cumulative abnormal return calculated over specified windows.

Figure 5 highlights the mean percent change in stock price over the five-day window given historical error types. Following prior studies, predicted bankruptcies were costlier than Type I errors. The decrease in stock price was 8.69 times larger for Type I errors. The mean decrease in stock price on a five-day window around Type I errors was 19.519%. The mean decrease for Type II errors was 2.247%. However, that did not correspond to the same percentage decrease in enterprise value due to differing capital structures within the historical sample. For this study, I defined the market cost as the total decrease in market capitalization among firms classified into different error groups based on historical GCO in t and Bankruptcies filed in t+1. Firms with GCOs in t and bankruptcies in t+2 were classified as a separate group and not included in the cost analysis.

	No Bankruptcy in t+1	**Bankruptcy in t+1**
Unmodified Audit Opinion in t	No Error: -0.041%	Type I Error: -19.519%
Modified Audit Opinion in t	Type II Error: 2.247%	No Error: -39.156%

Figure 5: Diagram of Mean Estimated Percent Change in Stock Price on 5-Day Window by Error Type

The vast body of bankruptcy prediction research evaluates the accuracy and effectiveness of BPMs using a simple count or percentage of correct classification. I used this methodology in part one. Other studies question whether a pure count adequately measures effectiveness of a method.

I hypothesis that an error in predicting bankruptcy for a firm with greater market capitalization is costlier to the market than errors predicting bankruptcy for firms with lower value. By multiplying the mean change in CAR per share (Figure 3) by the total outstanding shares for each firm, I can compare a naïve estimate of total market cost for each bankruptcy model. I apply the mean change in CAR to estimate the change in market capital in time t for each firm. Then, instead of evaluating the precision of the BMP (i.e. the count of percentage of correctly classified firms), I compare the total estimated market cost of errors for each model. As Table 4.33 indicates, auditor's historical GCOs have the lowest total market cost per firm and outperform bright-line testing from BPMs, except for the Merton-KMV model.

Table 4.33 Summary of N and Mean estimated total market cost of errors on a 5-day window by BPM (dollars in thousands)

	Cost per Error Condition				Total	Average Cost (per firm)
	Type 0: Predicted Survivor	Type I	Type II	Type III: Predicted Failure		
Auditor's GCO Judgment	$4,758 36,838	($2,164) 201	$528 904	($674) 59	$1,392 38,002	$0
1968 Z-Score	$38,587 18,724	($2,218) 52	($1,499,572) 13,278	($35,268) 347	($1,498,470) 32,401	($46)
1993 Z-Score	$58,891 21,958	($7,019) 60	($386,814) 10,044	($25,637) 339	($360,579 32,401	($11)
2004 Z-Score	$38,587 31,995	($2,218) 52	($1,499,572) 13,278	($35,268) 347	$63,641 32,401	($46)
1980 O-Score	$932 11,912	($13,794) 462	($423,119) 12,115	($54,815) 101	($490,796) 24,590	($20)
2004 O-Score	$19 324	($26) 6	($473,136) 23,703	($82,434) 557	($555,577) 24,590	($23)
Shumway	$8,512 23,758	($39,398) 495	($7,708) 269	($3,453) 68	($42,047) 24,590	($2)
Distance to Default	$83,596 60,332	($24,296) 312	($5,469) 2,446	($83,405) 887	($29,573) 63,977	($0)

Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing. Where possible, firm-level variables are consistent with Compustat labels.

Altman et al. (1977) estimates that Type I errors are 35 times costlier than Type II errors. I hypothesis (4a) that the cost of Type I errors is more than 35 times the cost of the average Type II Error. My naïve model for estimated market costs finds that the mean historical cost per Type I error was ($2,164 thousand) and the mean cost per Type II error resulted in a $528 thousand increase in market capitalization. Because the data requirements for each model differ, the firms included in each sample differ. It is therefore necessary to compare the average change in market capitalization value per firm for each model. This measure indicates that Type I errors are costlier than Type II errors by a factor of 5.1. This cost trade-off is significantly different than Altman et al.'s 1977 estimate.

Bright line testing based on each model found that the models are sensitive to relatively small (i.e. planning materiality) misstatements. My data provides empirical evidence to reject the hypothesis that the change in total cost of errors due to simulated misstatements is zero.

Hypothesis 4(c) predicts that a decrease in Type I errors would result in a greater than 35% increase in Type II error costs. I find that the Z-Score models (1968, 1993, 2004), the 2004 O-Score model, and Merton-KMV have better Type I accuracy when using bright-line testing to replace auditor judgments. However, average market cost is higher for the 1968 Z-Score, 1993 Z-Score, 2004 Z-Score and 2004 O-Score. Merton-KMV has a lower rate of Type I error but a significantly higher Type II error rate. The average estimated market cost per firm is closer to auditor judgment (and $0) than models with lower Type I and Type II error rates. This evidence suggests that Merton's-KMV is more accurate in predictions for firms with high market capitalization. This provides empirical evidence that costs in addition to accuracy rates should be considered when evaluating model usefulness.

CHAPTER 5: SUMMARY OF RESULTS AND INFERENCES

This dissertation encompasses two parts. The first part includes testing the feasibility of employing four BMPs in the planning phase of an audit. This part includes simulations to test the sensitivity of models to an audit environment where immaterial misstatements may subsequently be identified and adjusted without altering an overall audit opinion. The preliminary results from this testing suggest that certain BMPs would qualify more companies as uncertain going concerns. The results also highlight that audit judgment has historically outperformed models at limiting Type II errors. While some research suggests this may indicate a conflict of interest, my testing highlights the need for systematically valuing the trade-off between lowering Type I errors while simultaneously increasing Type II errors. A more detailed discussion of these results follows.

5.1 Part 1. Discussion of Results Models and Simulations

As described above and in Tables previously presented, I have examined the results of four seminal BPMs from finance and accounting research: Altman-Z Score, Ohlson's O-Score, Shumway's Default Probability Score, and Merton's EDF Score. Regulation requires auditors to evaluate management's assertions about whether "substantial doubt" exists for a company to not continue as a going concern. Using the 50% and 70% probability threshold established by "substantial doubt", a bright-line test for each BPM evaluates the feasibility of substituting auditors' judgment with a binary decision model to issue a GCO. I first tested the classic Z-Score model using the definition of a score less than or equal to 1.8 as distressed and at risk for a going concern opinion. I then tested updates Z-Score models after converting the results to a probability. Three other models were tested. Unlike the Z-Score model, these models produce scores that can directly be interpreted as probabilities of default. I defined bright-line thresholds for decision making as a company being identified as distressed if the probability of default produced through Ohlson's, Shumay's, or Merton's model was greater than 50%, and 70%. The results of the initial bright-line tests are summarized in Table 5.1.

In general, historical predictions by auditors resulted in fewer total errors when compared to application of the tested models. However, four models (the test Z-Scores as classically defined, the 2004 Z-Score, the 2004 O-Score, and Merton's EDF) reduced

Type I errors but increased Type II errors. Anecdotal evidence of public reaction, litigation results and reputation effects from Type I errors suggest that the cost of Type I errors is higher than the cost of Type II errors. Quantifying the cost trade-off between these types of errors is difficult, yet important in evaluating the usefulness of these four mathematical models in GCO predictions.

Table 5.1 Summary of Results from Bright-line Tests

Bright-Line Test	No Error: Correctly Predicted Surviving Firm	Type I Error: Bankrupt Firms with No Warnings	Type II Error: Surviving Firms with Predicted Bankruptcies	No Error: Correctly Predicted Bankruptcy	Total
Historical Auditor Judgment	233,222	1,944	46,539	1,514	283,219
1968 Z-Score <1.8 Auditor Judgment	52,568 125,331	**387^** 1,469	87,726 14,963	**2,069^** 987	142,750 142.750
1968 Z-Score Prob >0.5 Auditor Judgment	71,050 125,331	1,471 1,469	69,244 14,963	985 987	142,750 142.750
1993 Z-Score Prob >0.5 Auditor Judgment	75,706 125,331	1,831 1,469	64,588 14,963	625 987	142,750 142.750
2004 Z-Score Prob >0.5 Auditor Judgment	52,551 125,331	**474^** 1,469	87,743 14,963	**1,982^** 987	142,750 142.750
1974 O-Score Prob >0.5 Auditor Judgment	246,638 251,410	3,909 2,017	51,468 46,696	277 1,549	302,292 301,672
2004 O-Score Prob >0.5 Auditor Judgment	204,709 251,410	2,092 2,017	93,397 46,696	**2,094^** 1,549	302,292 301,672
Shumway's Score – 50% Auditor Judgment	**79,483^** 77,734	1,171 908	**962^** 2,711	195 458	81,811 81,811
Shumway's Score – 70% Auditor Judgment	**79,784^** 77,734	1,232 908	**661^** 2,711	134 458	81,811 81,811
Merton's EDF – 50% Auditor Judgment	39,087 60,341	**141^** 787	23,701 2,447	**1,058^** 412	63,987 63,987
Merton's EDF – 70% Auditor Judgment	43,358 60,341	**206^** 787	19,430 2,447	**993^** 412	63,987 63,987

Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing. Where possible, firm-level variables are consistent with Compustat labels.

^ indicates prediction counts that are more accurate than historic GCOs in a given sample

Recent regulation requires management to make a going concern assertion and defines the auditor's role of testing these assertions. My research examines the usefulness of BPMs in testing management assertions. Results from my testing suggest that BPMs may be useful as a screening tool in the planning stage of an audit. Auditors could use discriminate analysis BPMs (such as the 1968 or 2004 Altman Z-Score) in the planning stage of the audit to identify a large pool of distressed firms based on probability thresholds established by regulation. However, if auditors use these BMPs for planning and testing, auditor judgment would still be necessary to reduce the number of Type II errors in final GCO opinions. The Shumway Hazard model predicts fewer bankruptcies overall, thus limiting Type II errors. However, historical auditor judgment does a better job predicting bankruptcies and limiting Type I errors. Merton's Distance to Default also has a lower Type I error rate with a high Type II error rate compared to auditor judgment. This model also suffers from sample loss due to data availability. This model may be less practical than the Z-Score.

Beyond testing the precision of bankruptcy models, proposing that these models be used as analytical procedures in the planning stage of the audit environment introduces the concept of materiality to the usefulness of the models. My research examined the sensitivity of BMP-based decisions in an environment where immaterial misstatements may exist. The results of the models' financial data with simulated errors is discussed by model in Chapter 4. Overall, bright-line decisions based on the models were sensitive to manipulations set at the threshold of commonly used quantitative materiality thresholds. This suggests that auditors should reduce common quantitative materiality thresholds during audit planning for firms identified as having net loss, little net income, or at high risk for default. Overall, the simulation results provide evidence that the models would perform as expected in the planning stage of an audit, but if misstatements are identified judgments of uncertainty should be reassessed regardless of materiality.

5.2 Part 2: Discussion of Results of Cost Estimation

The first part of this research examines the precision of four types of BPMs by count and percentages of Type I and Type II errors and the sensitivity of each model to manipulations at the level of planning materiality. In the second part, I calculated CAR over several windows surrounding historical auditors' reports and subsequent bankruptcies or 10-K filings. I compared the results of the change in stock price for each error type. The distribution of CAR was non-normal. I graphed the distribution and gained confidence that Type I errors were much more costly in the market than Type II errors. Looking at the results over a 95% confidence interval supports this conclusion. I found that the results were not sensitive to the window used, so I applied the mean change in stock price over a five-day window at the auditors' report in time t and the subsequent auditors' report or bankruptcy filing. The results suggest that BMP usefulness should be evaluated based on more than precision count and error percentages.

Table 5.2 summarizes the sum and mean change in estimated market capitalization over a 5-day window for each error type given the bright-line decisions from Part 1. Historical GCO's, the Shumway model, and the Merton model result in the lowest mean cost across all companies. However, note that the total estimated market cost of Type II errors is higher than the cost of Type I errors for the 1993 Z-Score, 2004 Z-Score, the Shumway's hazard model, and the Merton's distance to default. Overall, the total change in market capitalization is only positive using the actual auditor decisions. This provides evidence that going concern opinions based on auditor judgment, not the BMPs tested, results in the highest market valuation. These results provide evidence to support the continued use of auditor judgment over the application of bright-line testing for GCO decisions.

Table 5.2 Summary of Changes in Market Cost Estimated by Applying CAR to Market Capitalization over a 5-Day Window (in thousands of dollars)

Bright-Line Test		No Error: Correctly Predicted Surviving Firm	Type I Error: Bankrupt Firms with No Warnings	Type II Error: Surviving Firms with Predicted Bankruptcies	No Error: Correctly Predicted Bankruptcy	Total
Historical Auditor Judgment	Sum	$4,758	($2,164)	($528)	($674)	$1,392
	Mean	$0	($25)	($1)	($27)	($0)
1968 Z-Score <1.8	Sum	38,587	(2,218)	(1,499,572)	(35,268)	(1,498,470)
	Mean	2	(43)	(113)	(102)	(46)
1993 Z-Score Prob >0.5	Sum	58,891	(3,360,133)	(808)	(25,637)	(3,327,687)
	Mean	3	(335)	(13)	(76)	(103)
2004 Z-Score Prob >0.5	Sum	0	(31,396,475)	0	(39,717)	(31,436,192)
	Mean	0	(981)	0	(100)	(970)
1980 O-Score Prob >0.5	Sum	932	(13,794)	(423,119)	(54,815)	(490,796)
	Mean	0	(30)	(35)	(543)	(20)
2004 O-Score Prob >0.5	Sum	19	(26)	(473,136)	82,434)	(555,577)
	Mean	0	**(4)^**	(20)	(148)	(23)
Shumway's Score – 50%	Sum	8,512	(39,398)	(7,708)	(3,453)	(42,047)
	Mean	0	(80)	(29)	(51)	(2)
Merton's EDF – 50%	Sum	83,596	(24,296)	(5,468)	(83,405)	(29,573)
	Mean	1	(78)	(2)	(94)	0

Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year; Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy; Type II indicates a firm with a Type II error, where a warning was issued but the firm did not file bankruptcy within 730 days; Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing. Where possible, firm-level variables are consistent with Compustat labels.

^ indicates mean change in market capitalization is lower than historic auditor judgment

CHAPTER 6: DISCUSSION AND CONCLUSIONS

One goal of this dissertation is to identify patterns in the data that suggest future inferences that are interesting to regulators, preparers, auditors, or other stakeholders. My results suggest several important inferences. First, Table 9.1 suggests that bright-line testing using four BPMs would warn investors about more bankruptcies while simultaneously issuing many more warnings for firms that would survive. GCOs issued by auditors resulted in fewer bankruptcies being predicted and fewer “false positive” going concern opinions (Type II errors), but more bankruptcy surprises (Type I errors). Type II errors are not costless. In looking at a simple proxy for the cost trade-off between Type I and Type II errors, my results suggest that bright-line tests for GCOs are not a good substitute for auditor judgment. However, they may be a useful compliment if employed during the planning stage of an audit.

In addition, the results demonstrate that going concern predictions based on bankruptcy models are sensitive to quantitative thresholds of materiality. Initial assessments on GCO uncertainty based on unaudited amounts using these models require updating when misstatements are identified even when those misstatements fall below common thresholds for quantitative planning materiality. This suggests that the common quantitative thresholds should be lowered for at-risk firms for BMPs to be used appropriately.

Finally, the results suggest that my research may inform practice. Regulatory agencies have cautioned against setting static quantitative materiality thresholds. My results highlight that the use of a bright-line test for all firms may not be appropriate, particularly in cases where quantitative planning materiality is set using the 5% of net income “rule-of-thumb”. Table 3 also provides support for the practice of setting lower materiality thresholds for distressed firms during the planning stages of an audit.

Several researchers and regulators have suggested the use of analytical tools in the planning stage of an audit. My preliminary results suggest that while bankruptcy models may highlight distressed firms, they also over-predict bankruptcies. The use of bankruptcy models during analytical procedures may be justified for firms with specific identifiable features. Further testing will be required to determine if this finding is a limitation of only this specific model.

Furthermore, my results inform default prediction research by exploring a naïve model to evaluate BPMs based on the change in overall market value. My results suggest that the usefulness of BPMs need to be evaluated on more than accuracy counts because a surprise bankruptcy is costlier in larger firms with higher initial market capitalization than in small firms and firms with already low stock prices.

6.1 Limitations

I am aware of several limitations to my research. The design of this study is limited by the bankruptcy models selected, the availability of data, and the proxies available.

Kurruppu et al. (2003) argues that bankruptcy is not the best proxy for going concern given that the debtor-oriented bankruptcy laws in the U.S. They argue that statistical models to predict corporate distress and liquidation are better proxies as filing for bankruptcy does not necessarily mean that a company is not a going concern. The research argues that a bankrupt company can be regarded as a going concern until the resolution of bankruptcy, and that company bankruptcy is less costly compared to company liquidation. They further argue that corporate bankruptcy is not as costly as liquidation to shareholders and to other stakeholders, citing that “50 percent of companies that re-emerge from bankruptcy generate a return that exceeds the return available on benchmark portfolios”.

I acknowledge that in countries with debtor-oriented insolvency laws (i.e. the USA), corporate bankruptcy procedures encourage companies in financial difficulty to continue as going concerns (Franks, Nyborg, & Torour, 1996). I further acknowledge that companies that file for bankruptcy can either reorganize and emerge from bankruptcy or merge with another entity as a going concern (Carson, et al., 2013); therefore, filing for bankruptcy is not synonymous with uncertainty of the going concern assumption (Schultz, 1995). However, research has shown that investors expect GCO’s to predict bankruptcy and respond to GCOs as a signal for impending bankruptcy. I follow this large body of expectation gap and going concern literatures that use bankruptcy as a proxy for going concern failure. I present data highlighting Chapter 7 bankruptcy predictions and error rates for BMP studied.

While accountants use quantitative analysis to identify potential material events and transactions, materiality is not a simple calculation. The SEC warns that exclusive reliance on any specific quantitative benchmark for working materiality is not appropriate (Vorhies, 2005). By definition, if an amount would change a user’s decisions, then that amount is material. Therefore, any amount that changes the bankruptcy decision in a hardline test would be material. However, in practice, quantitative materiality thresholds, such as the 5%-rule, are commonly used. Therefore, examining the sensitivity of decision outcomes of BPMs during the planning stage of audits to set quantitative materiality thresholds is informative.

Limitations for each BPM's usefulness exist. Some limitations impact a class of BPMs. Discriminate-based models are only as accurate as the data that goes into it; therefore, earnings management and fraud affect the usefulness of these measures. Other models use market reactions to capture information outside of the annual report (good and bad news) that may affect a company's ability to continue as a going concern.

Limitations are also model specific. For example, the original Z-Score was intended to be used among manufacturing firms only (Altman E. I., 1968). The Z-Score also isn't an effective tool for evaluating new companies with little or no earnings. These companies, regardless of their financial health, will score low. Moreover, the Z-Score does not directly address the issue of cash flow. Another limitation of the Z-Score is volatility. Z-scores can swing from quarter to quarter when a company records one-time write-offs. These can change the final score, suggesting that a company that's really not at risk is on the brink of bankruptcy.

I estimate market costs using methods from prior literature. I limit my estimation of the cost of going concern opinions and bankruptcies to the impact of these announcements on stock prices. This estimation method provides some information about the overall costs in changes of prediction accuracy. Other costs associated with Type I and Type II errors are ignored in this estimation. I acknowledge the conflicting sources of cost between auditors and other stakeholders. A Type I error is misclassifying a failed company as non-failed and are costliest to auditors, where it would lead to the possible loss of audit fee, professional reputation and litigation from shareholders (Koh, Model Predictions and Auditor Assessments of Going Concern Status, 2012). The costs of Type II errors (misclassifying a healthy company as failed) to auditors include the loss of professional reputation, loss of audit fee, and litigation due to financial injury to the client due to the inappropriate audit opinion (Louwers & Richard, 1999). I acknowledge that my research considers neither the client retention or litigation costs to auditors nor other related costs to employees, creditors, or other stakeholders.

6.2 Directions for Future Research

This research was largely exploratory and initially sought to inform regulators about the appropriateness of using statistical BPMs in the planning stage of an audit. I established the hypotheses and research design during the discussion of changing regulations around the auditing of going concern opinions. These questions remain relevant as the subsequent issuance of SAS No. 132 provides general testing guidance, does not address specific testing for assessing going concern risk through analytical procedures. My dissertation provides empirical evidence of the sensitivity of BPMs in the planning stage of an audit due to its unique environment concerning materiality. However, my tests were limited to certain seminal models within the research. As models that are more current emerge, research should consider how each of these models would perform in this environment. After all, BPMs are only as good as the data that they are built from and the financial statements used in the planning stage contain (by definition) unaudited and unverified amounts.

This research also builds on Mai's 2010 dissertation from Rutgers University that identifies the same BMPs for testing. Like so many researchers, Mai assesses the precision of the models using a simple count of errors. Not only does count fail to consider the difference in cost to different classes of stakeholders between types of errors, but it also fails to consider the enterprise value of the firms underlying the errors. If a model is better able to catch a bankruptcy for a larger and more highly-valued firm, that model may be more useful for auditor decision making models that perform well in predicting failures among start-up companies. My research provides empirical evidence of one other evaluation scheme: a naïve costing model based on changes in market capitalization using an estimate of CAR. Further research is needed to address the relative usefulness of specific models for new firms, large firms, and firms with negative net income.

My research explores one model for estimating costs of errors within publicly traded markets. Additional models for estimating market costs related to privately held companies should be examined. This study also ignores switching and litigation costs. Researchers should take up the call to develop a more comprehensive model for estimating costs for all stakeholders.

6.3 Conclusion

Results suggest that BPMs provide a quantitative measure of going concern uncertainty, which may be important for documentation in the planning stage of an audit. The results also highlight a tradeoff between Type I and Type II errors and suggests additional information and auditor judgment is necessary to eliminate excessive Type II errors. Assuming misstatements at the magnitude of “material misstatements” under common materiality thresholds influenced accuracy of going concern predictions. When misstatements are identified auditors using these models as analytical procedures should update their Going Concern uncertainty assessments. This suggests that materiality thresholds may be set too high when assessing going concern uncertainty during the planning stages of an audit.

My study informs the ongoing debate over auditors' responsibility to predict bankruptcies and warn investors by issuing a going concern opinion. I test the inherent limitations of the information environment and current prediction models. The trade-off between Type I and Type II errors does not justify the use of BPMs as a bright-line test in the absence of auditor judgment. At most, these models may be useful in the planning stage of an audit to provide quantitative documentation for firms that are low-risk. While accuracy rates and the cost of errors has been explored in the literature, the difference in my research and prior studies is that I used simulation to test the sensitivity of the models to detect bankruptcies given commonly used quantitative materially thresholds. Investigating quantitative materiality levels provides information about the impact of materiality thresholds on the use of these models as analytical tools in the planning stage of an audit. I am unable to make normative conclusions about the equilibrium; rather this research provides evidence that, given current predictive models and common thresholds for “material misstatements”, I fail to find a model where the cost trade-off between Type I and Type II errors improves by substituting bright-line testing for auditor judgment. I identified no model that could replace auditor judgment, certain models—where data is available-- may be useful in the planning phase of an audit to provide quantitative documentation of going concern uncertainty testing. Discriminate analysis models come with a high total market cost of failure and auditor judgment is necessary to limit Type II errors. Merton’s Distance to Default and Shumway’s Hazard Model limit Type II errors, but fail to timely identify bankruptcies better than auditor judgments.

APPENDICES

Appendix A Glossary

Term	Definition
BPM	Bankruptcy prediction models are a set of financial models that are used to predict the likelihood of default.
Chapter 7 Bankruptcy	A straight or liquidating bankruptcy that can clear away many types of unsecure debt with no plan for restructuring.
Chapter 11 Bankruptcy	A form of bankruptcy that involves reorganization giving a debtor a fresh start and keeps the business in operation to pay creditors over time.
Chapter 15 Bankruptcy	Means to deal with insolvency cases involving debtors, assets, claimants, and other parties of interest involving more than one country. This case is generally ancillary to a primary proceeding brought in another country.
MDA	Multiple discriminant analysis. Statistical method in finance models used to evaluate multiple variables at once.
Type 0	Type 0 indicates that a firm was correctly identified as a going concern (i.e. no warning was issued) in year t and no bankruptcies were filed in the subsequent year.
Type I Error	Type I indicates a firm with a Type I error where a firm was identified as a going concern, but subsequently filed bankruptcy within 730 days.
Type II Error	Type II indicates a firm with a Type II error, where a GCO warning was issued, but the firm did not file bankruptcy within 730 days.
Type III	Type III indicates a firm with a GCO warning issued within 730 days before a bankruptcy filing.
CAR	Cumulative Abnormal Return is the sum or the differences between the expected return on a stock and the actual return over a defined time window.
SCAR	Average standardized cumulative abnormal return across all firms.

Appendix B Variable definitions

Variable	Description
GCO Indicator	GCO Indicator equals 1 for firms with going concern qualifications in the audit report.
Bankruptcy Indicator	Bankruptcy Indicator equals 1 for firms with a bankruptcy filed within 730 days of the audit report filing date.
AT	Total Assets
ACT	Total Current Assets
LT	Total Liabilities
LCT	Total Current Liabilities
NI	Net Income
EDF	Expected Default Frequency, probability of default expressed as a percentage.
MU	Expected Asset Return
VDIF	ASSETVOL – Penultimate VA
ASSETVOL	Volatility of Total Market Capitalization
F	Current Debt
RE	Retained Earnings
EBIT	Earnings before interest and taxes
ROA	Return on Assets
LM	Leverage Measure. Total Liabilities/Total Assets
N	Number of firms-year observations
CHSO	Common Shares Outstanding
PRCC_F	Price per share of common stock at fiscal year end
ΔMRKTCAP	Change in Market Total Capitalization = (CAR x CHSO x PRCC_F)

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