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The Predictive Role of Auditor Going Concern Opinion and Auditor Characteristics in Corporate Bankruptcy: Evidence From Firms Listed on the Egyptian Stock Exchange

Abstract

The primary objective of this study is to investigate the informativeness and the incremental predictive power of audit related disclosures of listed firms for corporate bankruptcy prediction beyond that of financial variables. To attain this objective, several predictive models are constructed and compared using different types of explanatory variables: (1) auditor going concern opinion (auditor GCO), (2) auditor characteristics, and (3) standard financial ratios.

Using an imbalanced sample of 25 technically bankrupt firms and 50 healthy firms, logit models are constructed to examine the information content and the incremental predictive power of audit related disclosures beyond that of Altman (1986) financial ratios. Several evaluation metrics are utilized including the Pseudo-R^2 statistic, AUC, Accuracy, Type I and Type II errors.

Results reveal that auditor GCO has significant predictive power for corporate bankruptcy; however, this predictive power is not incremental to a financial ratios–based model. On the other hand, auditor characteristics; specifically, auditor type, auditor rotation, and auditor industry specialization, are not useful in predicting corporate bankruptcy.

Keywords: Auditor Going Concern Opinion, Auditor Characteristics, Auditor Type, Auditor Rotation, Auditor Industry Specialization, Corporate Bankruptcy Prediction

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دور رأي مراقب الحسابات بشأن استمرارية الشركة وخصائص مراقب الحسابات في التنبؤ بإفلاس الشركات: أدلة من الشركات المقيدة في البورصة المصرية

ملخص البحث

الهدف الرئيسي من هذه الدراسة هو التحقق من المحتوي المعلوماتي والقدرة التنبؤية الإضافية للإفصاحات المرتبطة بالمراجعة علي التنبؤ بإفلاس الشركات المقيدة في البورصة المصرية مقارنة بالمتغيرات المالية.

باستخدام عينة من ٢٥ شركة مفلسة إفلاس فني و ٥٠ شركة ناجحة، تم تطوير نماذج الانحدار اللوجستي، للتحقق من المحتوي المعلوماتي والقدرة التنبؤية الإضافية للإفصاحات المرتبطة بالمراجعة مقارنة بالنسب المالية المتضمنة في نموذج (1986)   Altman. وقد تم استخدام العديد من معايير التقييم لنماذج التنبؤ منها؛ دقة التنبؤ ، الخطأ من النوع الأول، والخطأ من النوع الثاني.

وتشير النتائج إلي أن رأي مراقب الحسابات بشأن استمرارية الشركة له قدرة جوهرية علي التنبؤ بالإفلاس، ولكنه لا يقدم قيمة تنبؤية إضافية زيادة عن القيمة التنبؤية للنموذج المبني علي النسب المالية. علي الجانب الأخر، توضح النتائج أن خصائص مراقب الحسابات؛ وبصفة خاصة، حجم مكتب المراجعة، تدوير مكتب المراجعة، والتخصص الصناعي لمراقب الحسابات، ليس لها دور في التنبؤ بإفلاس الشركات.

الكلمات المفتاحية: رأي مراقب الحسابات بشأن استمرارية الشركة، خصائص مراقب الحسابات، حجم مكتب المراجعة، تدوير مكتب المراجعة، التخصص الصناعي لمراقب الحسابات، التنبؤ بإفلاس الشركات

1. Introduction

The firm financial stability and performance evaluation are of great significance to several parties in the society, including stockholders, creditors, governmental/regulatory organizations, and auditors. Importantly, the credit assessment of listed firms is a substantial indicator not only to the stock market for stockholders to adjust the stock portfolio they own, but also to the capital market for creditors to estimate the costs of loan default and consider the borrowing terms for their customers. It is also the responsibility of the governmental and regulatory bodies to monitor the general financial position of firms in order to set appropriate economic and industrial policies.

Moreover, for the interest of the firms' stakeholders, the auditors of firms need to maintain a scrutiny over the going concern of their clients for the foreseeable future and fairly present their neutral technical opinion in the audit report attached to each of their client's financial statements. In this regard, International Accounting Standard 1 (IAS 1) requires management to make an evaluation of a firm's ability to continue as a going concern. If management has significant concerns about the firm's ability to continue as a going concern, the uncertainties must be reported. Furthermore, according to (ISA 570, 2015), auditors are required to make judgment concerning the appropriateness of the managers' use of going concern assumption in the preparation of the financial reports and in determining if there is a significant doubt on the firm's ability to continue as a going concern. Typically, the cessation of a firm as a going concern is assessed by investigating the occurrence of bankruptcy, which is the extreme form of financial difficulties that firms may encounter in the near future.

Importantly, a single firm's bankruptcy will impact a chain of members of the economy, especially its creditors and employees. But, if a group of firms in an economy simultaneously face corporate bankruptcy, it will not only leave scars on the national economy, but also on its neighbors. The evidence is confirmed by the financial storm clouds gathered over Thailand in July 1997, which produced immediate losses to most Asia–Pacific countries. Consequently, the development of bankruptcy theory and bankruptcy prediction models, which can

safeguard the market from preventable damages, is crucial. This can also assist governmental administrations in setting suitable rules and policies on time to preserve industrial solidity and minimize the harm triggered by the widespread corporate bankruptcy to the economy as a whole (Wang, Lin, Kuo, & Piesse, 2010).

Therefore, the issue of corporate bankruptcy prediction is of utmost importance to several stakeholders of the firm. Timely detection of firms' bankruptcy is certainly indispensible. International economies have become watchful of risks involved in corporations' debts, especially after the collapse of giant organizations like WorldCom and Enron. Thus, it is essential to develop models to recognize potentially bankrupt firms. Subsequent to the leading research by Altman (1968) that show a significant role for financial ratios in corporate bankruptcy prediction, an enormous body of research studies has been developed in both accounting and finance disciplines on corporate bankruptcy prediction.

Significantly, the majority of literature on corporate bankruptcy prediction focuses on financial ratios analysis as a popular prediction method. However, the financial ratios–based models suffer from several shortcomings. Firstly, the discovery of an adverse ratio may drive managers to change their course of action so as to avoid financial distress or bankruptcy as they realize that the use of these ratios is so popular among all firm's stakeholders. Besides, breaching a preset ratio level may cause the firm violating a loan covenant; hence the extensive dependence on financial ratios analysis may trigger default. Secondly, there is academic evidence that firms in general, and unhealthy or failing firms in particular, have incentives to manipulate or manage their accounting numbers (Ooghe & Joos, 1990; Burgstahler & Dichev, 1997).

Thirdly, Beaver et al. (2005) reveal that there is actually a minor drop in financial ratios' predictive performance over time because of greater managerial discretion or because of greater amounts of intangible assets (Danilov, 2014). Finally, bankruptcy prediction models based on financial ratios implicitly presume that all relevant failure or success indicators—both internal and external—are reflected in the accounting figures. However, it is obvious that not all important

information is represented by the annual accounting figures. For this reason, a number of authors have recommended including non-financial or qualitative distress predictors in distress prediction models (e.g., Becchetti & Sierra, 2003; Ohlson, 1980).

In this regard, numerous studies show information content of auditor GCO for predicting corporate bankruptcy (e.g., Carson et al., 2013; Desai, Kim, Srivastava, & Desai, 2017). Other studies (Lennox, 1999; Raghunandan & Subramanyam, 2003; Tan, 2002) have compared the accuracy of the auditor GCO relative to publicly available information and show that bankruptcy prediction models based on financial ratios and market variables outperform auditor GCO in predicting corporate bankruptcy. Additionally, Lennox (1999) show that audit reports do not provide valuable incremental information about the probability of bankruptcy. In contrast, Gutierrez, Krupa, Minutti-Meza, and Vulcheva (2018) show that the predictive power of all default models in their study rises when auditor GCOs are included. As a consequence to this debate, this research aims to investigate the informativeness and the incremental predictive power of auditor GCO for bankruptcy prediction beyond that of a financial ratios-based model.

Moreover, there is a large gap in accounting literature on studies examining the informativeness and the incremental predictive power of auditor characteristics for bankruptcy prediction. Where only few studies show that auditor qualitative features (e.g., auditor type, auditor tenure and auditor industry specialization) are significantly associated with bankruptcy (Cenciarelli, Greco, & Allegrini, 2018; Mansi, Maxwell, & Miller, 2004; Jones, 2017). Specifically, big auditors, long-tenured auditors, and Industry experts are more capable of providing early warning signals to potentially distressed firms. Such early warnings can be accompanied with better consultation services that guide directors to take proper actions in order to avoid bankruptcy. Because of better auditor examination, firms' stakeholders can be motivated to provide aid to firms in financial distress (Cenciarelli et al., 2018; Mansi et al., 2004). Therefore, this research addresses whether auditor characteristics have information content and incremental pre-

dictive power for bankruptcy prediction beyond that of a financial ratios–based model.

The importance of this research can be attributed to numerous factors. Firstly, the current research bridges the gap in the literature with regard to the informativeness and the incremental role of various audit–related disclosures in bankruptcy prediction beyond financial variables which would, in turn, direct stakeholders to the more value–added elements of corporate reporting that entails scrutinized analysis before making their investment and credit decisions. Secondly, the research informs the debate of whether audit–related disclosures contain value added information or are subsumed by financial ratios analysis; which would, in turn, guide standard setters and regulators on potential avenues to improve the corporate reporting as an essential communication mechanism to firm's stakeholders. Thirdly, the research explores other channels that potential investors and creditors can utilize in evaluating the firm health and creditworthiness before making their investment and credit decisions, especially that recent studies finds a declining trend in the usefulness of financial ratios. On the other hand, recent studies provide evidence for the role of non–financial information in predicting bankruptcy in developed countries. Thus, this research extends those studies in Egypt as an emerging economy.

2. Literature Review and Hypotheses Development

Financial distress is a position that originates when the firm's revenues are not enough to pay back its obligations as they come due to lenders. Financial distress comes in two forms: technical insolvency and bankruptcy. Technical insolvency means that the firm's assets exceed its liabilities; however, it is unable to satisfy short term debts as they come due. Theoretically, there would be sufficient proceeds resulting from assets' sale to pay off all credit holders totally if the firm were to be liquidated. In spite of positive net worth, the firm cash is not sufficient to satisfy short term liabilities (Danilov, 2014).

As for corporate bankruptcy, it is the extreme form of financial distress. From the accounting perspective, it refers to the case when the market value of the firm's assets is less than its liabilities and hence, its net worth is negative and credit

holders will not be paid back fully when the firm is liquidated. From the legal perspective, it refers to the state when the firm files for bankruptcy in court which would lead to either firm liquidation or firm reorganization depending on the economic value of the firm's assets (Altman & Hotchkiss, 2010; Danilov, 2014).

The majority of studies on distress and bankruptcy prediction concentrate on financial ratios analysis as a common prediction technique to classify firms that are relatively weaker financially than others. According to the theory of ratios analysis, the firm is regarded as a "reservoir of liquid assets". The reservoir is filled by cash inflows from the one side and drained by cash outflows from the other side. The inflows in the form of revenues are normally changeable, and the reservoir offers the required buffer when inflows and outflows (expenditures) are mismatched. When the reservoir is drained, the firm is not able to pay its expenditures or to satisfy its debts, resulting in financial distress. This strategy has four significant inferences regarding the distress likelihood. Firstly, the reservoir volume is vital as the distress probability decreases with a bigger reservoir. Secondly, the net flow of funds from operations is similarly important; because there is a comparable favorable impact of greater cash-flows on growing the reservoir. On the other hand, higher levels of debt or operating expenses raise the distress likelihood through reducing the reservoir. Accordingly, the ratios that reflect the elements of the reservoir must differ, on average, between distressed and non-distressed firms (Beaver, 1966; Danilov, 2014).

However, the use of financial ratios as predictors of bankruptcy is accompanied by numerous shortcomings. Firstly, as ratios analysis is prevalent among all firms' stakeholders, the detection of an inverse ratio can give an incentive for management to alter their actions in order to avoid financial distress or bankruptcy. In these cases, an adverse ratio can become the trigger of positive amendments instead of indication of distress and hence the predictive power of the ratio is weakened. Additionally, lenders are heavily dependent on financial ratios when assessing whether or not to extend or maintain credit. Breaking a predetermined ratio level may result in the firm violating a loan covenant, which may

lead to default. Both of these factors prevent the precise measurement of the real predictive power of financial ratios (Danilov, 2014).

Secondly, prior research indirectly presumes that accounting numbers offer a fair and true presentation of the financial state when predicting distress based on financial ratios. However, it seems reasonable to suggest the opposite as there are several studies showing that firms, especially distressed ones, have motives to manipulate their accounting numbers (Ooghe & Joos, 1990; Ooghe, Joos, & De Bourdeaudhuij, 1995; Burgstahler & Dichev, 1997). Using creative accounting practices, distressed firms manage their earnings upwards and give a more positive view of their financial condition, especially when the instant of distress is very close (Argenti, 1976; Watts & Zimmerman, 1986; Ooghe & Joos, 1990; Ooghe et al., 1995). Second, annual accounting figures may be unreliable, especially in smaller firms, because of the lack of an internal control system (Keasey & Watson, 1987). Because of the unreliability of accounting numbers, distress prediction models based on financial ratios may be misleading and have limited worth in the real–world practice.

Thirdly, corporate distress prediction models based on financial ratios are subject to the incidence of extreme ratio values, errors, and missing values. As a consequence of extreme ratio values, models may be strongly biased or contaminated (Moses & Liao, 1987) and may display biased coefficients for the ratios incorporated. Moreover, as a consequence of accounting numbers errors, models based on erroneous accounting data may become valueless. Potential solutions to these accounting information problems are to trim the ratios with extreme values at certain percentiles and to replace the missing values by the average or random numbers (Tucker, 1996).

Fourthly, distress prediction models based on financial ratios do not embody all significant distress or success indicators. In this context, Argenti (1976) stated that, "While these [financial] ratios may show that there is something wrong. I doubt whether one would dare to predict collapse or failure on the evidence of these ratios alone" (p. 138). Additionally, Zavgren (1985) indicated that, "any econometric model containing only financial statement information will not

predict with certainty the failure or non-failure of a firm" (p. 22-23). Further-more, Maltz et al. (2003) pointed out that the use of financial measures as exclu-sive predictors of organizational performance is inadequate.

Accordingly, there is a growing demand in accounting and finance literature for integrating non-financial features when developing the bankruptcy predic-tion model (Ohlson, 1980; Zavgren, 1983; Lussier & Corman, 1994; Becchetti & Sierra, 2003). Therefore, the research will review literature related to the role of audit variables as a part of non-financial disclosures in predicting corporate bankruptcy.

2.1. The Informativeness and the Incremental Power of Audi-tor Going Concern Opinion for Corporate Bankruptcy Prediction

International Standard on Auditing (ISA), 570- Going Concern, demands the auditor to examine the appropriateness of the management usage of the going concern assumption in the preparation of the annual report and to decide, whether in the auditor's judgment, there are conditions or events, that raise sig-nificant doubt on the firm's ability to continue as a going concern. When these conditions or events are recognized, the auditor practices professional judgment to investigate whether there is a "material uncertainty" that causes a substantial doubt about the firm's going concern position. There is a "material uncertainty" if the size of its possible effect is such that, in the auditor's professional judgment, clear disclosure of the nature and consequences of the uncertainty is essential for the presentation of the annual report not to be misleading.

The inference the auditor draws about the managers' going concern evalua-tion will determine the implications for the nature of opinion stated in the audi-tor's report (AICD & AUASB, 2009). Specifically, the auditor issues unqualified opinion, accompanied with an emphasis of matter paragraph, if he concludes that a material uncertainty is present, which results in a significant doubt about the ability of the firm to continue as a going concern and this uncertainty has been adequately disclosed in the annual firm report.

Nonetheless, the auditor expresses qualified or adverse opinions (according to his professional judgment) in the event of inadequate disclosures of the uncertainty. Particularly, the auditor issues a qualified opinion if the impacts of inadequate disclosures are material and not pervasive to the annual report and an adverse opinion if the impacts of inadequate disclosures are material and pervasive or if the firm cannot continue as a going concern in spite of the annual report being prepared on that base.

Numerous studies examine the usefulness of auditor GCO for predicting corporate bankruptcy. For instance, Maingot and Zeghal (2010) examine the explanatory paragraphs of the auditor opinions of 112 US bankrupt firms following SAS No. 59 during the period 2001–2003. They find that the firms that are not given a GCO tend to outperform firms that are given a GCO. Further, they show that 73.21% of the firms got a GCO whereas 26.79% of the firms did not get a GCO. They interpret the findings that auditors are pursuing the guidelines of SAS No. 59, more carefully by expressing more GCOs that, at least, inform stakeholders about a forthcoming difficulty for the firm.

Consistently, Carson et al. (2013) investigate the occurrence of bankruptcy within a sample of U.S. firms. They then test whether the audit opinion issued immediately before the bankruptcy filing incorporated a GCO. They find that 60.10% of bankruptcy filings are preceded by opinions that are modified for going-concern uncertainties. Moreover, the proportion of surviving firms that received a prior GCO is just 15.71%. This is consistent with a self-fulfilling prophecy; a GCO is more likely to be issued to a firm that will file for bankruptcy than to a firm that will survive.

More recently, Desai et al. (2017) explore the relationship between first-time GCOs and the financial viability of the GCO recipients as measured by delisting from the stock exchange. They find that around 26% of the firms that receive their first GCOs are delisted within a period of one year of the audit opinion date, and 50% of the firms that receive their first GCOs are delisted within a period of three years. The bankruptcy rate of first-time GCO firms within one year is around 9%.

Nevertheless, several studies (Lennox, 1999; Tan, 2002; Raghunandan & Subramanyam, 2003) have compared the accuracy of the auditor GCO relative to publicly available information and find that bankruptcy models based on financial ratios and market variables outperform auditor GCO in predicting corporate bankruptcy. More specifically, Lennox (1999) tries to estimate the accuracy and informativeness of audit reports in classifying distressed firms. Using a sample of 976 firms (including 90 bankrupt firms), he finds that a bankruptcy model could be more accurate than audit reports. Also, he evaluates whether audit reports contain incremental information, after controlling for public information about the economic cycle, firm size and industry sector. Findings reveal that audit reports did not provide value-added information about the probability of bankruptcy. He attributed the results to auditors not giving enough consideration to macroeconomic and industry events when forming their audit opinions as well as lower accuracy of audit reports due to strong persistence in audit reporting.

In the same line, Raghunandan and Subramanyam (2003) compare the relative accuracy of audit opinions vis-à-vis a model that contains both financial statement and market-based indicators for forecasting bankruptcy. Using a sample of distressed firms during the period 1992 to 2001, they show that a model integrating financial statement and market-based indicators performs better than audit opinions for forecasting bankruptcy. Nonetheless, audit opinions encompass private information incremental to financial statement and market information due to auditors' professional expertise. The failure of auditors to outperform the model is attributed to auditors overemphasizing financial ratios and operating cash flows and underemphasizing market values and stock returns.

Furthermore, Tan (2002) hypothesizes and finds that the GCO has information content merely for firms not showing clear signs of distress (i.e., the lack of adverse financial ratios). He finds that the GCO issued for firms that are previously classified as seemingly healthy (using financial ratios) significantly decreases the market's negative reaction surrounding the bankruptcy filing. On the contrary, Gutierrez, Krupa, Minutti-Meza, and Vulcheva (2018) show that GCOs and

a default model using financial ratios have similar predictive power for a firm's ability to continue as a going concern. They also show that the inclusion of auditor GCO enhances the predictive performance of all distress prediction models in their study.

Even though, some studies confirm the predictive power of auditor GCO for corporate bankruptcy; however, there is a lack of studies investigating this issue in Egypt. Additionally, there is a large debate in literature regarding whether this predictive power is subsumed by or incremental to bankruptcy prediction models based on quantitative information. Therefore, the following hypotheses are tested:

H1: **Auditor GCO has significant predictive power for corporate bankruptcy in Egypt**.

H2: **Auditor GCO has significant incremental predictive power for corporate bankruptcy beyond that of a financial ratios-based model in Egypt**.

2.2. The Informativeness and the Incremental Power of Auditor Characteristics for Corporate Bankruptcy Prediction

Prior research shows that auditor features (e.g., auditor size, auditor rotation, and auditor industry specialization) are significantly associated with bankruptcy (Cenciarelli, Greco, & Allegrini, 2018; Mansi, Maxwell, & Miller, 2004; Jones, 2017). Regarding auditor size, Cenciarelli et al. (2018) argue that big auditors are inversely correlated with the probability of bankruptcy for several causes. First, big auditors have the proficiencies and capacities to express early warning signals on financial distress and are well prepared to effectively consult on ways to deal with it (Geiger, Raghunandan, & Rama, 2005; Behn, Choi, & Kang, 2008). Second, stockholders and creditors recognize firms examined through big auditors as having less risk and more reliable annual reporting competencies, thus allowing such firms to take advantage of less capital costs, less debt costs and more ability of dealing with financial distress conditions (Khurana & Raman, 2004; Gul, Zhou, & Zhu, 2013).

Third, big auditors are more prepared to assess complicated measurements that necessitate, for instance, goodwill impairments, cash flow estimates, or financial assets' valuations. As a result, big auditors can provide superior audits regarding fair value assessments (Bratten, Gaynor, McDaniel, Montague, & Sierra, 2013). Fourthly, additional argument backing the view that firms audited by big auditors being less likely to enter bankruptcy, relates to the selection of client firms by large auditors. Big-4 auditors tend to choose big, profitable, and solvent firms which are capable of satisfying their premium fees (Lawrence, Minutti-Meza, & Zhang, 2011). These firms are less probable to encounter distress ex-ante. In addition, big auditors may evade more risky firms in order to alleviate potential reputational costs associated with distressed and bankrupt firms.

With respect to auditor rotation as a proxy for auditor tenure, Mansi et al. (2004) find that longer tenures of the auditors with the client decrease the information asymmetry between auditors and firms, thus permitting an improved audit. An improved audit would lead to lower capital costs. Further, long-tenured auditors are more capable to issue early warning signals and deliver superior consultancy services to firms facing bankruptcy because of low information asymmetry and more profound understanding of the firm, which would, help managers to take preventive actions before default (Mansi et al., 2004). Due to superior auditor examination, shareholders and lenders can be more willing to assist firms facing bankruptcy (Cenciarelli et al., 2018).

With regard to auditor industry specialization, Carcello and Nagy (2004) show that industry specialization is inversely related to firms committing financial fraud. Cenciarelli et al. (2018) argue that auditor industry specialization can aid to lessen the probability of bankruptcy. Industry specialists can, at an early phase, recognize whether and how the firm's accruals and profits diverge from industry trends. They can compare the accruals and earnings of related firms which they are reviewing. These initial evaluations can incentivize the management of the firm to take timely decisions (e.g., reviewing a strategy or renegotiating a loan), thus decreasing the default probability. Industry specialists may also specify

whether goodwill impairment will be required and they can express early warning signals regarding a prospective decline in earnings and cash flows of the firm.

Based on the above, it can be noted that there is a lack of research addressing the impact of auditor characteristics on the probability of bankruptcy. Hence, this research tests whether auditor characteristics have information content for predicting bankruptcy. The research also investigates whether the inclusion of such variables will enhance the bankruptcy model predictability. Accordingly, the research hypotheses state that:

H3: **Auditor characteristics in Egypt have significant predictive power for corporate bankruptcy**.

H4: **Auditor characteristics in Egypt have significant incremental predictive power for corporate bankruptcy beyond that of a financial ratios–based model**.

3. Sample Selection, Variable Measurement, and Research Design

3.1. Sample Selection

There are two methods of sampling for bankruptcy prediction; balanced sampling and imbalanced sampling. Balanced sampling means that the ratio of distressed to non–distressed samples is equal. Most bankruptcy prediction researches used balanced samples (Altman, 1968; Shin, Lee, & Kim, 2005). However, Zmijewski (1984) showed that if the ratio of distressed to non–distressed samples evidently deviated from the real–world population, it would distort the model's prediction capability. Accordingly, some bankruptcy prediction studies applied imbalanced samples, also called proportional samples, in which the proportion of distressed sample should be closer to that in the real–world population. Namely, bankruptcy prediction experiments should use fewer distressed and more non–distressed firms. For bankruptcy prediction with imbalanced datasets, assessing models only by predictive accuracies may provide misleading information. For example, a model can produce an accuracy of 99% when predicting all the sam-

ples as non-distressed, if the dataset consists of 99% non-distressed samples and 1% distressed samples. Hence, bankruptcy prediction researches based on imbalanced datasets should consider the Type I and II error rates and some other measures such as sensitivity, specificity, and F-measure (Sun, Li, Huang, & He, 2014).

Sun et al. (2014) argue for using the imbalanced sampling approach because the real-world data of this problem is imbalanced. Therefore, the researcher will use imbalanced sampling and use multiple evaluation metrics in the analysis. Specifically, the ratio of bankrupt to non-bankrupt firms in each sector in the sample ranges from 1:1 to 1:5, depending on the availability of data, as shown in table 1. The peer group is composed by determining non-bankrupt firms operating in the same industry as that of the bankrupt firms. Similar to prior research, financial services firms are excluded because of their unique financial ratios attributes and absence of meaningful comparability to non-financial firms. The final sample includes a treatment sample of firms that got technically bankrupt during the period 2009 to 2018 and a control sample of the healthy firms listed on the Egyptian stock exchange at 2017 and do not suffer from technical bankruptcy. According to article 69 of the Egyptian Companies Law. No. 159/1981, if the losses of the company reach half the issued capital, the board of administration should promptly convoke the extraordinary General Assembly for consideration of the dissolution of the company or its continuance. This case is referred to as technical bankruptcy and is used as a proxy for bankruptcy in this study.

The data are preprocessed as follows;

— Mean imputation is applied to missing values.

— The log transformation is applied to the total asset variable.

Table 1. Sector Classification of Sample Firms

Sector	Non-Bankrupt	Bankrupt
Basic Resources	3	3
Construction and Materials	6	6
Food and Beverages	10	4
Healthcare and Pharmaceuticals	5	1
Industrial Goods and Services and Automobiles	7	2
Personal and Household Products	4	2
Real Estate	12	3
Telecommunication	1	2
Travel and Leisure	2	2
Total	50	25

Sample Characteristics

The detailed sector grouping breakdown is presented in Fig. 1. Specifically, the largest number of bankruptcies happens in the Construction and Materials sector that included 24% of the technically bankrupt sample firms. Food and Beverages, Real Estate and Basic Resources are the following largest sectors, having 16%, 12% and 12% of the technically bankrupt sample firms respectively. After adjustment for industry size, Telecommunication had the largest bankrupt–cy rates at 67% as displayed in Fig. 2.
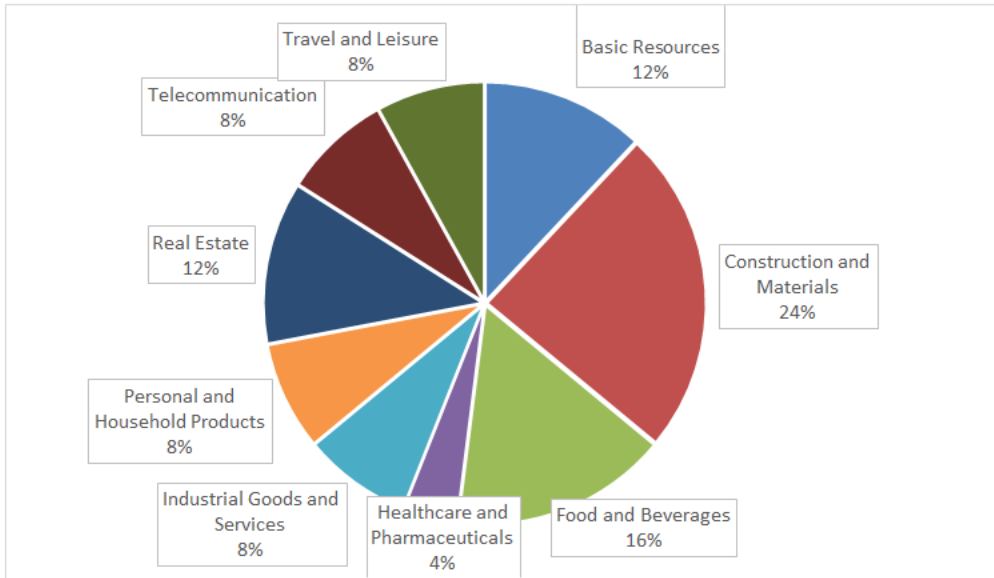
Fig. 1. % of Bankruptcies across Sectors
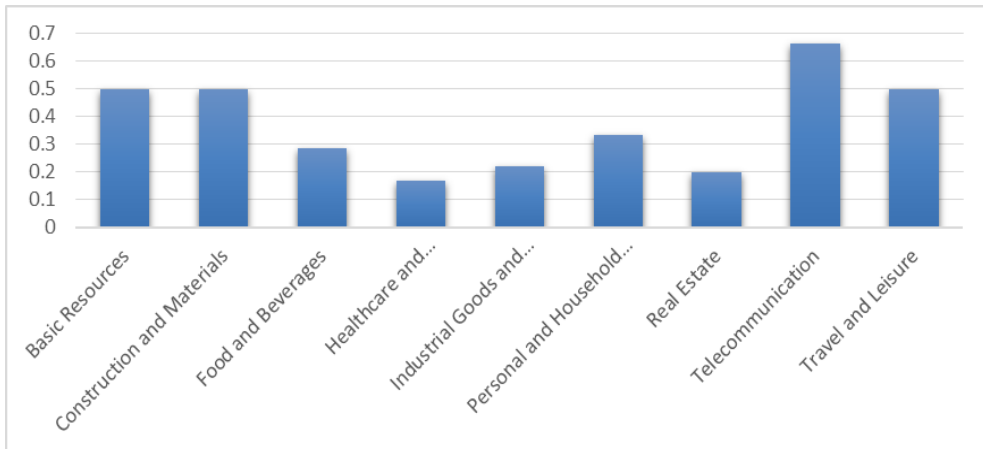Source: The researcher

Fig. 2. Sample Industry Bankruptcy Rates
Source: The researcher

The ratio of bankrupt to non–bankrupt firms in each sector in the sample ranges from 1:1 (e.g., Basic Resources and Construction and Materials sectors) to 1:5 (e.g., Healthcare and Pharmaceuticals) except for the Telecommunication sector where the bankrupt firms are twice the non–bankrupt firms as shown in Fig. 3.
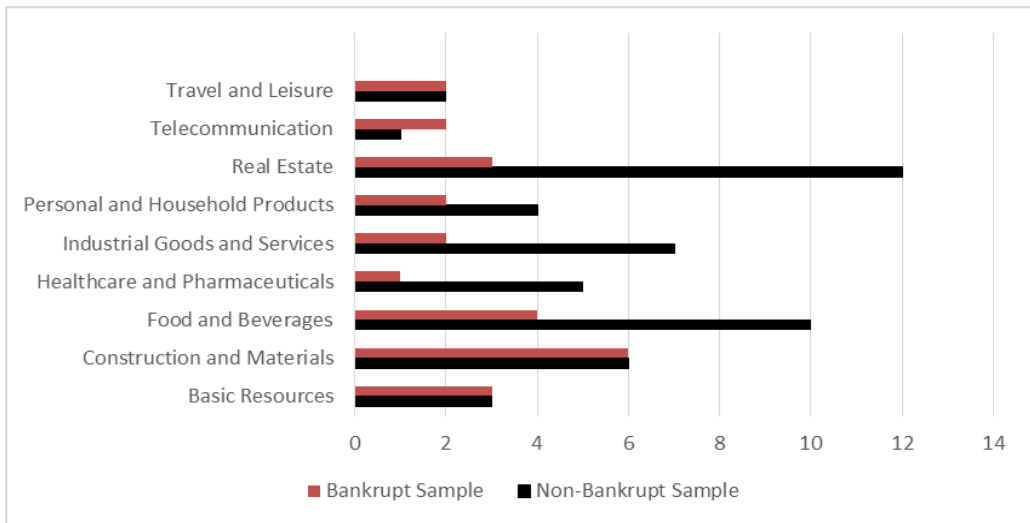

Fig. 3. Industry Distribution of Bankrupt and non-Bankrupt Samples
Source: The researcher

3.2. Variables Measurement

To evaluate the usefulness and the incremental predictive ability of the audit–related disclosures compared to other quantitative information in the annual report, a benchmark model of financial indicators is used as they have received the most attention in prior research. Following previous studies (Altman, 1968; Ohlson, 1980; Shumway, 2001), the ratios of working capital to total assets (WC/TA), retained earnings to total assets (RE/TA), earnings before interest and taxes to total assets (EBIT/TA), market value of equity to total liabilities (MVE/TL), and sales to total assets (SALES/TA) are taken into consideration. The detailed descriptions of chosen financial and non–financial variables are presented in table 2. Consistent with previous studies, the coefficients on WC/TA,

RE/TA, EBIT/TA, MVE/TL, and SALES/TA are expected to be nega‒
tive.Therefore, the researcher will test the incremental predictive ability of audit
variables selected based on reviewing the literature in the prior chapter, beyond
that of the above selected financial ratios of Altman (1968).

Table 2: Measurement of Financial and Audit Variables for Developing the Bankruptcy Model

Category	Variables	Measurement	References
Financial Variables	WC/TA	Working Capital divided by Total Assets	– Altman (1968) – Mayew et al. (2015)
	RE/TA	Retained Earnings divided by Total Assets	
	EBIT/TA	Earnings Before Interest and Taxes divided by Total Assets	
	MVE/TL	Market Value of Equity divided by Total Liabilities, where MVE = stock price at the end of the fiscal year * number of shares outstanding	
	SALES/TA	Sales revenue divided by Total Assets	
Audit	Auditor GCO	A dummy variable set to 1 if auditors expressed a significant doubt regarding the firm ability to continue as a going concern in the independent auditor report section, and 0 otherwise.	– Mayew et al. (2015) – Desai et al. (2017)
	Auditor Type	A dummy variable set to 1 if the auditor is one of the Big-X auditors and 0 otherwise.	– Jones (2017) – Cenciarelli et al. (2018)
	Auditor Rotation	A dummy variable set to 1 if the auditor in charge has changed from the preceding year and 0 otherwise.	– Cenciarelli et al. (2018)
	Auditor Industry Specialization	A dummy variable set to 1 if the auditor is industry specialist and 0 otherwise.	

3.3.The Research Design

3.3.1. The Research Model

Because the independent variables of the bankruptcy prediction equation are neither linear nor normally distributed (Ohlson, 1980), the following logit model is estimated to investigate the research hypotheses, where the dependent variable (Bankrupt) is binary (equals 1 if the firm is bankrupt and 0 otherwise).

$$Pr(Bankrupt)_{t+1} = \beta_0 + \sum \beta_k X_{kt} + v_t \qquad (1)$$

β_k is the set of coefficients of the indicator variables X (financial ratios, and auditor variables). The model performance is evaluated by the Pseudo-R^2 statistic, AUC, Accuracy, Type I and Type II errors.

3.3.2. Evaluation Metrics

Four model performance evaluation metrics are used in the current research (Beaver, 1966; Fawcett, 2003) as follows;

1. **Accuracy** is the percentage of correctly classified firms. It is one of the most widely used classification performance metrics.

$$Overall\ Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (2)$$

where TP, TN, FP, and FN respectively represent true positive, true negative, false positive, and false negative. TP is the number of correctly classified bankrupt firms. TN is the number of correctly classified non–bankrupt firms. FP is the number of non–bankrupt firms misclassified as bankrupt. FN is the number of bankrupt firms misclassified as non–bankrupt.

2. **Area under ROC curve** (**AUC**): ROC graphs are two–dimensional graph in which Sensitivity is plotted on the Y axis and 1–Specificity is plotted on X axis. Where specificity (TN rate) measures how well a classifier can recognize non–bankrupt firms. An ROC graph depicts relative trade–off between benefits (true non–bankruptcy) and costs (false non–bankruptcy), which is useful for organizing classifiers and visualizing their performance especially in the domains with skewed class distribution and unequal classification error costs.

The AUC of a classifier is equivalent to the probability that the classifier will rank a randomly chosen positive instance higher than a randomly chosen negative.

3. **The Type I Error Rate** is the probability of misclassifying a non– bankrupt firm as a bankrupt one.

$$Type\ I\ Error\ Rate\ = \frac{FP}{TP+FP} \tag{3}$$

4. **The Type II Error Rate** is the probability of misclassifying a bankrupt firm as non–bankrupt one.

$$Type\ II\ Error\ Rate\ = \frac{FN}{TN+FN} \tag{4}$$

4. Empirical Results
4.1.Descriptive Statistics

Table 3 shows the descriptive statistics for the variables used in the empirical analyses for the bankrupt and non–bankrupt firms separately. For the bankrupt firms, descriptive statistics relate to the year prior to the year of technical bankruptcy for the period 2008–2017. The non–bankrupt firm observations consist of observations for non–bankrupt firms at 2016. Importantly, there are remarkable differences in the features of the bankrupt observations compared to their non-bankrupt counterparts regarding several study metrics. Largely, the variable indicators of the bankrupt group tend to be worse than their peers for the year prior to bankruptcy. Hereunder, the research demonstrates a detailed comparative profile analysis of the ratios that have a significant difference in the mean according to t–test statistics of difference in mean values between the two groups.

As for financial ratios, firstly, the working capital to total assets (WC/TA) ratio is a proxy for the firm's overall liquidity whereas the greater this ratio, the greater the liquidity obtainable. The mean of the WC/TA ratio is much lower (1.6% versus 24.7%) for firms facing bankruptcy. Secondly, the Market Value of Equity to Total Liabilities (MVE/TL) is a gauge of how much the firm's asset value can fall before the firm becomes insolvent. As expected, the median of MVE/TL is much lower (84.4% versus 125.1%) for firms facing bankruptcy. Thirdly, the Retained Earnings to Total Assets (RE/TA) ratio measures overall cumulative

profitability via the amount of reinvested earnings over a firm's entire life. Evi‐dently, firms facing bankruptcy have a negative RE/TA mean of –19% versus a positive mean of 10.5% for non–bankrupt firms.

Fourthly, the Earnings before Interest and Tax to Total Assets (EBIT/TA) ra‐tio measures the operating income relative to firm size. Firms facing bankruptcy have a negative EBIT/TA mean of –6.7% versus a positive mean of 7.2% for non–bankrupt firms. Finally, the Sales to Total Assets (Sales/TA) ratio, which captures the ability of the firm's assets to generate revenues, shows no significant mean difference between the two groups.

Regarding audit variables, only auditor GCO shows a significant mean differ‐ence between the two groups. Specifically, the mean of auditor GCO is much higher (0.44 versus 0.02) for firms facing bankruptcy.

Finally, table 4 reports correlation matrix of variables used to test the study hypotheses (i.e., Altman financial ratios and the study audit variables). Variables used in correlation matrix and hypotheses testing are winsorized at the 5% and 95% levels to lessen the influence of outliers. The financial predictors, with the exception of SALES/TA, are negatively correlated with the bankruptcy variable (Bankrupt) at the significant level 5%. Out of the audit variables, only auditor GCO are significantly positively correlated with Bankrupt. However, table 4 shows that many of the financial variables are correlated with the audit variables. In order to assess whether audit–related disclosures have information content and incremental power for predicting bankruptcy over other information contained in financial reports, multivariate analyses will be used in the next section.

TABLE 3								
Descriptive Statistics								
			Bankrupt firms			**Non-Bankrupt firms**		
			(n=25)			(n=50)		**t-stat of Diff. in Means**
		Variables	**Mean**	**Median**	**Std. Dev.**	**Mean**	**Median**	**Std. Dev.**	
Financial Variables	X1	**WC/TA**	0.016	-0.076	0.282	0.247	0.228	0.304	3.175***
	X2	**RE/TA**	-0.190	-0.132	0.405	0.105	0.101	0.123	4.749***
	X3	**EBIT /TA**	-0.067	-0.079	0.110	0.072	0.059	0.088	5.941***
	X4	SALES/TA	0.552	0.294	0.630	0.955	0.666	1.168	1.608
	X5	**MVE/TL**	1.192	0.844	1.522	4.017	1.251	7.578	1.84*
Audit Variables	X6	**GCO**	0.440	0.000	0.507	0.020	0.000	0.141	-5.483***
	X7	Auditor type	0.680	1.000	0.476	0.520	1.000	0.505	-1.318
	X8	Auditor rotation	0.120	0.000	0.332	0.060	0.000	0.240	-0.896
	X9	Auditor Ind Spec.	0.293	0.250	0.210	0.232	0.143	0.212	-1.172

***, **, * Denote statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
Descriptive statistics for the variables are reported for bankrupt firms for the year prior to bankruptcy and non-bankrupt firms for the year 2016 separately.

TABLE 4										
Correlation Matrix										
Variables	**Bankrupt**	**WC/ TA**	**RE/ TA**	**EBIT/ TA**	**MVE/ TL**	**Sales /TA**	**GCO**	**Auditor type**	**Auditor rotation**	**Auditor Ind Spec.**
Bankrupt	1									
WC/TA	**-0.34***	1								
RE/TA	**-0.57***	**0.29***	1							
EBIT/TA	**-0.56***	**0.23***	**0.82***	1						
MVE/TL	**-0.24***	**0.41***	0.12	0.04	1					
Sales/TA	-0.19	-0.19	0.03	0.14	-0.22	1				
GCO	**0.54***	**-0.25***	**-0.52***	**-0.61***	-0.186	0.008	1			
Auditor type	0.15	-0.10	0.08	0.08	**-0.37***	-0.03	0.08	1		
Auditor rotation	0.10	-0.14	-0.09	0.005	0.22	0.096	-0.13	-0.04	1	
Auditor Ind. Spec.	0.14	0.07	-0.09	-0.034	-0.21	-0.16	0.15	**0.57***	-0.08	1

Correlation matrix for the regression variables. * Denote statistical significance at the 5 percent level. All continuous variables are winsorized at 5 percent and 95 percent

4-2 Hypotheses Testing Using Logistic Regression

This section covers the steps followed in order to test the research hypotheses based on financial and audit–related disclosure variables.

4-2-1 Testing the Informativeness and the Incremental Power of Audit Variables for Corporate Bankruptcy Prediction

In this section, the information content and the incremental predictive ability of the audit variables (i.e., auditor GCO and Auditor Characteristics) relative to other financial information in the financial reporting package are assessed. Table 5 reports the results of estimating Equation (1) in a sequential manner for comparison of the predictive ability of audit variables relative to bankruptcy financial predictors.

Column (1) shows the benchmark model of only financial variables. Findings reveal that the Pseudo–R^2 of the benchmark financial variables model has a Pseudo–R^2 of 46.37%, AUC of 91.84%, Accuracy of 84%, Type I error of 10% and Type II error of 28%. Consistent with prior research, the coefficients on WC/TA, RE/TA, EBIT/TA, MVE/TL, and SALES/TA are negative. However, only the coefficients on WC/TA, RE/TA, and SALES/TA are significant at 10% level.

The information content of Audit variables is investigated and the results are reported in columns (2–4) of Table 5. The coefficient on auditor GCO is significantly positive at 1% level. A model consisting of only GCO provides a Pseudo–R^2 of 22.89%, AUC of 71%, Accuracy of 80% (see column (2)). **Therefore**, **the hypothesis that Auditor GCO has significant predictive power for corporate bankruptcy can be accepted** (**accept H1**).

Column (3) presents the results of testing the incremental predictive ability of GCO for corporate bankruptcy prediction. As shown, the coefficient on GCO is not statistically significant and the incremental Pseudo–R^2 of the model is not statistically significant; thus, it can be inferred that GCO does not have incremental predictive ability for corporate bankruptcy for the year prior to bankruptcy. **Therefore**, **the hypothesis that auditor GCO has significant incre–**

mental predictive power for corporate bankruptcy beyond that of a financial ratios–based model cannot be accepted (reject H2).

Collectively, the results provide some evidence for the informativeness of auditor GCO for predicting corporate bankruptcy consistent with prior studies (e.g., Carson et al., 2013; Desai et al. (2017)). However, auditor GCO does not improve the performance of corporate bankruptcy model consistent with Lennox (1999) findings. This could be attributed to the significant negative correlation between financial ratios (i.e., WC/TA, RE/TA, and EBIT/TA) and auditor GCO as shown in table 4.

In column (4), the three variables corresponding to Auditor Characteristics are included. The coefficients on Auditor Type, Auditor Rotation, and Auditor Ind. Spec. are statistically insignificant, with a Pseudo–R^2 of only 3.14%. **Therefore, the hypothesis that Auditor Characteristics have significant predictive power for corporate bankruptcy cannot be accepted (reject H3)**.

Next, all audit variables are included in column (5). The coefficient on GCO is still significantly positive at 1% level and the coefficient on Auditor Rotation turns to be significantly positive at 10% level. A model consisting of all Audit variables registers a Pseudo–R^2 of 27.04%, and accuracy of 84% equivalent to that of the financial ratios–based model, but AUC of 77.96% lower than that of the financial model due to high type II error of 44% but low type I error of 2%. Thus, it can be inferred that audit variables exhibit a reasonable predictive ability when compared to a standard set of financial variables.

In columns (6–8), the coefficients on Auditor Type, Auditor Rotation, and Auditor Ind. Spec. are statistically insignificant and the incremental Pseudo-R^2s of the respective models are statistically insignificant as well.

Results presented in Table 5, column (9) suggest that a combined model of financial variables and Auditor Characteristics registers a Pseudo–R^2 of 50.09%, AUC of 93.28%, improves accuracy to 89.33%, and reduces type I and type II errors to 8% and 16% respectively. However, the coefficients on Auditor Type, Auditor Rotation, and Auditor Ind. Spec. are still not statistically significant and

the incremental Pseudo-R^2 of the combined model is not statistically significant too. Collectively, the results indicate that the inclusion of Auditor Characteristics in corporate bankruptcy prediction model increases its predictive ability in terms of AUC, accuracy, type I and type II errors. **However**, **neither the incremental Pseudo–R^2s of the individual models nor the combined model of Auditor Characteristics are statistically significant using a Likelihood Ratio test statistic; thus**, **hypothesis (4) cannot be accepted**.

This result is inconsistent with prior research showing that auditor characteristics are significantly associated with bankruptcy (Cenciarelli et al. 2018; Mansi et al. 2004; Jones, 2017). This can attributed to the fact that auditor characteristics including auditor type, auditor industry specialization, and auditor rotation, are indicators of the perceived audit quality rather than the actual audit quality. Perceived audit quality relates the notion that firms' stakeholders expect improved audits by big–X auditors, industry specialists, and long–tenured auditors. Additionally, those auditors are more likely to select big, solvent and profitable firms that are capable of satisfying their premium services (Lawrence et al. 2011). These firms can be less probable to encounter distress ex–ante. Furthermore, those auditors can avoid risky firms to mitigate potential reputational and litigation risks associated with bankruptcies. However, this perceived audit quality is limited in Egypt due to the lack of effective laws and regulations that would obligate such auditors to provide high–quality audits.

Finally, column (10) suggest that a combined model of financial variables and all audit variables registers a Pseudo-R^2 of 51.87%, AUC of 92.33%, accuracy of 89.33%, and type I and type II errors of 6% and 20% respectively. The incremental Pseudo-R^2 is negligible compared to the model without GCO.

Table 5: The Informativeness and the Incremental Predictive Power of Audit Variables beyond Altman Financial Ratios

	Financial Variables	GCO Info	GCO	Auditor Char. Info	Auditor Var.	Auditor Type	Auditor Rotation	Auditor Ind.Spec.	Auditor Char.	Audit-based Model
Audit Variables	1	2	3	4	5	6	7	8	9	10
GCO		3.6507*** [0.001]	1.790598 [0.274]		3.8441*** [0.001]				Plot Area	2.050728 [0.236]
Auditor Type				.5179488 [0.404]	.739428 [0.324]	1.024144 [0.219]			1.289843 [0.206]	1.166608 [0.256]
Auditor Rotation				.871139 [0.321]	1.51966* [0.093]		1.635549 [0.185]		1.613914 [0.203]	1.973136 [0.146]
Auditor Ind. Spec.				.7646994 [0.577]	.0347984 [0.984]			.4392913 [0.814]	-1.463337 [0.551]	-1.642936 [0.530]
Financial Variables										
WC/TA	-2.791* [0.069]		-2.61365* [0.100]			-2.74116* [0.094]	-2.6476* [0.087]	-2.81548* [0.068]	-2.414071 [0.146]	-1.973566 [0.249]
RE/TA	-9.426* [0.088]		-9.6702* [0.077]			-10.6608* [0.081]	-7.952136 [0.163]	-9.39719* [0.092]	-9.607254 [0.127]	-9.554459 [0.118]
EBIT/TA	-8.7259 [0.241]		-3.271449 [0.699]			-8.210292 [0.296]	-11.09208 [0.162]	-8.672762 [0.247]	-10.86858 [0.190]	-4.940926 [0.585]
MVE/TL	-.1555 [0.292]		-.149518 [0.310]			-.0900753 [0.571]	-.2036667 [0.185]	-.145352 [0.343]	-.1596993 [0.347]	-.1874617 [0.279]
SALES/TA	-.6338* [0.070]		-.78007* [0.057]			-.60301* [0.096]	-.74685** [0.050]	-.6157* [0.086]	-.76703* [0.052]	-.97213** [0.034]
Pseudo-R^2	0.4637	0.2289	0.4785	0.0314	0.2704	0.4803	0.4829	0.4642	0.5009	0.5187
AUC	0.9184	0.7100	0.9184	0.6144	0.7796	0.9240	0.9208	0.9168	0.9328	0.9280
Accuracy	84.00%	80.00%	84.00%	70.67%	84.00%	86.67%	86.67%	85.33%	89.33%	89.33%
TYPE I	10.00%	2.00%	10.00%	0.00%	2.00%	8.00%	10.00%	10.00%	8.00%	6.00%

This table reports the results from estimating regression Equation (1) with various predictors individually and collectively . P-Values are included in brackets. ***, **, * Denote statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

5. Conclusion and Future Research

The primary objective of this study is to develop a combined model for corporate bankruptcy prediction based on financial and audit–related disclosures of Egyptian firms. To attain this objective, predictive models are constructed and compared using different types of explanatory variables: (1) auditor GCO, (2) auditor characteristics, and (3) standard financial ratios. Using logit models for testing hypotheses, **results reveal the following**:

– Accept Hypothesis (1), where the empirical study shows the usefulness of auditor GCO for predicting corporate bankruptcy consistent with prior studies (e.g., Carson et al., 2013; Desai et al., 2017). Nevertheless, Hypothesis (2) is rejected where auditor GCO does not provide incremental information content for bankruptcy prediction consistent with Lennox (1999) findings. This could be due to the high negative correlation between financial ratios and auditor GCO and thus auditor GCO does not signal additional information beyond that of the financial ratios.

– Rejecting Hypotheses (3) and (4) regarding whether auditor characteristics have information content and incremental power for predicting bankruptcy. These results are inconsistent with prior research showing that auditor characteristics are significantly associated with bankruptcy (Cenciarelli et al. 2018; Mansi et al. 2004; Jones, 2017). This can be attributed to the fact that auditor characteristics in Egypt are not good indicators of the actual audit quality.

Based on the results, **it is recommended** that standard setters and regulators set policies and regulations in order to enhance non-financial disclosures of listed firms on the Egyptian stock exchange. Moreover, they should develop effective laws and regulations that would obligate auditors to provide high-quality audits.

Additionally, thorough research is indispensable for developing machine learning based models using Egyptian data. However, this requires the availability of large amount of data in order to develop generalizable models based on financial and non-financial disclosures. To attain this goal, it is necessary to provide a comprehensive database for Egyptian firms that include not only annual reports but also all forms of non-financial disclosures related to Egyptian firms.

Future research can examine the informativeness and incremental power of other forms of non-financial disclosures for corporate bankruptcy prediction. Also, the usefulness of other data mining and AI tools for corporate bankruptcy prediction can be explored.

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