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Modelling business bankruptcy for audit purposes

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ABSTRACT

To facilitate informed decision-making and foster transparency, stakeholders require access to reliable financial information. Financial audits serve the purpose of assisting companies in achieving success by assuring the accuracy and transparency of their financial statements. However, due to the evolving and increasingly competitive nature of markets, companies may exhibit indicators of financial vulnerability, commonly referred to as "red flags." These warning signs could potentially lead to business failure and bankruptcy. To mitigate such risks, predictive models for assessing the likelihood of business failure have been developed. Such models offer valuable decision-making support for auditors, enabling them to identify and mitigate risks associated with financial distress. The primary objective of this study is to develop a predictive model based on logistic regression and compare its effectiveness with traditional audit opinions. The sample comprises Portuguese small and medium-sized enterprises from the textile sector. Data were collected from the SABI database (Iberian Balance Analysis System). For the years 2017 and 2018, 371 insolvent SMEs and 2412 active SMEs were obtained. Through empirical analysis, it was found that regression models possess greater predictive capability compared to conventional audits. The application of these models significantly enhances the accuracy of assessing a company's financial status, thereby enabling professionals to provide more informed and appropriate opinions.

Keywords: Logistic regression, Bankruptcy, Audit, Financial risk

INTRODUCTION

Entrepreneurial activity plays a pivotal role in driving both the economic and social advancement of a nation. Companies, driven by the imperative to maximize their performance, aim to generate substantial value for their investors and other key stakeholders. In this pursuit, stakeholders rely heavily on access to comprehensive financial information that enhances the credibility and transparency of decision-making processes, thereby facilitating the path to success.

The fundamental purpose of financial audits is to assist companies in attaining success by ensuring the accuracy and integrity of their financial data. However, in the dynamic and increasingly competitive landscape of modern markets, companies may encounter challenges that manifest as signs of financial vulnerability, commonly termed "red flags." These warning signals necessitate proactive measures to avert the risk of bankruptcy and sustain business operations.

The demand for audit professionals has increased, paralleled by a rise in their responsibility. The objective is to obtain sufficient evidence to substantiate the assumption of continuity, opining on the presence or absence of materially relevant uncertainties that may challenge this assumption.

To address this concern, predictive models for assessing the likelihood of business failure have emerged as essential tools, offering invaluable support to auditors in their decision-making processes. By leveraging these models, auditors can effectively identify and mitigate potential risks associated with financial instability, thereby safeguarding the long-term viability of businesses.

The empirical study aims primarily to construct a model for predicting corporate failure, specifically tailored to the textile and apparel sector in Portugal. To achieve this, we will utilize a sample of companies from this sector and apply logistic regression analysis. The data utilized originate from the SABI database (Iberian Balance Analysis System).

The sector under scrutiny is pertinent as it encompasses a significant portion of the Portuguese business landscape, boasting one of the highest employment rates in the northern region of the country. Moreover, it includes an industry that experienced a notable surge in insolvency proceedings in the fourth quarter of 2021.

Consequently, the following research question is posed: Does the predictive capacity of the logistic regression-based model align with the forecasts made by audits?

This study delves into the multifaceted realm of financial risk assessment, unravelling the symbiosis between traditional audit opinions and cutting-edge predictive models. As we navigate the intricacies of modern business environments, the pursuit of a nuanced understanding of financial risk becomes imperative, heralding a new era where the synergy of established wisdom and technological innovation propels us toward more informed and resilient financial decision-making.

The study involves a meticulous examination of historical financial data, encompassing diverse industries and economic contexts. Through the lens of logistic regression, the research aims to unravel the latent patterns and relationships within the data that may elude traditional audit methodologies. Concurrently, audit opinions rendered during the same period will be scrutinized to establish a comparative baseline.

After the introduction, it follows the literature review about models for business bankruptcy. Section 3 describes the methodology regarding data collection. The presentation and discussion of results are in section 4. Finally, the conclusions, limitations, and proposals for future research are presented.

LITERATURE REVIEW

As companies strive for excellence, the pursuit of optimal performance becomes a paramount objective, driven by the overarching goal of creating value for investors and other key economic agents. Central to this pursuit is the imperative for companies to furnish accurate and reliable financial information, laying the foundation for transparent and credible decision-making processes. The financial audit emerges as a critical mechanism for ensuring the veracity and integrity of financial records. Its role extends beyond mere compliance, transcending into a strategic tool that aids companies in navigating the complex terrain of financial management, thus fostering an environment conducive to success.

Yet, in the contemporary business landscape characterized by volatility, uncertainty, complexity, and ambiguity (VUCA), companies may find themselves exposed to financial risk hard to anticipate. Even so, there are some key indicators of corporate financial fragility, colloquially known as "red flags", that must be carefully interpreted by auditors. The manifestation of these warning signs could potentially herald the onset of dire consequences, including the ominous specter of bankruptcy. Recognizing the need for proactive measures, predictive models have been devised to serve as vanguards against impending financial crises, offering auditors a robust decision-making support system. To comprehend the significance of financial audit in corporate governance, one must delve into its historical evolution and contemporary relevance. Scholars such as DeAngelo (1981) and Watts and Zimmerman (1986) have expounded on the agency theory, which posits that the separation of ownership and control in corporations necessitates mechanisms to align the interests of management with those of shareholders. Financial audits, as a manifestation of these mechanisms, play a pivotal role in ensuring accountability and transparency, fostering the trust of stakeholders. Moreover, the agency theory underscores the importance of information asymmetry in corporate relationships. The audit process serves as a mechanism to mitigate this asymmetry by providing an independent and objective assessment of a company's financial health. This not only instils confidence among investors but also facilitates informed decision-making by various economic agents involved in the company's ecosystem.

The burgeoning complexity of the business environment introduces a plethora of challenges, chief among them being the identification of red flags indicative of financial vulnerability. Altman (1968) pioneered the concept of financial distress prediction models, positing that certain financial ratios could serve as early warning signals of a company's deteriorating financial condition. These red flags, ranging from declining profitability to excessive leverage, act as harbingers of potential distress, prompting the need for timely intervention.

The volatility of financial markets and the unpredictable nature of economic cycles amplify the importance of identifying red flags. Through empirical studies, researchers have endeavoured to refine and expand upon Altman's initial models, incorporating a diverse array of financial indicators and leveraging advanced statistical techniques. The goal is not merely to predict financial distress but to empower auditors with the ability to proactively address underlying issues, thereby averting the perilous path to insolvency.

In response to the evolving landscape of financial risk, predictive models have emerged as indispensable tools in the auditor's arsenal. By harnessing the power of statistical techniques such as logistic regression, these models transcend the limitations of traditional audit methodologies. The advent of machine learning algorithms further amplifies the predictive capabilities, allowing auditors to sift through vast datasets and discern nuanced patterns that may elude conventional analysis.

Noteworthy studies, such as those by Beaver (1966) and Zmijewski (1984), have laid the groundwork for incorporating quantitative methodologies into financial analysis. Logistic regression, in particular, has gained prominence for its ability to model the probability of an event occurring, making it a fitting choice for predicting the likelihood of business failure. The amalgamation of financial ratios, industry-specific variables, and macroeconomic indicators empowers auditors with a holistic view of a company's financial health, facilitating more nuanced decision-making.

Although the ‘financial auditing mission is not intended to predict the bankruptcy risk, the users of financial statements consider that a modified audit opinion is an alert of possible failure’ (Feghali, et al., 2022: 583). Zultilisna et al. (2022: 4191) refer that a ‘going concern audit opinion becomes a signal to predict the company's ability to continue its business in the future’. Some studies suggest that auditors improve the quality of financial reports because they detect errors and other intentional misreporting (Yetman and Yetman, 2012, Gaynor et al., 2016).

According to Amat (2019) audit report users expect the auditor to notify when the audited company presents a high probability of insolvency. In these situations, the auditor questions in their report the appropriateness of applying the going concern accounting principle. For Eutsler et al. (2016: 383) a ‘going concern opinion is most often issued because of financial distress, the audit report may be regarded as a warning of impending bankruptcy and afford the auditor some amount of protection against potential investor litigation’.

As the business landscape undergoes seismic shifts, the efficacy of traditional audit opinions in assessing financial risk comes under scrutiny. The static nature of audit procedures, coupled with the retrospective focus, may render them less adept at capturing the dynamic interplay of factors influencing a company's financial trajectory. Indeed, as a consequence of a changing and more and more demanding market, companies may at some point show some indicators of financial fragility, known as red flags. To prevent companies from going bankrupt and their business from going to an end, business failure prediction models have been created, providing an important decision-making support tool for auditors. Although the first empirical studies of bankruptcy prediction were developed around the thirties (Pereira et al., 2015), the topic gained new visibility and new academic relevance in the sixties, with the research of Beaver (1966) and Altman (1968). Since then, this topic has been a field of increasing interest to researchers all around the world.

In most cases, authors tend to use the bankruptcy state as the dividing line when they distinguish the failed and non-failed firms (Sharipova, 2023). As there is no general theory about failure, an exact definition of financial distress is not determined yet. After the pioneering work by Altman (1968) who applied multi-discriminant analysis, in the following years were published several works that used other methods, such as logit (Ohlson, 1980), probit (Zmijewski, 1984), and hazard analysis (Shumway, 2001, Pereira et al. 2020). Thanks to the development of technology in recent years, different predictive methods have been applied to establish a bankruptcy prediction model with better accuracy. In artificial intelligence technology, neural network has become one of the most widely used promising tools (Tam and Kiang, 1992, Wilson and Sharda, 1994, Lacher et al., 1995, Desai et al., 1996, Yang et al., 1999, Atiya, 2001, Lee, et al., 2005). However, there are also other methods based on machine learning and artificial intelligence adopted by many authors in this area. These methods include, for example, decision tree (Frydman, et al., 1985, Li, et al., 2010), genetic algorithm (Varetto, 1998, Shin and Lee, 2002), case-based reasoning (Park and Han, 2002, Li and Sun, 2011), support vector machine (Min and Lee, 2005, Lin, et al., 2011, Kim, 2011, Li, and Sun, 2012), rough sets theory (Beynon and Peel, 2001, McKee 2003, Slowinski and Zopounidis, 1995, Xiao, et al., 2012, Wang and Wu, 2017) or random forests (Huang, et al., 2017).

METHODOLOGY

Regression methods are crucial for analyzing data and establishing relationships between a dependent variable and one or more independent or predictive variables. In logistic regression, the dependent variable is a dichotomous one that can only take on two distinct values, specifically one and zero.

Logistic regression is characterized by minimal assumptions and states a linear relationship between the logarithm of the odds of the dependent variable (logit) and the independent variables. The correlation between independent variables should not be high so that it does not result in the exclusion of important variables in the explanation of the dependent variable, as well as the inclusion of irrelevant variables for the model. It quantifies the likelihood of a specific result, hence allowing clear interpretation of the findings.

To achieve the best model, the stepwise approach can be employed to determine the independent variables that best explain the dependent variable. This method simply explores a restricted succession of models and is a good alternative for identifying the best subset of independent variables, as it is computationally lighter. The output is given by the probability of the dependent variable belonging to one of two possible categories, the category that takes the value one and the category that takes the value zero. The sample comprises Portuguese small and medium-sized enterprises (SMEs) from the textile sector, as defined by criteria set forth by IAPMEI (Portuguese Agency for Competitiveness and Innovation). Data were collected from the SABI database (Iberian Balance Analysis System). For the years 2017 and 2018, 371 insolvent SMEs and 2412 active SMEs were obtained.

When using logistic regression (logit model) for predicting business failure, a wide variety of variables can be considered. However, the model typically constructs the prediction of business failure based on a smaller set of variables that are deemed more relevant. This selection process is driven by the aim to identify the most influential factors that contribute to the likelihood of business failure. Considering the literature, the following explanatory variables were selected:

- Financial Autonomy;
- Solvency;
- Indebtedness;
- Sales and Services Provided/Equity;
- General Liquidity;
- Asset Profitability;
- Pre-Tax Income/Asset;
- EBITDA - Earnings Before Interest, Taxes, Depreciation and Amortization;
- Interest and Similar Expenses Incurred/EBITDA;
- EBIT - Earnings Before Interest and Taxes
- Current Assets/Total Assets;
- Total Assets/Total Liabilities;
- Current Assets/Current Liabilities;
- Total Liabilities/Total Assets;
- Current Liabilities/Current Assets;
- Current Liabilities/Sales;
- Current Liabilities/Equity;
- Sales/Total Assets;
- Interest and Similar Expenses Incurred/Current Liabilities;
- Financial Leverage;
- (Carried Forward Profits + Net Income for the Period)/Total Assets;
- Net Income for the Period/Total Liabilities;
- Net Income for the Period/Total Assets;
- Pre-Tax Income/Current Liabilities;
- Pre-Tax Income/Total Assets;
- (Pre-Tax Income + Interest and Similar Expenses Incurred)/Sales;
- Cash Flow/Current Assets;

- Cash Flow/Total Assets;
- Cash Flow/Total Liabilities;
- Accounts Receivable/Total Liabilities;
- Personnel Expenses/Operating Income.

Two logistic regression models were fitted for prediction. One model employs data from 2018, while the other model uses data from 2017. The dependent binary variable takes a value of one to indicate that the company has gone bankrupt (positive result), and a value of zero to indicate that the company is still operational (negative result). The model calculates the probability of the dependent variable being equal to one, which indicates that the company has gone bankrupt.

Before conducting any analysis, the data was examined. Specifically, the presence of missing values and outliers can have a substantial impact on the estimate of the model parameters. Cases containing an excessive number of missing values were eliminated. To detect outliers, the Mahalanobis distance was computed for every subsample that was categorized by the status of the company (active or bankrupt). The Mahalanobis distance is a statistical multivariate distance that incorporates the covariance matrix to weigh the calculated distances in consideration of the variances and correlations between variables. Higher-valued observations with a p-value below 0.001 were removed. In the same manner, unaudited companies were omitted from the study.

The samples were partitioned into a training sample and a test sample. The training samples were selected at random to ensure an equal representation of both operating and bankrupt organizations, with a total of 100 samples for each category. Although the value is rather modest, it is nevertheless acceptable considering the limited number of failed companies.

The stepwise technique, along with the size of the estimated coefficients, the analysis and interpretability of the independent variables, and the model's discriminatory capacity, were utilized to determine the best final model in the training sample. The referenced data came from the year 2018. The model constructed using data from 2017 employed the same set of variables, and their coefficients were estimated using the training sample from that year. This procedure is justified through an examination of the outcomes obtained via the stepwise approach, as well as to facilitate comparisons.

The classification of the companies achieved by logistic regression was compared with that of the audits on the test samples. This approach helps prevent overfitting of the data.

RESULTS PRESENTATION AND DISCUSSION

In logistic regression, the goal is to model the probability of a binary outcome, such as business failure or success, based on a set of independent variables. The challenge lies in determining which variables have the strongest predictive power and should be included in the model. Variables that are statistically significant, have high correlation with the outcome, or demonstrate theoretical relevance are typically prioritized for inclusion in the model. In spite we have used thirty one variables, twenty seven were excluded in the final model, namely: Financial Autonomy; Solvency; Indebtedness; Sales and Services Provided/Equity; General Liquidity; Asset Profitability; Pre-Tax Income/Asset; EBITDA - Earnings Before Interest, Taxes, Depreciation and Amortisation; Interest and Similar Expenses Incurred/EBITDA; EBIT - Earnings Before Interest and Taxes; Current Assets/Current Liabilities; Total Liabilities/Total Assets; Current Liabilities/Sales; Current Liabilities/Equity; Sales/Total Assets; Interest and Similar Expenses Incurred/Current Liabilities; Financial Leverage; (Carried Forward Profits + Net Income for the Period)/Total Assets; Net Income for the Period/Total Liabilities; Net Income for the Period/Total Assets; Pre-Tax Income/Current Liabilities; Pre-Tax Income/Total Assets; (Pre-Tax Income + Interest and Similar Expenses Incurred)/Sales; Cash Flow/Total Assets; Cash Flow/Total Liabilities; Accounts Receivable/Total Liabilities; Personnel Expenses/Operating Income.

The ultimate logistic regression model was achieved using the set of independent variables listed in **Table 1**. The coefficients, p-values, and odds ratios are shown as well.

Table 1. Coefficients, p-values, and odds ratios for the logistic model using 2018 data

	Coefficient	p-value	Odds Ratio
Constant	-2.187	0.095	
Current Assets/Total Assets	3.658	0.001	38.779
Total Assets/Total Liabilities	-0.887	0.012	0.412
Current Liabilities/Current Assets	0.934	0.022	2.544
Cash Flow/Current Assets	-1.064	0.072	0.345

The Current Assets/Total Assets variable exerts the most important impact on the likelihood of bankruptcy (Table 1). As its value increases, the likelihood of the company experiencing bankruptcy also increases.

The classification of companies (active or bankrupt) in both the training and test sets, is expressed by the confusion matrices displayed in Table 2.

Table 2. Confusion matrices in the training and test sets of the model built using data from 2018

	Training sample			Test sample		
	Active forecast	Bankrupt forecast		Active forecast	Bankrupt forecast	
Active	77	23	Specificity = 77.0%	1342	710	Specificity = 65.4%
Bankrupt	29	71	Sensitivity = 71.0%	47	133	Sensitivity = 73.9%
			Global = 74.0%			Global = 66.1%

The test sample's sensitivity, the true positive rate (percentage of businesses that the model accurately predicted would fail) was 73.9%. The model's specificity, the true negative rate (percentage of accurately predicted active companies) was 65.4%. Accuracy as a whole was 66.1%.

In terms of the audits' predictions, the confusion matrices applied to the same samples (for the aim of making comparisons), are presented in Table 3.

Table 3. Confusion matrices in the training and test sets for the audits' predictions using data from 2018

	Training sample			Test sample		
	Active forecast	Bankrupt forecast		Active forecast	Bankrupt forecast	
Active	96	4	Specificity = 96.0%	1998	54	Specificity = 97.4%
Bankrupt	99	1	Sensitivity = 1.0%	176	4	Sensitivity = 2.2%
			Global = 48.5%			Global = 89.7%

As can be observed, there is a notable propensity in auditing to perceive companies as operational, resulting in an abnormally low sensitivity and an exceptionally high rate of false negatives (a percentage of businesses that the model wrongly predicted would be active). Likewise, specificity becomes very high. In the test sample, the overall accuracy increased from 66.1% to 89.7% in comparison to the logistic regression model. However, these figures are not comparable. This improvement is misleading, as auditors tend to perceive companies as active, and the test sample contains a substantial percentage of active companies. By taking into account the outcomes in the training sample, where the proportion of successful and insolvent businesses is equal, this bias is removed. Thus, the overall accuracy is lower than that obtained in the test sample using the logistic regression, where the value dropped from 66.1% to 48.5%. The difference is even bigger when compared to the logistic regression training sample (74.0% versus 48.5%).

Using 2017 data, the coefficients, p-values, and odds ratios estimated using logistic regression. are shown in Table 4.

Table 4. Coefficients, p-values, and odds ratios for the logistic model using 2017 data

	Coefficient	p-value	Odds Ratio
Constant	-0.444	0.688	
Current Assets/Total Assets	1.434	0.105	4.194
Total Assets/Total Liabilities	-0.725	0.027	0.484
Current Liabilities/Current Assets	0.538	0.097	1.712
Cash Flow/Current Assets	-0.742	0.231	0.476

Again, the Current Assets Total Assets variable has the highest impact on bankruptcy probability.

In order to assess the ability of logistic regression to differentiate between active and bankrupt companies, the confusion matrix was constructed in both the training and test data (**Table 5**).

Table 5. Confusion matrices in the training and test sets of the model built using data from 2017

	Training sample			**Test sample**		
	Active forecast	Bankrupt forecast		Active forecast	Bankrupt forecast	
Active	72	28	Specificity = 72.0%	1316	683	Specificity = 65.8%
Bankrupt	35	65	Sensitivity = 65.0%	45	65	Sensitivity = 59.1%
			Global = 68.5%			Global = 65.5%

The test sample's sensitivity, the true positive rate was 59.1% (decreased from 73.9%, when the 2018 data was used). The model's specificity, the true negative rate was 65.8% (almost the same value when the 2018 data was used). The overall accuracy was 65.5%, which is nearly identical to the accuracy of 66.1% when the 2018 data was utilized. The results obtained are somewhat comparable to those obtained with data from 2018.

In terms of the audits' predictions, the confusion matrices applied to the same samples, are presented in **Table 6**.

Table 6. Confusion matrices in the training and test sets for the audits' predictions using data from 2017

	Training sample			**Test sample**		
	Active forecast	Bankrupt forecast		Active forecast	Bankrupt forecast	
Active	96	4	Specificity = 96.0%	1940	59	Specificity = 97.0%
Bankrupt	99	1	Sensitivity = 1.0%	105	5	Sensitivity = 4.5%
			Global = 48.5%			Global = 92.2%

Similar to the 2018 data, the audit exhibits a pronounced tendency to classify the company as active, resulting in an overly low sensitivity and excessively high specificity. Regarding the 2018 data, the overall accuracy demonstrated an improvement in comparison to the logistic regression model in the test sample, increasing from 65.5% to 92.2%. However, it should be noted that these results are not directly comparable. The overall accuracy value significantly decreases to 48.5% in the training sample.

The findings indicate that auditors typically categorize organizations as active, meaning that they struggle to make accurate predictions about the companies' future health in the subsequent one or two years. Logistic regression demonstrated superior discriminatory power in predicting bankruptcy for enterprises one or two years in advance. Thus, auditors should employ logistic regression to confirm their findings.

CONCLUSIONS

As companies strive for excellence and pursue optimal performance to create value for investors, financial audits emerge as critical mechanisms ensuring the veracity of financial records. However, in today's volatile landscape, predictive models like those discussed above play a pivotal role. They empower auditors to proactively identify early signs of financial distress, enabling timely interventions to avert dire consequences such as bankruptcy and ensuring the sustainability of businesses amidst evolving market demands. By leveraging advanced statistical techniques and incorporating diverse financial indicators, modelling Business Bankruptcy became crucial for auditors because it provides them with valuable insights, ultimately safeguarding the continuity and stability of businesses amidst the complexities of the modern market.

This study embarks on a comprehensive exploration, seeking to develop a prediction model based on logistic regression and subsequently comparing its predictive prowess with the opinions rendered within the purview of traditional audits. The research framework draws inspiration from seminal works such as the studies by Dechow et al. (2011) and Krishnan (2005), which advocate for the integration of quantitative models into the audit process to enhance its effectiveness.

The analysis seeks not only to quantify the predictive accuracy of the logistic regression model but also to discern instances where the model outperforms or diverges from audit opinions. The goal is not to undermine the value of audits but to explore avenues where predictive models can serve as complementary tools, enhancing the overall efficacy of financial risk assessment.

The empirical study carried out led to the conclusion that regression models have a greater predictive capacity than audits. Their application contributes to a significantly higher level of success in assessing a company's financial status, thus allowing the opinion expressed by professionals to be more appropriate.

The implications of the research extend beyond the binary choice of regression models versus audit opinions; rather, it opens a dialogue on the symbiotic relationship between traditional audit practices and modern predictive methodologies.

The potential for innovation in financial risk assessment lies at the intersection of established practices and emerging technologies. This study contributes to the ongoing dialogue surrounding financial risk assessment by developing and evaluating a predictive model for business failure using logistic regression, and comparing its effectiveness with traditional audit opinions. While the findings suggest that regression models exhibit greater predictive capacity than audits, several limitations must be acknowledged, including concerns regarding sample generalizability, data quality, model evaluation metrics, and the need for ethical considerations in predictive modeling practices. Moreover, the independent variable are very vulnerable to accounting criterious (Pereira, et al., 2015). Despite these limitations, the study underscores the potential of predictive models to complement traditional audit practices and emphasizes the importance of a dynamic and adaptive approach to financial risk assessment in the face of evolving technological advancements and business landscapes. In future researcher opportunities, it would be interesting to develop a framework for continuously updating predictive models with real-time data streams to adapt to changing market conditions and enhance the timeliness and accuracy of risk assessments.

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