

Determinants of default prediction of the tourism sector: the case of Portuguese SMEs

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Abstract

This study intends to understand the determinants of default of tourism SMEs (Small and Medium Enterprises), i.e., which aspects impact the probability that the company will not comply with its financial obligations. For this purpose, a panel data composed from a sample of 3,945 Portuguese SMEs, over ten years, was analysed. An ex-ante criterion (based on a set of financial ratios) was used to classify firms in default or compliant. This criterion helps to detect financial problems early. Then, in addition to the firm's specific characteristics, which are the most used determinants, governance variables and macroeconomic factors were analysed in the firm's default prediction logit model. Results prove that the three groups of determinants are relevant to explain firms' financial difficulties probability. The proposed model presents a success rate (predictive ability to classify as compliant and default) of around 80%. Furthermore, as a test of the robustness of the results, the sample period was divided into two subperiods (2010 to 2014 and 2015 to 2019) with different investment rates in the sector, allowing the conclusion that what determines the default of SMEs in the Portuguese tourism sector depends on the period analysed.

Keywords: Default; Tourism sector; SME; Portugal, Financial ratios, Governance Variables, Macroeconomic variables; Logit; Panel Data.

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1. Introduction

The exponential globalization that has occurred in recent decades has made tourism a social and economic phenomenon that has seen continuous development worldwide. The tourism sector is one of the most important economic activities in several countries, contributing to wealth generation (World Tourism Organization, 2023).

In 2019, according to the World Bank, the tourism sector was valued at more than 9 trillion US dollars, more than 10% of global gross domestic product (GDP). In Portugal, in 2019, this sector represented 8.8% of the Portuguese firms (Pordata, 2023) and contributed 8.5% to Portuguese gross value added (GVA) (INE, 2020), and 4.7% to total revenues (Pordata, 2023). Tourism consumption represented around 15.4% of Portuguese GDP.

Despite its high economic and social contribution, it is a vulnerable sector, highly affected by the international crisis, mainly due to its seasonality and high fixed cost structure (Wieprow & Gawlik, 2021; Zhang & Xie, 2021). To survive in a highly competitive market, tourism firms need to quickly adapt to a constantly changing environment and, for that, need proactive stakeholders (Glowka & Zehrer, 2019). The bankruptcy of tourism firms could cause serious damage to the country, government, and the companies involved, making economic development difficult (Li *et al.*, 2013).

From 2012 till 2018, the mortality rate of tourism firms in the 27 countries of the European Union was, in the mean, 8.5%, and 7.9% in the Eurozone. Portugal presented the second highest mortality rate (mean 13.25% from 2010 till 2019), only being surpassed by tourism firms in Bulgaria (mean 14.28%) (Pordata, 2023). Moreover, in Portugal, from 2010 to 2012, the mortality rate of this sector increased from 12.9% to 16.3%, and in 2019 was 14.7% higher than the mean value of the mortality rate of Portuguese firms (13.1%).

This study intends to identify which determinants can influence the likelihood of an SME in the tourism sector fulfilling (or not) its financial obligations. For it, a sample of Portuguese firms from the tourism sector, more precisely, accommodation and food services, over the years 2010 to 2019, is analysed.

First, we classify firms in compliant or default using an ex-ante criterion (a set of financial ratios) that helps to detect financial problems early. Then, the logit model is used to identify which determinants are more relevant to explain the default of Portuguese tourism firms. Three types of determinants are used: to measure firms' specific characteristics, corporate governance variables, and macroeconomic factors.

Several contributions to literature are made. First, as far as we know, few studies analyse the default risk of the tourism sector (e.g., Pelaez-Verdet & Loscertales-Sanchez, 2021; Wieprow & Gawlik, 2021; Shroj *et al.*, 2024), even if it is a relevant sector that contributes to countries' wealth. Therefore, this work adds knowledge about the tourism sector by presenting which determinants are more relevant to explain the default probability of tourism SMEs. This information, besides covering a gap in the literature about the theme, can help to reduce the mortality rate of the sector, which is one of the industries with the highest one.

Second, to explain default probability, different type of determinants is included: to measure a firm's specific characteristics, which are the determinants most used to explain default risk (Shroj *et al.*, 2024); to measure macroeconomic factors, as firms are inserted in a country and externalities impact its financial position and decision-making; and to measure corporate governance, since the owners' involvement in the business may impact its decisions. Adding different types of determinants allows us to have an overall picture of the aspects that impact firms' financial sustainability.

Third, the few studies that analyse the default risk of the tourism sector mainly focus on listed or large-size firms (Wieprow & Gawlik, 2021). Although, the tourism industry is characterized by being made up of a large percentage of SMEs (Altin *et al.*, 2021). Therefore, studying this type of firm is relevant to help managers and all stakeholders to better understand firms from the tourism industry. SMEs are apart from large-size firms due to their access to financial resources and the firm's financial stability. Moreover, SMEs have less information transparency, more risk exposure, and less stable performance (Srhoj *et al.*, 2024). Thus, this work contributes to expand the literature on default about tourism firms. Furthermore, most studies applied to the tourism sector use legal criteria to distinguish a compliant from a default company (Gu & Gao, 2000; Gu, 2002; Kim & Gu, 2006; Pelaez-Verdet & Loscertales-Sanchez, 2021, Shroj *et al.*, 2024). This criterion strongly depends on the context (country and period) of the analysis. The use of an ex-ante criterion, which considers financial ratios that characterize the company's financial health, allows for an analysis of different contexts, allowing the use of conclusions for early decision-making (Situm, 2023). Therefore, our conclusions can help managers and other stakeholders in their decision-making to promote the firm's sustainability.

Finally, considering the investment rate of the sector, we divided the sample into two sub-samples, and the results are singular, showing that the investment made in the sector impacts results. To our knowledge, we are the first study to address this analysis. Our results suggest that changes in the way the tourism sector operates have impacts on tourism firms' financial situation and sustainability.

The organization of the paper is as follows. After this introduction section where the work's aim and its relevance are introduced, the next section presents the main literature review about default prediction. The model, sample, and variables used are explained in section 3, followed by the empirical results in section 4. The work finishes with the main conclusion and future lines of research.

2. Literature Review

2.1. Default definition

Every company needs to identify and manage several risks to ensure its sustainability. Default risk is one of the most relevant as it can lead to a company's bankruptcy, with serious consequences for all stakeholders (Habib *et al.* 2020). A firm presents default risk when there is a probability of having difficulties meeting its financial obligations (Ashraf *et al.*, 2019; Tinoco & Wilson, 2013; Pindado *et al.*, 2008). It can be a temporary situation but, if not solved, it can lead to bankruptcy, i.e., its inability to pay financial obligations (Beaver, 1966).

There are different criteria to classify companies in compliant or default, which can be grouped into three: ex-post, ex-ante, and mixed criteria (Costa *et al.* 2022). Ex-post criterion is also known as legal criteria. It is country-specific and depends on the sample period since every country has its legislation and it can change over the years (Tinoco & Wilson, 2013). Altman (1968); Becerra-Vicario *et al.* (2020); Blums (2003); Gamez *et al.* (2016); Kim and Gu (2010) and Ohlson (1980) are examples of studies that use the ex-post classification.

In turn, the ex-ante classification uses a set of financial ratios to classify companies in default or compliant. Some examples are Abinzano *et al.* (2020), Costa *et al.* (2022), Lisboa *et al.* (2021), Nagar and Sen (2018), and Salloum *et al.* (2012). According to Nagar and Sen (2018), a company is in default when EBITDA (Earnings Before Interest, Taxes, Depreciation, and Amortization) has been negative in the last two consecutive years. Salloum *et al.* (2012) classify a company as default when the net income divided by financial expenses is less than 0.8. For Abinzano *et al.* (2020) a company is in default when its assets are less than its liabilities on the debt maturity date. Costa *et al.* (2022) and Lisboa *et al.* (2021) classify a company as compliant when the financial capital ratio is higher than 5%, EBITDA over financial expenses is greater than 1.3, and the net debt ratio is between 0 and 10, with each indicator being met

at least once in the previous three years and at least 50% of the indicators, considering all possible combinations.

Some authors use both classifications simultaneously, i.e., a default company is already in bankruptcy or that met a set of financial ratios (e.g., Ashraf *et al.*, 2019 and 2020; Pindado *et al.*, 2008; Tinoco & Wilson, 2013). According to Pindado *et al.* (2008), a listed company is considered in financial difficulties not only when it declares bankruptcy (ex-post criterion), but also when it fulfils two requirements cumulatively, during two consecutive periods (ex-ante criterion): EBITDA lower than financial expenses and decrease in the company's market value. These criteria were also used by Tinoco and Wilson (2013). According to Ashraf *et al.* (2019), a company is in financial difficulties when, for three consecutive years, the share price is less than 50% of the book value and there is a management failure at the annual general meeting; there is a reduction/omission of payment of dividends/bonuses for five consecutive years and dividends are not paid for two consecutive years (ex-ante criterion). The authors also consider that a company is in financial difficulties when it is removed, suspended, liquidated, dissolved, or went bankrupt (ex-post criterion). Ashraf *et al.* (2020) classify companies as in financial difficulties whenever the following conditions are met: 1) the company is inactive, merged, dissolved, or went into liquidation or went bankrupt (ex-post criterion); 2) the net income is negative for three consecutive years (ex-ante criterion).

2.2. Default models and determinants

The theme of default is not new. Beaver (1966), considered the pioneer in the default literature, has identified six accounting ratios (cash flow to total liabilities, net income to total assets, total liabilities to total assets, working capital to total assets, current assets to current liabilities, and interval without credit) more accurate for predicting bankruptcy five years before it occurs. However, an analysis of each ratio separately can bias results since the value of one ratio influences another one.

After Beaver (1966), models have been presented and compared, often they are divided into parametric and non-parametric intelligent models (Li *et al.*, 2013). Within the parametric, the most easily understood and widely referred to and used are multivariate discriminant analysis (MDA), logit, and probit. Regarding the multivariate discriminant analysis (MDA), Altman (1968) identifies the five ratios (working capital to total assets, retained earnings to total assets, operational earnings to total assets, market value to total liabilities, and turnover to total assets) with better capacity to predict bankruptcy. To solve some problems of MDA, namely the fact that the variables need to follow a normal distribution, Ohlson (1980) proposed a logit model and identified four categories of indicators that are statistically significant for predicting bankruptcy: size, leverage, performance, and liquidity. Zmijewski (1984) proposed a three-factor probit model, based on profitability, leverage, and liquidity. Shumway (2001) proposed the Hazard model that includes both market and accounting-based ratios. Blum (2003) proposed the D-model based on liquidity, profitability, and magnitude of resources. More recently, Altman *et al.* (2023) present the Omega Score which includes, beyond financial indicators, payment behaviours. The model was developed specifically for SMEs.

Despite the attempt of non-parametric models to overcome some disadvantages pointed out by parametric models, such as linearity, normality, and independence between predictor and input variables, the difficulty of interpretation and application continues to be a limiting aspect (Pelaez-Verdot & Loscertales-Sanchez, 2021). The most used non-parametric methods are Support Vector Machine (SVM) and Artificial Neural Network (ANN).

The Neural Networks (ANN) model resembles the human neural process. Complex non-linear relationships are established (Jones *et al.*, 2017). However, the researcher has a passive role in the application of this methodology and may present prediction failures in the case of multimodal data

(Zieba *et al.*, 2016; Jones *et al.*, 2017). To overcome this issue data normalization can be used, but according to Zieba *et al.* (2016), it reduces the predictive power of the model.

The Support Vector Machine (Shin *et al.*, 2005) is based on the concept of hyperplanes separated according to a kernel function (Jones *et al.*, 2017) distinguished from linear probabilistic binary models (e.g. logit). However, it presents itself as a difficult model to interpret. Both NN and SVM are limited in terms of predictive capacity when faced with samples with a high number of irrelevant inputs and data with different characteristics.

The conclusion regarding the best predictive model is still not consensual, studies that compare parametric models, e.g., Ashraf *et al.* (2020) point to the logit model as the most appropriate since it allows any variation in time covariates and adjusts for any unobservable heterogeneity. However, when comparing parametric and non-parametric models, there is a dichotomy between interpretability and accuracy in forecasting that must be balanced (Costa *et al.*, 2022).

More recently, researchers have focused on identifying the most relevant determinants that can explain default probability. Usually, researchers focus on determinants that measure firms' specific characteristics, such as leverage, profitability, liquidity, age, size, and others (e.g., Abinzano *et al.*, 2020; Becerra-Vicario *et al.*, 2020; Costa *et al.*, 2022; Lisboa *et al.*, 2021). However, macroeconomic factors as well as corporate governance variables are also relevant, even if are less studied in the context of default probability (Li *et al.*, 2020; Lohe & Calabrò, 2017; Wilson *et al.*, 2013).

2.3. *Tourism Default*

Each sector has singular characteristics that can impact default probability. For instance, tourism firms are affected by seasonality, which impacts financial performance and can cause financial constraints, influencing their economic sustainability (Zhang & Xie, 2021). The bankruptcy of tourism companies can have a high impact on both the government and the companies involved. Therefore, a growing number of studies on default in this sector have emerged, but there are still few works on the theme. However, most studies focus on studying the US (e.g., Gu & Gao, 2000; Gu, 2002; Kim & Gu, 2006; Kim, 2011); China (e.g., Li & Sun, 2011; Li *et al.*, 2013); and more recently other countries (e.g., Spain is studied by Pelaez-Verdet & Loscertales-Sanchez, 2021; Lado-Sestayo *et al.*, 2016; and Gémár *et al.*, 2016; Korea by Kim, 2011; Poland by Wieprow & Gawlik, 2021; Norway by Zhang & Xie, 2021; Austria by Situm, 2023; and Croatia by Shroj *et al.*, 2024). This calls for the need to extend the study of this theme to other countries to corroborate results and enlarge the knowledge of the theme (Shroj *et al.*, 2024). Regarding default classification, the majority of studies on tourism default use the legal criterion to classify companies as bankrupt, using databases with this information, as Bankruptcy Database in LEXIS/NEXIS (e.g., Gu & Gao, 2000; Gu, 2002); New Business Generation Research (Kim & Gu, 2006) or the classification of extinct provided by the database used in the collection of financial information (Pelaez-Verdet & Loscertales-Sanchez, 2021, Zhang & Xie, 2021). The ex-ante criterion, the other way to classify a firm as compliant or default and that can help to detect financial problems in advance, helping to support timely decisions is less explored and can give relevant information to all stakeholders, especially managers.

Like the general literature on default, also in the literature applied to the tourism industry, some studies are focusing on the issue of the best predictive model (e.g., Youn & Gu, 2010; Li & Huang, 2012; Kim, 2011; Li *et al.*, 2013), but the majority centering in the default determinants issue (e.g., Gu & Gao, 2000; Kim & Gu, 2006; Pelaez-Verdet & Loscertales-Sanchez, 2021; Wieprow & Gawlik, 2021). Regarding the first group of studies, i.e., the analysis of the best predictive model, when applied to most studies concludes that parametric models continue to present a competitive advantage in terms of efficacy, interpretability, and wide application (Youn & Gu, 2010; Li & Huang, 2012; Li *et al.*, 2013).

In terms of determinants, the literature that focuses on the tourism sector points to the strong predictive power of debt, profitability, and growth, in other words, firms' specific characteristics. The companies' survival depends on the prudent growth of sales (growth) with control of operating expenses and increase profitability, and lower indebtedness (Gu & Gao, 2000; Kim & Gu, 2006). These determinants are also the most used in the default probability thematic, analysing other industries. Some studies have introduced specific variables of tourism firms such as location, and concentration, and concluded that location may have some impact on financial difficulties, justifying that even in the same country, the location of tourism firms impacts the probability of financial difficulties (Pelaez-Verdet & Loscertales-Sanchez, 2021; Wieprow & Gawlik, 2021; Situm, 2023). Other variables as governance and macroeconomic factors can help to improve the model's accuracy.

3. Research methods

3.1. Model

The present study intends to understand the main determinants of the default risk of Portuguese SMEs in the tourism sector. The analysed determinants can be subdivided into 3 areas according to the proposed conceptual research model presented in Figure 1:

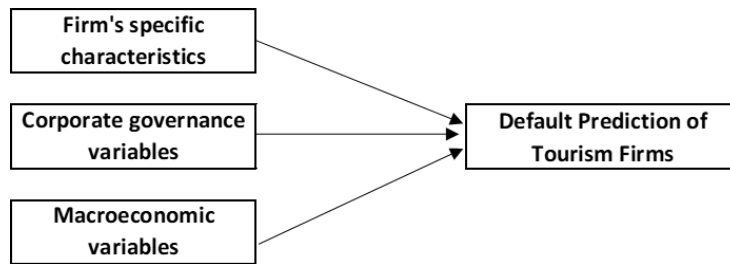


Figure 1. Conceptual research model

To analyse the impact of the determinants, the logit model will be used:

$$P = \left(1 + \exp \left\{ - \left[\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \right] \right\} \right)^{-1}$$

Where:

X₁- Firm's specific characteristics; X₂- Corporate governance variables and X₃- Macroeconomic variables

There is no consensus about which model is more appropriate, nevertheless, Ashraf *et al.* (2020) argue that the logit model allows any variation in time covariates and adjusts for any unobservable heterogeneity. Moreover, this model does not require the normality of variables, nor the same number of firms per group (compliant and default), and it is easy to implement and analyse (Ohlson, 1980; Jones *et al.*, 2015).

A panel data will be used by Pindado *et al.* (2008) and Costa *et al.* (2022) to control unobservable heterogeneity and to eliminate the bias of omitted variables. Moreover, the models will be estimated with robust standard errors to avoid heteroscedasticity problems.

3.2. Variables

Dependent variable

The dependent variable is a dummy, coded one when the company is in default and zero otherwise. Firms are classified as default or compliant using an ex-ante criterion. This criterion allows to identify a firm's economic and financial situation in advance, enabling timely decision-making, helping to surpass financial problems, and avoiding situations of bankruptcy (Nagar & Sen, 2018). Following Costa

et al. (2022) and Lisboa *et al.* (2021), a firm is considered to be compliant when the capital ratio (total equity divided by total assets) is greater than 5%, the net debt ratio (financial debt divided by EBITDA) is between 0 and 10, and the EBITDA divided by financial interest is greater than 1.3. The three criteria must be analysed for three consecutive years, each one must be met once in that period and 50% of the criteria in every year. All the other firms are classified in default.

Independent variables

From the literature that intends to study what determines default, there is a set of indicators referenced but whose impact depends, among other aspects, on the country, the industry, and the context that is analysed (Pelaez-Verdet & Loscertales-Sanchez, 2021). However, based on the literature, we can subdivide them into three groups: firm's specific determinants, corporate governance determinants, and macroeconomic determinants.

Determinants to measure firms' specific characteristics are the most used by researchers in this area. This group includes ratios of leverage, efficiency, size, age, cash flows, financial costs, asset structure, liquidity, and profitability. To tourism firms, leverage, profitability, and efficiency have been identified as the most relevant determinants (Gu & Gao, 2000; Kim & Gu, 2006), but not all were included. Corporate governance characteristics can also impact firms' default probability since managers are responsible for the firm's decisions. The type of owners (major or minority owners), as well as the board of directors' size, have a great impact on the supervision of managers (Jensen & Meckling, 1976). Therefore, it may impact the firm's decision-making as well as its financial problems. Finally, macroeconomic factors impact all firms. Recession periods cause significant shocks in liquidity and profitability, increasing firms' uncertainties and financial distress (Cathcart *et al.*, 2020).

Table 1 summarizes the variables selected from the literature review, as well as the expected sign.

3.3. Sample

To understand the default determinants of tourism firms, a sample of Portuguese SMEs from the tourism sector, more precisely the accommodation and service sector (Portuguese Economic Activity Classification, section I, 55 – accommodation, and 56 – food service) is analysed. The classification of SME follows the European Union classification, i.e., firms with annual sales of less than 50 million and with less than 250 employees.

In the literature on default, it is usual to study a particular industry, and a more homogeneous group since not all determinants and models have the same effectiveness in all sectors of activity (Pelaez-Verdet & Loscertales-Sanchez, 2021; Shroj *et al.*, 2024). Companies in the same sector are subject to the same regulation, and similar market conditions, avoiding activity bias in financial ratios.

We choose the tourism industry as it is one of the most important sectors in several countries. In 2019, tourism contribution to the worldwide GDP was 4.1%, and 4.3% in Europe (World Tourism Organization, 2023). International tourist arrivals reached 1.5 billion, which represented 1,493.7 billion USD in receipts (909.7 billion USD in Europe) (UNWTO, 2020). However, the emergence of COVID-19 and consequently the travel restrictions and the lockdown caused a hugged impact in this sector, reducing economic activity worldwide (UNWTO, 2021). The international arrivals decreased by 74%, and the tourism contribution to the GDP reduced to 1.8%. These facts show the vulnerability of the sector (Arcese *et al.*, 2021).

Table 1. Variables description

Variables	Formula	Expected Sign	Main references
Panel A: Firms' specific characteristics			
Leverage	Debt/Total Assets	+	Abinzano <i>et al.</i> (2020); Becerra-Vicario <i>et al.</i> (2020); Fernández-Gómez <i>et al.</i> (2016); Gu (2002); Lisboa <i>et al.</i> (2021); Md-Rus <i>et al.</i> (2013); Ohlson (1980); Santos <i>et al.</i> (2015); Tinoco and Wilson (2013); Udin <i>et al.</i> (2017); Wilson <i>et al.</i> (2013); Zmijewski (1984).
Efficiency	Sales/Total Assets	-	Ahmad (2013); Becerra-Vicario <i>et al.</i> (2020); Fernández-Gómez <i>et al.</i> (2016); Lisboa <i>et al.</i> (2021); Santos <i>et al.</i> (2015).
Size	Ln(Total Assets)	+/-	Becerra-Vicario <i>et al.</i> (2020); Chancharat <i>et al.</i> (2010); Gottardo and Moisello (2017); Manzanque <i>et al.</i> (2016); Turetsky and McEwen (2001); Wilson <i>et al.</i> (2013).
Age	Age Age ²	- +	Becerra-Vicario <i>et al.</i> (2020); Lisboa <i>et al.</i> (2021); Wilson <i>et al.</i> (2013).
Cash Flow	Operational Cash Flow/Debt	-	Fernández-Gómez <i>et al.</i> (2016); Kim and Gu (2010); Li <i>et al.</i> (2020); Lisboa <i>et al.</i> (2021); Ohlson, (1980); Tinoco and Wilson (2013).
Financial interest	EBITDA/Financial interest	-	Gottardo and Moisello (2017); Tinoco and Wilson (2013).
Asset Structure	Fixed Assets/Total Assets	-	Gottardo and Moisello (2016); Lee <i>et al.</i> (2011); Li <i>et al.</i> (2020); Wilson <i>et al.</i> (2013).
Liquidity	Working Capital/Total Assets	-	Ahmad (2013); Altman <i>et al.</i> (2017); Becerra-Vicario <i>et al.</i> (2020); Fernández-Gómez <i>et al.</i> (2016); Ohlson (1980); Santos <i>et al.</i> (2015).
Profitability			Abinzano <i>et al.</i> (2020); Ahmad (2013), Altman (1968); Altman <i>et al.</i> (2017); Gu (2002); Kim and Gu (2010); Li <i>et al.</i> (2020); Santos <i>et al.</i> (2015).
- ROA	EBIT/total assets	-	
- ROE	Net income/total equity	-	Ahmad (2013); Gottardo and Moisello (2016).
- ROS	Net Income/Sales	-	Becerra-Vicario <i>et al.</i> (2020); Fernández-Gómez <i>et al.</i> (2016); Lee <i>et al.</i> (2011).
Panel B: Corporate Governance			
Ownership	% of direct ownership	-	Salloum <i>et al.</i> (2012); Wilson <i>et al.</i> (2013).
Board size	Ln(number of board members)	-	Lohe and Calabrò (2017); Wilson <i>et al.</i> (2013)
Panel C: Macroeconomic			
GDP	GDP growth	+/-	Salloum <i>et al.</i> (2012)
Inflation	Inflation rate	+	Costa <i>et al.</i> (2022)
Unemployment	Unemployment rate	+	Li <i>et al.</i> (2020)

The European Union is the world's number one tourism destination. Tourism activities are relevant not only to contribute to economic wealth and employment but also to the social and cultural development of European countries. In 2019, the inbound tourism expenditure of the European Union (28 countries) was 405 billion euros, while domestic tourism expenditure was 759 billion euros. The total outbound tourism expenditure was 299 billion euros (Eurostat, 2019).

Portugal is one of the countries in which the tourism industry contributes the most. In 2019 this sector contributed 8.5% of GVA (INE, 2020), 52.3% of services export, and 19.7% of total export (TravelBI, 2019). Tourism consumption in the economic territory represented around 15.4% of GDP. Moreover, this sector represented 9.4% of full-time employment (INE, 2020). The number of overnight stays increased by around 7.2% per year from 2010 to 2019, with a total of receipts of 18.4 billion euros in 2019 (Turismo de Portugal, 2023). In 2019 there were 6,833 establishments, 193,164 rooms, and 443,157 beds (TravelBI, 2019). The occupancy rate of rooms was 65%, and of beds, 53%, being Portugal the 7th European country with the highest occupancy rate (World Tourism Organization, 2023). Lisbon region was the one with the most international tourists and the North region with domestic tourism (TravelBI, 2019).

Despite its high economic and social contribution, the tourism sector is highly affected by macroeconomic changes, mainly due to its seasonality and high fixed cost structure (Wieprow & Gawlik, 2021). These facts explain why this sector is one of the industries with the highest mortality rate. The mean value of total industries in Europe is 8.4%, and for the tourism sector is 8.5% (Pordata, 2023). Portugal is the second European country with the highest mortality rate in the tourism sector with a mortality rate of 13.25%, while at the top is Bulgari with a percentage of 14.28% (Pordata, 2023).

Therefore, understanding the default risk of the tourism sector in Portugal is crucial due to the relevance of the sector to the Portuguese economy and the percentage of firms bankrupt in this sector. The bankruptcy of tourism firms can cause serious damage to the country, government, and the companies involved, making economic development difficult (Li et al., 2013).

The sample comprises ten years of analysis, 2010-2019. 2010 was the year of implementation of the current Portuguese accounting standards. The last year analysed is 2019 since in 2020 Portugal (like other countries) was affected by Covid-19. In March 2020, the Portuguese government forced the temporary closure of some establishments, and several restrictions were applied to mobility which strongly impacted the tourism sector. Therefore, the number of tourism arrivals to Portugal decreased by 73.7%, and domestic tourism also decreased by around 41.1% (INE, 2021). This situation has impacted the financial stability of tourism firms, which can have consequences on their probability of default, and it is not intended to capture this effect. This way, all information is analysed until 2019.

The sample was divided into two subsamples: 2010-2014 and 2015-2020. In 2015, the tourism sector in Portugal underwent a structural change, having been the best year in tourism in the last 10. A National Tourism Authority was created, which effectively implemented its strategy in 2015. As can be seen in Figure 2, 2015 presents itself as a turning point in terms of investment in the sector (Turismo de Portugal, 2015).

Financial and corporate governance information was collected in the SABI database (Iberian Balance Sheet Analysis System database from the Van Dijk Bureau), while macroeconomic data was collected from Pordata. To apply the ex-ante criterion, only companies that had at least 3 years of financial information were considered.

The final sample includes 3,945 SMEs, over ten years of analysis. It is an unbalanced sample, as most of the works analyse the tourism sector. Liu *et al* (2013) argue that a balanced sample may not reflect the reality of the industry.

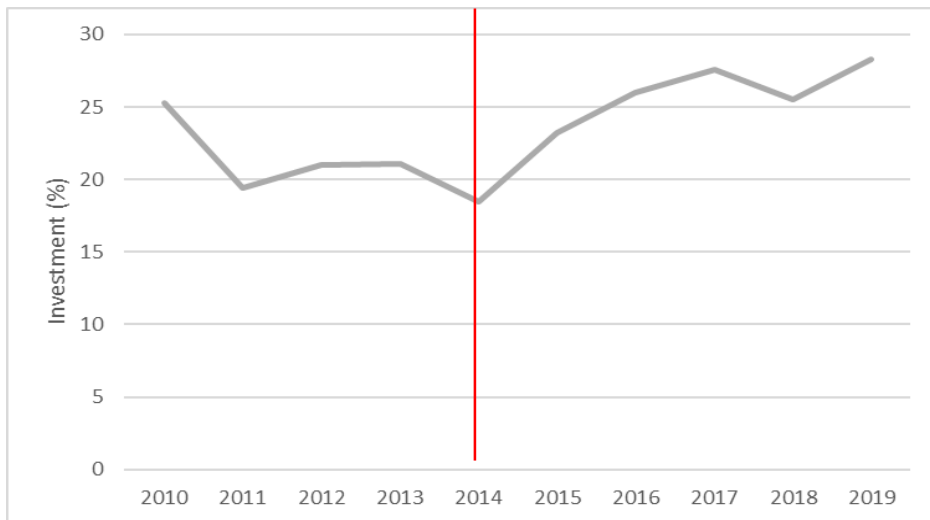


Figure 2. Investment in the tourism sector (%).

4. Results

4.1. Sample characterization

Figure 3 presents the percentage of firms in the sample in default and compliant by year as well as the evolution of Portuguese GDP growth and inflation rate.

The percentage of default firms surpasses the percentage of compliant firms in the years from 2012 to 2016. In this period the inflation rate increased, and since 2013 GDP growth decreased, leading to a contraction of the economic growth in Portugal. The tourism sector was one of the industries most affected by this recession due to the loss of purchasing power customers (Ribeiro, 2016). Moreover, in this period Portugal asked for economic assistance from the Troika (commission composed of the European Commission, the International Monetary Fund, and the European Central Bank) to surpass the high public deficit. Several contraction measures were applied, one with a direct impact on the tourism industry since the value-added tax increased from 13% to 23%.

4.2. Descriptive statistics

From the variables shown in Table 1, an analysis of correlation and multicollinearity problems was accomplished. We have performed the correlation matrix as well as the VIF (Variance inflation factor) analysis (results in appendix). Due to the high correlation between the ROA and ROS (both profitability determinants) and between GDP growth and unemployment rate (macroeconomic determinants), the variables ROA and the unemployment rate were not considered. The ROS variable was chosen since has been a variable used in studies on the tourism sector (Becerra-Vicario *et al.*, 2020; Fernández-Gómez *et al.*, 2016; Lee *et al.*, 2011). In the tourism sector, the percentage of temporary/seasonal work is quite high, which is why the GDP growth was selected.

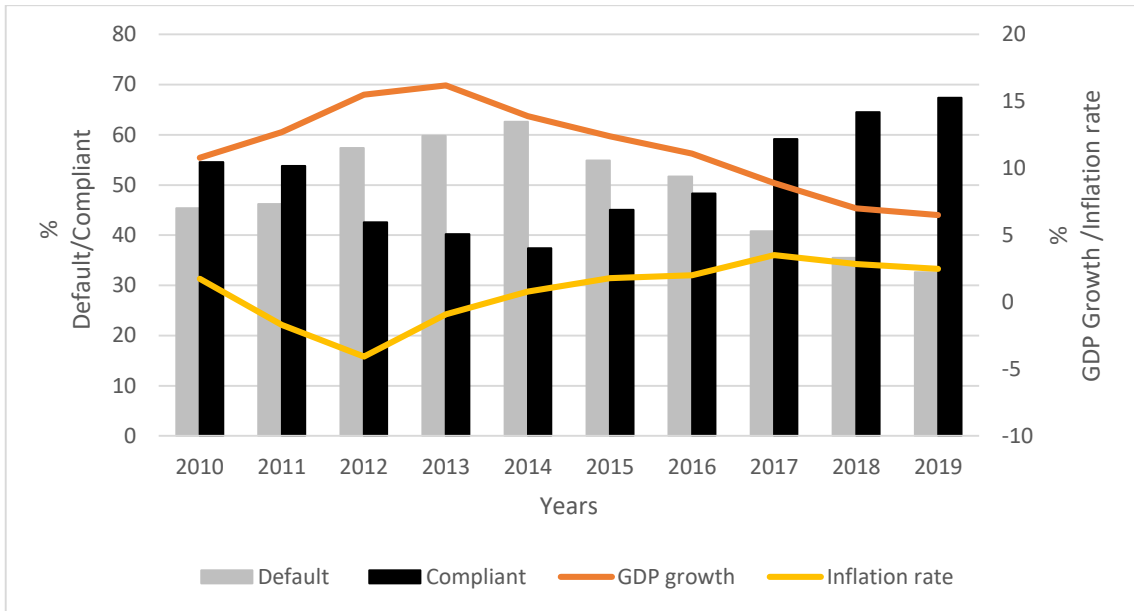


Figure 3. Firms' characterization and macroeconomic evolution.

Table 2 shows the descriptive statistics (mean, median, standard deviation, minimum, and maximum) for the final variables. Results are presented to the total sample and both groups: default and compliant. The Kolmogorov-Smirnov test was performed to verify the normality distribution. The result shows that the variables are not normally distributed. Therefore, the Mann-Whitney nonparametric test (MW) was performed to test if the medians for both groups of firms are statistically equal.

Table 2 shows (through the Mann-Whitney test) that, for a significance level of 1% (except for the variables % direct own, with 10%, and board size, with 5%), the median value of each determinant is singular for both groups of firms. This suggests that the determinants have a different influence on compliant and default companies.

Default firms present higher levels of indebtedness compared to compliant firms, confirming the literature results. Especially for tourism firms, the higher the firm's debt level, the greater its financial risk which increases the probability of having financial difficulties (Gu & Gao, 2000; Kim & Gu, 2006; Zhang & Xie, 2021).

Default firms are more efficient regarding asset turnover, i.e., generate (in median) more sales per unit of investment. This conclusion, which contradicts the main findings of default prediction literature, was also found by Zhang and Xie (2021) who suggested that the total assets of failed hotels could be relatively small. However, there is a high asymmetry among the default firms in the sample, which can cause bias in the results.

Default firms are smaller and younger than compliant ones. Small-size firms and new ones in the market usually have fewer resources and experience. Therefore, these firms have more difficulty adapting to adverse situations, which increases their probability of default (Zhang & Xie, 2021). Wilson *et al.* (2013) argue that older firms are less likely to default due to the increase in the experience of boards of directors in managing it.

Table 2. Descriptive Statistics

Variables	Groups	Mean	Median	Std. Deviation	Minimum	Maximum	MW P-value
Leverage	Default	1.215	0.906	2.871	0.000	142.598	0.000
	Compliant	0.561	0.574	0.220	0.003	1.524	
Efficiency	Default	2.477	1.766	4.029	0.000	306.093	0.000
	Compliant	1.765	1.568	1.222	0.000	12.335	
Size	Default	5.570	5.433	0.737	2.037	8.899	0.000
	Compliant	5.859	5.759	0.606	4.310	8.402	
Age	Default	18.430	14.000	16.357	2.000	115.000	0.000
	Compliant	19.430	16.000	15.167	2.000	117.000	
Cash flows	Default	0.089	0.032	1.190	-10.637	39.850	0.000
	Compliant	0.217	0.148	0.776	-11.848	17.291	
Financial interest	Default	2.690	2.190	2.708	-6.971	18.332	0.000
	Compliant	3.259	2.955	2.144	-3.976	16.691	
Asset Structure	Default	0.481	0.485	0.298	0.000	2.436	0.000
	Compliant	0.456	0.440	0.277	0.000	1.093	
Liquidity	Default	-0.307	-0.083	2.410	-141.598	1.000	0.000
	Compliant	0.111	0.086	0.323	-1.267	1.031	
Prof - ROE	Default	0.714	0.057	50.955	-490.420	4566.808	0.000
	Compliant	0.195	0.126	1.586	-59.550	151.761	
Prof - ROS	Default	-0.316	0.002	11.934	-1069.009	94.678	0.000
	Compliant	0.060	0.035	0.294	-1.494	29.717	
% direct own	Default	0.376	0.000	0.422	0.000	1.000	0.061
	Compliant	0.372	0.000	0.421	0.000	1.000	
Board size	Default	1.178	1.099	0.700	0.000	3.638	0.019
	Compliant	1.146	1.099	0.675	0.000	3.401	

With concern to cash flow, default firms present higher operational cash flow about debt, suggesting that high cash flows can lead to inefficient investments that can increase the firms' uncertainties. This result is contrary to the findings of previous research by Tinoco and Wilson (2013) and Kim and Gu (2010). Although it can be explained as firms in the sample present high ownership concentration and managers, who are less controlled, can opt to invest in projects that maximize their benefits when there is free cash flow (Jensen & Meckling, 1976).

For the financial expense ratio, compliant companies have more EBITDA over financial expenses. This result confirms the literature that argues that firms with greater coverage of financial costs have a

greater probability of meeting debt covenants, and thus less probability of default (Manzaneque *et al.*, 2016).

Default firms present a higher investment in fixed assets (asset structure) than compliant ones. To face investment in fixed assets they need more financial resources to support it, which causes more uncertainties and so greater probability of default. With regards to liquidity and profitability, default firms are less liquid and profitable, meaning that compliant firms have a better ability to meet financial obligations due to the level of liquidity and profitability. Similar results were found by Liang *et al.* (2020).

Finally, default firms present more direct ownership and large board sizes. The sample includes small and medium size firms and normally these firms have only one owner or a family owner. The weak legal protection of minority investors in Portugal also discourages the existence of smaller investors in companies (Fama & Jensen, 1983). The major owner can satisfy their interests, even if more uncertainties are added to the firm, which can hurt the firm's survival.

Moreover, most of the firms in the sample have less than 5 members on their board of directors, which is explained by the size of the firms analyse. If firms are of smaller and medium size, with less than 50 employees but more than 10, it is expected that the board is also of a smaller dimension. Even if a large board size can increase information transparency, as suggested by Lohe and Calabrò (2017) and Wilson *et al.* (2013), it is difficult to communicate, especially in small-size firms, and can delay decision-making, which can hurt the probability of default.

In summary, default firms are more leveraged, more efficient, smaller, and younger, with less financial interest coverage, greater asset structure, less liquidity, and less profitability. Moreover, governance variables are also relevant to explain a firm's default/compliant.

4.3. Model results

Table 3 reports the estimation results of the logit model estimation. In model I, the results are presented using the time horizon from 2010 to 2019. Models II and III present the results when the sample is subdivided into 2 subperiods, 2010 to 2014 and 2015 to 2019, respectively. The median difference of default of both subgroups of periods was analysed using the Mann–Whitney nonparametric test and results show that the two subsamples are statistically different at 1% of significance, validating the relevance of this division.

Analysing Table 3, we can conclude that the determinants of the model explain around 22% of default probability. This percentage increases when the sample is subdivided. Manzaneque *et al.* (2016) obtained a McFadden R-square between 11% and 12%, while Ahmad (2013), Donker *et al.* (2009), and Lee *et al.* (2011) were able to obtain a result between 40% and 57%.

All variables are statistically significant except for efficiency, asset structure, and profitability. However, some variables have different significance when the sample period is subdivided. Debt positively explains the probability of default, suggesting that the higher the firm's indebtedness, the greater the probability of default, as it lowers the capacity to meet financial obligations. According to Gu *et al.* (2002), Gu and Gao (2000), and Kim and Gu (2006), debt to tourism firms is one of the most important determinants of default. The result obtained corroborates the descriptive statistics and previous literature results (e.g., Abinzano *et al.*, 2020; Becerra-Vicario *et al.*, 2020; Donker *et al.*, 2009; Gu, 2002; Tinoco & Wilson, 2013; Md-Rus *et al.*, 2013; Ohlson, 1980; Santos *et al.*, 2015; Wilson *et al.*, 2013; Zhang & Xie, 2021; Zmijewski, 1984).

Table 3. Model results

	Variables	Expected Sign	Model I All Sample	Model II 2010-2014	Model III 2015-2019
Firms' specific characteristics	Constant		-5.795 ***	-7.529 ***	-4.478 ***
	Leverage	+	4.687 ***	4.392 ***	5.134 ***
	Efficiency	-	0.017	0.062	0.020
	Size	+/-	0.269 ***	0.618 ***	0.105
	Age	-	-0.026 ***	-0.013	-0.041 ***
	Age ²	+	0.000 ***	0.000 **	0.001 ***
	Cash Flow	-	0.131 ***	0.083	0.106 ***
	Financial interest	-	-0.096 ***	-0.212 ***	0.004
	Asset Structure	-	0.188	0.333	0.114
	Liquidity	-	0.342 **	0.218	0.618 ***
	Profitability - ROE	-	0.002	-0.003	0.049 *
	Profitability - ROS	-	0.002	-0.005	0.007
Corporate Governance	% direct ownership	-	0.036	-0.006	0.104
	Board size	-	0.378 ***	0.241 ***	0.455 ***
Macroeconomic	GDP	+/-	-8.296 ***	0.211	-74.945 ***
	Inflation	+	-14.716 ***	-16.954 ***	100.353 ***
	R₂ McFadden		22.32%	23.81%	23.58%
	R₂ Adjusted		21.73%	22.58%	22.44%
	Success rate		79.72%	78.52%	81.74%
	Error Type I		93.18%	88.15%	95.48%
	Error Type II		49.71%	61.34%	44.39%

* 10% significance level; ** 5% significance level; *** 1% significance level.

Size has a positive impact on default, in line with Turetsky and McEwen (2001) and Chancharat *et al.* (2010). Larger firms can have more difficulties in managing and monitoring employees. However, when the sample is subdivided, it is only relevant for the period 2010 to 2014. We found a U-shaped effect of age on the firm's probability of default (for the total sample and the period after 2015). Until a certain age, a firm's uncertainties decrease due to more experience and the ability to generate earnings (Altman, 1968). Although older firms have more difficulties in changing their habits and adapting to new market needs, which leads to a greater probability of financial problems and default. Similar conclusions were found by Lisboa *et al.* (2021).

The higher the operational cash flow over debt the higher the probability of default (for the total sample and the period after 2015). Kim and Gu (2010) state that firms in the tourism sector must maximize their operating cash flows to avoid default, particularly in very competitive markets. Although, our findings show the opposite, suggesting that an increase in cash flows can lead to managers' opportunistic behaviours that can lead to more uncertainties instead of the maximization of the firm's value (Jensen & Meckling, 1976).

Regarding financial interest coverage, the ratio hurts the default probability for the total sample and in the period from 2010 to 2014. This indicates that the greater the ability to meet its financial expenses, the lower the probability of default. This result is in line with Gottardo and Moisello (2017) and Tinoco and Wilson (2013).

Concerning liquidity, the coefficient is positive and statistically significant (for the total sample and the period after 2015), which means that the higher the firm's liquidity, the greater the probability of default. The sign of this variable is contrary to what the literature suggests, and the findings of the descriptive statistics show that default firms have in median less liquidity than compliant ones. However, this

determinant is measured by the ratio of working capital divided by total assets and a high working capital level can be related to inefficiencies in managing the firm's resources.

In the period 2015 to 2019, the ROE has a significant and positive impact of a 10% significance level). This does not corroborate the conclusions of Ahmad (2013) and Gottardo and Moisello (2016), however, it may be related to the inefficiencies in the use of equity. Regarding governance variables, only the board size is statistically significant and explains positively the probability of default. Our results suggest that the larger the board of directors size, the greater the probability of the firm's probability of default. Even if contrary to previous works such as Lohe and Calabrò (2017) and Wilson *et al.* (2013), it can be explained by the divergence of ideas and ideologies within the board of directors, which makes the decision-making more difficult and increases the firm's uncertainties and probability of default.

Finally, both macroeconomic variables are relevant to explain the probability of default negatively. The higher the GDP growth and inflation rate the less probability of default. Economic recession causes more financial difficulties for firms, which can lead to an increase in default, as found by Cathcart *et al.* (2020). An increase in inflation was expected to have a positive impact on default due to a decrease in customers' purchase power. However, after an increase in inflation, normally when it decreases the prices do not follow the same tendency, which can explain this result. A similar conclusion to the inflation rate was found by Costa *et al.* (2022). It should be noted that the impacts are different when the sample is subdivided. GDP growth is only relevant in the period 2015 to 2019 and inflation has the opposite impact from 2010 to 2014 compared to the period 2015 to 2019. However, when the period is split this conclusion is only verified in the period 2015-2019 when the sample is divided.

Analysing the model predictive capacity, the overall success rate is 79.72%, being higher for the subperiod of 2015-2019 than for the subperiod 2010-2014 (81.74% vs 78.52%). These success rates are in line with what was obtained by Tinoco and Wilson (2013) who obtained success rates for their models between 80% and 85%. Pindado *et al.* (2008) obtained a higher success rate of 87%.

The success rate encompasses error Type I (a compliant firm is classified as default) and Type II (a defaulting firm is classified as compliant). The models better classify compliant companies, implying a small percentage of error Type II, than default firms, which implies a higher error Type I. Beaver (1966) and Tinoco and Wilson (2013) refer that the costs associated with error Type I are generally higher as it may reflect investment losses.

5. Conclusion

Default risk is not a new issue, but as firms are exposed to more risks, it is essential to anticipate and manage it, to try to avoid bankruptcy as it implies costs for the economy such as unemployment, consumption reduction, and contraction of the economy.

This work aims to identify which determinants better explain the default risk of Portuguese SMEs in the tourism sector. The tourism sector is a relevant sector to analyse due to its contribution to economic growth. SMEs are studied as the majority of tourism firms are small and medium size. Finally, in Portugal, the tourism sector was one of the sectors with a high mortality rate, and it was the second country when analysing European countries.

First, we classify firms in default using an ex-ante criterion to early detect signs of financial difficulties and provide relevant insights to help stakeholders in their decision-making. Most works that analyse the default probability of tourism firms use an ex-post classification, i.e., firms already in bankruptcy. Then the logit model and a panel data methodology were applied to the sample. Three groups of

determinants are used as explanatory variables: the firm's specific characteristics (the most used), governance characteristics, and macroeconomic factors.

Results show that default probability is impacted by the three groups of determinants included, suggesting that the combination of different types of determinants helps to improve default prediction. Although, singular to previous work that analyse the default probability of tourism firms, profitability, and efficiency are not relevant to explain the default probability of Portuguese SMEs from the tourism sector. This result confirms that findings depend on the country and sample analyzed (Pelaez-Verdet & Loscertales-Sanchez, 2021), giving relevance to studies that focus on different data to add knowledge to the literature.

Our results show that default probability increases with debt, firm size, operational cash flows over debt, liquidity, board size, and inflation rate, and decreases with coverage of financial interests, and GDP growth. To the firm's age, a U-shape relationship is found. Large-size firms, with more debt and with more difficulties in paying financial interests have more difficulty in fulfilling their obligations to third parties. Contrary to expected, firms with more operational cash flows over debt, and more working capital have a greater probability of default suggesting that less efficient investments due to higher liquidity can increase firms' financial difficulties. Tourism firms have more financial problems in expansion periods because, in economic growth periods, firms are not so concerned with financial problems. Moreover, large board sizes difficult to communicate, causing difficulties for firms. The proposed model presented a success rate around of 80%, showing its accuracy in correctly identifying cases of default and compliant.

The year 2015 was a turning point for companies belonging to this sector, it is a year where the decrease of non-compliant companies is notorious. When the time horizon is divided, that is, when the subperiods 2010 to 2014 and 2015 to 2019 are analysed, some determinants have a different explanatory impact. The level of investment made in the sector may influence the factors determining non-compliance.

The size and coverage of financial charges are no longer determining factors for 2015-2019, whether cash flow and liquidity variables are not relevant to explain default probability for the subperiod 2010-2014. Variables related to cash flow and net results start to show importance, however with signs contrary to those expected by the literature review, believing that this may be related to the inappropriate use of earnings. The change in the impact of macroeconomic variables is curious. Economic growth, measured by GDP growth, is only significant after 2015. This may be related to the investment made by the government itself in this sector, which is proportional to the country's growth. The inflation rate changes its impact. The decrease in the purchasing power of families ends up negatively influencing the ability of companies to fulfil their obligations.

This work contributes to the debate of default probability. Our results show that it is important to include governance characteristics as well as macroeconomic factors to help explain default probability. A firm's specific characteristics and determinants are important but do not measure all factors that can explain a firm's uncertainties, so additional variables as the ones included in this work are relevant. Moreover, our work found some specific conclusions about the tourism sector as cash flow and liquidity, suggesting that analysing different industries has an impact on firms' uncertainties. Finally, to SMEs, board size has a contrary effect from those found in large-size firms. To SMEs, large size increases default probability since communication is more difficult which can cause a delay in decision-making, contributing to an increase in the firm's instability.

In addition to the contributions to the literature review, this work's conclusions are also relevant to practice. Tourism firm is an important sector to several countries and promoting their sustainability helps to promote the activity of other companies, from other sectors, contributing to increasing countries' wealth. Understanding firms' uncertainties and the determinants that contribute to decreasing their financial situation in advance helps managers and investors make timely decisions to avoid situations of bankruptcy. Results suggest that subsidies contribute to increasing companies' efficiency and productivity, which in turn can help them to have a more stable financial situation. Creditors can also understand the factors that can increase the probability of the firm to fail its commitments. Finally, the government can create strategic measures and make investments to promote the activity of tourism firms, helping these firms to surpass financial difficulties.

The main aim of the work was achieved. Although, we acknowledge some limitations that could be addressed in future research. Firstly, the work focuses on a specific sector and SMEs, a more homogeneous group to avoid biased results. Although, results should not be generalized to other sectors or types of firms. It is suggested for future works to explore this sector for other samples/countries and/or other firm sizes to understand whether the results could be generalized.

Secondly, for SMEs, there are few governance variables available to analyse, which has limited the analysis of this area in this work. Future work can try to identify the CEO's gender or the presence of female members on the board as it can impact the firm's probability of default. Third, the majority of the determinants used in this work are the firm's specific characteristics, based on financial statements which can be affected by earnings management practices. For future studies, it is proposed to also include qualitative variables to surpass this limitation. Finally, this sector was highly affected by the pandemic situation of Covid-19, but we only analyse till 2019 to avoid this impact. Future works can analyse a larger sample period to try to understand the impact of Covid-19 on a firm's default risk.

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Appendix

Table 1A: Correlation matrix and VIF analysis

	Default	Leverage	Efficiency	Size	Age	Cash Flow	Financial interest	Asset Structure	Liquidity	Prof - ROE	Prof - ROS	Prof - ROA	% direct own	Board size	GDP	Inflation	Unemployment	VIF
Default	1.000																	
Leverage	0.476**	1.000																2.185
Efficiency	0.085**	0.150**	1.000															2.383
Size	-0.278**	-0.249**	-0.707**	1.000														2.868
Age	-0.078**	-0.213**	-0.176**	0.176**	1.000													1.149
Cash Flow	-0.314**	-0.319**	0.156**	-0.001	0.032*	1.000												1.051
Financial interest	-0.175**	-0.353**	0.304**	-0.136**	-0.018*	0.316**	1.000											1.467
Asset Structure	0.040**	0.153**	-0.310**	0.203**	-0.014*	0.003	-0.235**	1.000										1.541
Liquidity	-0.273**	-0.590**	0.009	0.017*	0.119**	0.129**	0.244**	-0.491**	1.000									2.311
Prof - ROE	-0.123**	0.027**	0.216**	-0.078**	-0.132**	0.224**	0.368**	-0.127**	0.070**	1.000								1.313
Prof - ROS	-0.408**	-0.436**	-0.027**	0.203**	0.031**	0.372**	0.502**	-0.169**	0.320**	0.403**	1.000							1.847
Prof - ROA	-0.366**	-0.366**	0.231**	0.025**	-0.037**	0.416**	0.520**	-0.235**	0.323**	0.422**	0.884**	1.000						2.193
% direct own	0.012	0.065**	0.065**	-0.069**	-0.123**	-0.048**	-0.006	-0.034**	-0.024**	0.016*	-0.025**	0.000	1.000					1.024
Board size	0.016*	-0.098**	-0.265**	0.344**	0.288**	-0.009	-0.096**	0.079**	-0.018**	-0.119**	-0.007	-0.103**	-0.255**	1.000				1.758
GDP	-0.145**	-0.112**	0.091**	0.060**	-0.029**	0.106**	0.368**	-0.079**	0.107**	0.186**	0.349**	0.336**	0.030**	-0.059**	1.000			4.942
Inflation	-0.037**	-0.018**	-0.025**	-0.008	-0.015*	-0.039**	-0.193**	0.022**	0.018**	-0.046**	-0.047**	-0.040**	-0.014*	0.024**	-0.113**	1.000		2.020
Unemployment	0.187**	0.139**	-0.078**	-0.070**	0.039**	-0.078**	-0.295**	0.075**	-0.125**	-0.153**	-0.305**	-0.291**	-0.028**	0.055**	-0.843**	0.022**	1.000	3.567