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Research Paper

The impact of Covid-19 on Portuguese Accommodation Sector Default

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ABSTRACT

Purpose: Worldwide travel restrictions and other measures to mitigate the pandemic situation caused a period of instability for accommodation companies. The consequences of this global phenomenon are still being explored. This study aims to understand the impact of Covid-19 on the probability of not fulfilling its obligations (default risk) and on its determinants in the Portuguese accommodation sector.

Methodology: A Logistic regression on a panel data of 8,688 companies located in Portugal, from 2017 to 2022 was used.

Results: The results show that Covid-19 contributed to an increase in the percentage of defaulters. Moreover, the pandemic situation had an impact on what determines financial difficulties. The determinants are different depending on the period analyzed, and the company's size.

Originality: This study adds empirical evidence on the impact of non-payment in the accommodation sector in Portugal and, to the best of our knowledge, there is a lack of literature on the impact of Covid-19.

Keywords: *Default risk; Accommodation sector; Logistic regression; Covid-19; Portugal.*

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1. Introduction

Faced with critical situations, as the economic/financial crisis of 2007/2008, and the one caused in 2020 by the Covid-19 virus, companies are subjected to conditions that put their survival at risk. Strategic and timely decision-making is the key to companies' livelihood.

The social, political, and economic impact of business failures has led to the development of several bankruptcy prediction models to avoid situations of financial default (Jones et al., 2017). In origin, the works of Beaver (1966), Altman (1968), Ohlson (1980), and Zmijewski (1984) stand out. More recently, the original default models have received several changes to overcome some gaps, improve predictive power, or adjust to the reality under study, such as Altman et al. (2017), Chen et al. (2022). Barboza et al. (2017) emphasizes the importance of new studies that explore different models and contexts, as well as various sets of data, since, to date, there is no consensus in the literature regarding the best model for predicting default.

The tourism sector (which includes accommodation companies) is one of the driving forces of economic development and growth in the world. In 2022, Europe represented 61.7% of international tourist arrivals, and Portugal was in the fourth place of European countries with a more favorable tourism balance (INE, 2022). According to the Organization for Economic Development Cooperation (OECD), in Portugal, in 2018, tourism was the sector that contributed most to the growth of the Portuguese Gross Domestic Product (GDP). Concerning the specific case of accommodation, catering, and similar industries, the largest subsector of tourism (Kuhzady et al., 2022), it was the third sector that contributed most to Gross Value Added (GVA) and the third that employed the largest number of workers (Pordata, 2022).

Additionally, tourist activity is strictly related to economic growth, and, in times of crisis, many tourist companies end up going bankrupt (García & Miguélez, 2021). This is confirmed by Anguera-Torrell et al. (2021) who say that, in relation to the Covid-19 pandemic, hotel companies (a specific case of accommodation) were one of the economic industries with the greatest negative impact, due to its nature and business model based on the free movement of people around the world. In Portugal, in 2020, 12.4% of companies in the accommodation sector ceased activity. This percentage is higher than the average percentage of companies that ceased activity in other sectors (11.8%) (Pordata, 2022).

This study aims to understand the impact of Covid-19 on the default risk of the Portuguese accommodation sector. It is intended to identify how Covid-19 has affected the financial health of accommodation companies and whether it has changed the determinants of default. To the best of our knowledge, there is a lack of studies that analyze default in the accommodation sector in Portugal and none of them analyze the impact of Covid-19.

Although much has been studied after the emergence of the Covid-19 pandemic, the consequences on the financial ecosystem still have unexplored aspects whose analysis is important (Boubaker, 2023). The long-term impact on competitiveness needs to be further explored (Li et al. 2021). Specifically, understanding how firms' financial situation is impacted by financial crises, directly and indirectly through companies’ specific characteristics, and how it can lead to situations of default is crucial to help firms react in those moments to prevent situations of bankruptcy.

The effect of Covid-19 also reinforces the innovation as, to our knowledge, there are only few studies that analyze the impact of it on the default risk, and specifically in the accommodation sector, which was one of the sectors most affected. The works of Wieprow and Gawlik (2021) and Matejić et al. (2022) stand out, but the aim is distinct from this paper. Both works focus on comparing the results of different default risk models in the years 2019 and 2020, analyzing listed tourism companies. The present work intends to understand the direct impact of Covid-19 on companies' default risk, and on the determinants that are more relevant to explain default. Moreover, this work analyzes a larger period, with more recent periods, where the effects of Covid-19 on companies’ financial situation are more pronounced.

Other studies have focused on the specific case of hotels but analyzing other countries and without considering the impact of Covid-19 (e.g., Escribano-Navas and Gemar, 2021; Crespí-Cladera et al., 2021; Kim and Gu, 2014; Pelaez-Verdet and Loscertales-Sanchez, 2021). In Portugal, the study by Pacheco (2015) can be highlighted. The present study differs from the latter due to the sample, as Pacheco (2015) studies small and medium-sized companies (SMEs) from accommodation and restaurants. Furthermore, companies were analyzed in 2014, thus not being a longitudinal study as the present one nor capturing the effect of Covid-19.

A sample of unbalanced panel data from 8,688 Portuguese accommodations, from 2017 to 2022, is analyzed, corresponding to 36,771 observations. Companies are classified as compliant or default using an ex-ante criterion (i.e., based on a set of financial indicators). As far as it is known, there is a scarcity of studies applied to this sector and most studies use the ex-post criterion (i.e., the legal situation of bankruptcy) to classify firms in default. The fact that an ex-ante criterion is used allows the study to be replicated for other samples and helps managers detect signs of financial difficulties in advance to make decisions that can promote the firm's sustainability.

To explain default, and in line with more recent literature (e.g., Crespí-Cladera et al., 2021; García & Miguélez, 2021; Vicario et al., 2020; Wieprow & Gawlik, 2021), to adjusting the model to the context studied (sector, sample period), a set of variables were used. Internal and external variables are included, more specifically firm's specific characteristics and macroeconomic variables. Then the Logit model is estimated for the total sample and for two subsamples: before and during the Covid-19 pandemic, to check whether it had an impact on the determinants that explain the risk of companies defaulting.

To analyze the robustness of the results, the impact is analyzed by dimension (micro, small, medium, and large). This allows us to understand the specificities of each firm dimension, giving specific insights to each. The specificities of firms can explain the different findings of previous work, as well as contribute to practice since firms, even from the same sector, are not a homogeneous group.

2. Literature Review

2.1. Impact of Covid-19 on the Accommodation Sector

The free movement of people and goods has been an important milestone for people, businesses, and the development of countries themselves. Tourism has been boosted by the growing movement resulting from globalization (Khan et al, 2020). This has led to the tourism sector developing into one of the driving forces behind economic development and growth as recognized by several international organizations (OECD, 2022; World Travel & Tourism Council (WTTC), 2023).

According to the UNWTO (2023), the tourism sector represented 7% of global trade in 2019. For some countries, it can represent more than 10% of their GDP (e.g., Macao, Fiji, Philippines) and overall, it is the third largest export sector in the global economy. Such results have led many government decision-makers to invest in this sector through a series of investment and disclosure policies to take advantage of the growth, employment, and development. It is recognized that tourism directly and indirectly promotes other economic industries such as transportation, hospitality, or retailing (Brida et al., 2020). In 2019, the international tourist arrivals were more than 1,400 million, presenting a growing trend until this year. In 2019, the average income from tourism exceeded 1.4 billion dollars (UNWTO, 2023). Despite the inherent seasonality of the sector, in 2019 it employed about 10% of the world's population.

However, 2020 brought strong challenges. The tourism sector was one of the sectors that suffered the most from the Covid-19 pandemic, essentially given the reduction in the number of visitors. The impact was felt on several levels: economic, financial, operational, organizational, and technological (Almeida et al., 2022). In 2020 there was a drop of 72% in international tourist arrivals, and revenues fell by around 63% compared to 2019 (UNWTO, 2023) which had a negative impact on the GDP contribution (going from 3.9% to 1.8% and 2.8% in OECD countries). More than 100 million direct jobs were at risk. In cultural terms, 90% of museums are closed, and 13% may never reopen.

The strong impact of Covid-19 on tourism required a coordinated response from governments and the private sector, to mitigate the effects of this crisis and support and consolidate a sustainable and resilient recovery of the sector (OECD, 2022). Most countries have adopted economy-wide stimulus packages (fiscal and monetary measures), as well as employment measures to avoid an increase of companies' failures. Additionally, one measure adopted was the promotion of domestic tourism (World Tourism Organization, 2020). Although slow, the sector is recovering, contributing around 2.5% of GDP in 2022, with exports exceeding $1,000 billion. In 2021, the sector recovered 11 million jobs (UNWTO, 2023). In 2022, it created 21.6 million new jobs (one in 11 jobs worldwide) (WTTC, 2023).

Accommodation is a key element of the tourism sector (Mas-Ferrando et al., 2024), and it is considered to be the largest subsector (Kuhzady et al., 2022). It is a significant part of the traveling expenditure, around a third of tourism spending is on accommodation (Eurostat, 2021). The performance of the tourism sector is ultimately closely linked to all the facilities that surround a travel experience, and indeed accommodation plays an important role. On the other hand, tourism growth also encourages the development of these facilities.

Occupancy rates fell dramatically with Covid-19, for example from 55% to 39% in China, from 66% to 44% in the US, and from 44% to 28% in Europe (WTTC, 2023). In Europe, the average spending per trip fell by more than 27% (Eurostat, 2021). Indeed, the biggest drop in monthly hotel revenue per available room worldwide was in Europe (down almost 90%), followed by the US (down almost 80%) (Statista Research Department, 2021).

In the specific case of Portugal, where the accommodation sector is the third sector that contributed most to GVA and to employment (Pordata, 2022), Covid-19 had a huge impact.

The number of guests in tourism accommodations decreased by 60.4% and the number of overnight stays by 61.1%. These drops have led to a reduction of 23.6% in the number of accommodations. Some establishments were temporarily closed, but some have never opened again (INE, 2020).

2.2. Accommodation Default

Default risk research dates back to the 1960s with Beaver (1966). Since then, it has been a topic that has received special attention due to the impact that corporate default and bankruptcy have on people, companies, sectors, and economies (Lisboa et al., 2021). To tourism firms, default risk has negative consequences for entrepreneurs and stakeholders, such as tourists, employees, travel agencies, and other activities that support tourists and local communities (Matejić et al., 2022).

Corporate default is defined as the ability of cash flows to meet current financial obligations (Beaver, 1966). Despite a consensus definition, the classification of a firm as compliant or default is not unique. The literature has presented several criteria that can be grouped into (i) ex-post criteria, when using the legal status of companies, represented by the end of business activity, and (ii) ex-ante criteria, when using financial indicators to detect the probability of companies defaulting a priori (Lisboa et al., 2021).

Although the ex-post criterion is often used, it has some limitations, as the legal criterion depends on the country analyzed (Pindado et al., 2008), the legal process can be a lengthy one, and the legal date of default may not represent the actual event of default (Tinoco & Wilson, 2013). Concerning the ex-ante criterion, it allows for the detection of signs of failure in advance, allowing for timely decisions and thus avoiding potential bankruptcy. Du et al. (2020), Chen et al. (2022), Costa et al. (2022), and Lisboa et al. (2021) are examples of the application of the ex-ante criterion. In the literature, some studies use the ex-ante and ex-post criteria simultaneously. For example, a firm is considered to be in financial distress when it files for bankruptcy (ex-post criterion), but also when it meets one or more ex-ante conditions.

Regarding the default definition in the accommodation sector literature, to the best of our knowledge, most studies use the ex-post criterion (e.g., Abidin et al., 2021; Fernández-Gámez et al., 2016; García & Miguélez, 2021; Gémar et al., 2016; Gemar et al., 2018; Escribo-Navas & Gemar, 2021, Pelaez-Verdet & Loscertales-Sanchez, 2021). Situm (2023) argues that there

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are a limited number of works that focus on the early detection of failures, specifically in the tourism sector.

The most common models in the literature are Beaver's univariate analysis (1966), Altman's Z-score model (1968) estimated by multiple discriminant analysis (MDA), Ohlson's Logit model (1980), and Zmijewski's Probit model (1984). More recently, authors have been focused on the most accurate statistic models. Therefore, data-driven models have been used to predict default using techniques such as decision trees, support vector machines (SVMs), and artificial neural networks (Habib et al., 2020). However, these techniques have been less widely used due to their complexity, difficulty in interpretation, and time requirements (Costa et al., 2022). According to Alaka et al. (2018), no estimation model is characterized better than all the others, as each model has its strengths and weaknesses, which in practice makes each model suitable for a particular situation. Jones et al. (2017) concluded that SVM and decision trees have similar accuracy and present consistent values in relation to traditional statistical models, namely Logit and MDA.

In terms of the statistical models used in accommodation industry studies, traditional models are used, such as Abidin et al. (2021), Gu (2002), Kim and Gu (2010), Lee et al. (2011), Li et al. (2013), Pacheco (2015), Srhoj et al. (2024), Vivel-Búa et al. (2018), Wieprow and Gawlik (2021), as well as more recent methodologies, such as Escribo-Navas and Gemar (2021), Fernández-Gámez et al. (2016), García and Miguélez (2021), Gémar et al. (2016), Gemar et al. (2018), Pelaez-Verdet and Loscertales-Sanchez (2021), Situm (2023), and Vivel-Búa et al. (2018). To analyze the robustness of the analyzes, some studies use mixed approaches (e.g., Matejić et al., 2022).

2.3. Default determinants

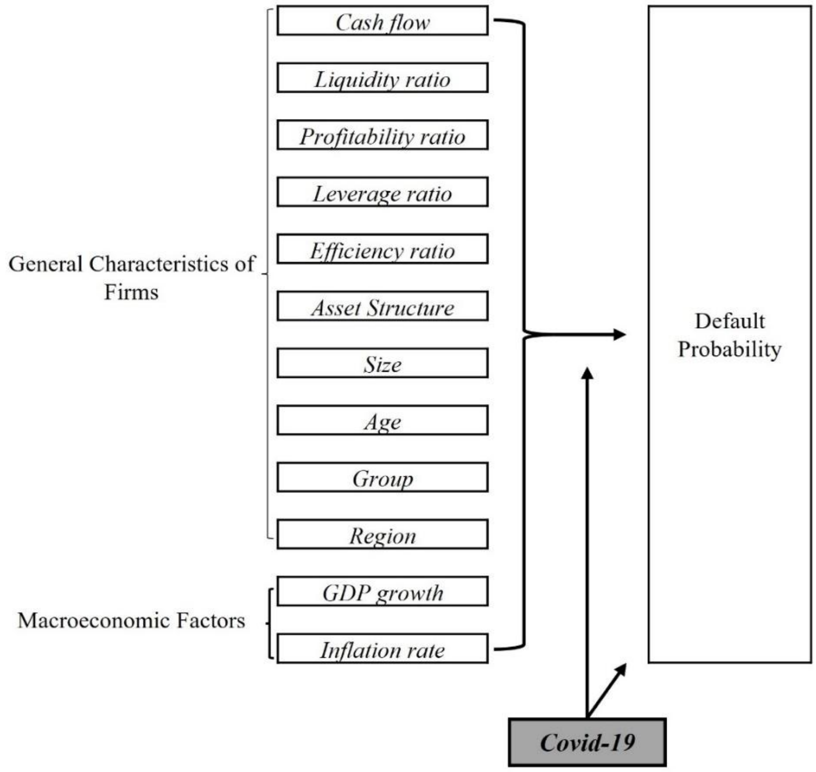
The literature, in general, has identified several default determinants to find the best predictive model most appropriate to the context studied (sector, sample period). The first bankruptcy prediction models were developed using accounting indicators and are still the most used in default prediction studies (Srhoj et al., 2024). Subsequently, models were developed using not only accounting ratios but also qualitative and market information variables as companies are connected to the market and interact with different stakeholders.

These determinants can be divided into i) general characteristics of firms (found in most default studies), which can be grouped into indicators of cash flow, liquidity, profitability, leverage, efficiency, size, and age, and also specific characteristics of the accommodation sector (the sector analyzed in this work) such as asset structure, group affiliation, and region; ii) macroeconomic factors such as GDP and inflation rate.

In addition to internal characteristics and macroeconomic factors, default can also be impacted by unexpected situations, such as social, political, and environmental as a disease (Covid-19). Castro (2016) found that the tourism sector is highly impact by crisis and recessions, due to the decrease of foreign tourists and changes in the consumers' habits. Kubickova et al. (2021) also argued that crises have a huge impact on tourism companies since are seen as a discretional consumer good. Covid-19 also impacted companies' financial situation. According to Sharma et al. (2021), the tourism sector, and the accommodation sector in particular, is characterized by a strong resilience that has taken advantage of the constraints imposed by Covid-19 to change in several ways, particularly in terms of increasing productivity, reducing costs, technological innovation, promoting local belonging and increasing consumer and employee confidence. Moreover, Kaczmarek et al. (2021) found that firms with low enterprise value, limited leverage, and high levels of investment suffer less impact of the negative effect of Covid-19 on travel and leisure companies' financial situation.

The following figure presents the conceptual model that this study aims to analyze.

Figure 1: Conceptual model



Source: Own Elaboration

3. Research methods

3.1. Sample

The main aim of this study is to understand the impact of Covid-19 on default risk and on its determinants in the Portuguese accommodation sector. According to the OECD, the direct economic impact on the tourism sector is far-reaching with spillover effects on the economy. Countries with large tourism sectors before Covid-19, such as Iceland, Mexico, and Portugal, have seen some of the largest declines in the sector's direct contribution to GDP (OCDE, 2022).

This work focuses on accommodation companies, a subsector of tourism. Only hotel establishments and holiday residences and short-term accommodations were included. Camping sites and youth hostels were not included as these types of accommodation include usually micro-companies, with more financial constraints, and with singular types of guests. Moreover, hotels and holiday residences represented, in Portugal, in 2022, 91.9% of guests and 90.3% of overnight stays (INE, 2022). Information was collected from micro, small, medium, and large companies. The dimension classification is based on the European Union directive (Law Decree n. 81/2017, which follows the recommendation number 2003/361/CE).

Until 2019, there was an increase in accommodation establishments, indicating that the sector followed the country's economic growth during this period. However, the year 2020 was marked by a decrease in the number of accommodations, which was attributed to the closure caused by Covid-19.

Company financial information was obtained from the Van Dijk Bureau's- Sistema de Análise de Balanços Ibéricos (SABI) database, while macroeconomic data was obtained from Pordata. The study focuses on the period from 2017 to 2022.

Regarding the impact of Covid-19 on the default determinants, two analyzes will be carried out. First, whether Covid-19 is a mediating variable of the impact of the determinants is analyzed, and then, the sample was divided into two subsamples: before (covering 2017 to 2019 inclusive) and during Covid-19 (covering the last three years).

Finally, we excluded from the sample all companies that did not provide information for at least three consecutive years. The final sample consists of an unbalanced panel of 8,688 establishments with a total of 36,771 observations.

3.2. Model and Variables

In line with Crespí-Cladera et al. (2021), Kim and Gu (2014), Lisboa et al. (2021), Pacheco (2015), and Vicario et al. (2020), this study uses Ohlson's Logit model (1980). There is no consensus about the best estimation model (Alaka et al., 2018). The Logit model is one of the most widely used models and has been applied in different samples. It does not impose certain requirements, such as the normality of the variables, as it is a model that is easy to implement and interpret.

The panel data methodology was used, as in Pindado et al. (2008), Escribano-Navas and Gémar (2021), Gémar et al. (2016) and Vivel-Búa et al. (2018). Panel data allow controlling for unobserved heterogeneity and can eliminate the omitted variable bias that arises when unobserved individual-specific effects are correlated with the explanatory variables (Pindado et al.,2008).

The dependent variable is a binary variable that takes the value one if the company is in a situation of default and zero if it is compliant. As it is intended to analyze what determines a company's financial difficulty, checking whether a global phenomenon such as Covid-19 has an impact on these determinants an ex-ante criterion was used. This criterion makes it possible to predict companies' financial difficulties in advance, which helps stakeholders to make early decisions that promote the company's continuity. Following Costa et al. (2022) and Lisboa et al. (2021), a company is considered compliant when analyzing the last 3 years, at least one of the following ratios is observed individually in at least one of the years and a 50% positive evaluation is obtained in all possible combinations, namely:

- Capital ratio of more than 5%;
- EBITDA/interest and similar expenses greater than 1.3;
- Financial debt / EBITDA equal to or greater than 0 and less than 10.

All companies that do not fulfil these criteria are classified as defaulters.

The explanatory variables were chosen based on previous literature about default prediction and for the specific case of tourism firms. These variables are divided into two main groups: specific determinants and macroeconomic factors. The following table presents the determinant, the proxy used, and the source.

Table I: Explanatory variables

Determinant	**Proxy**	**Source**
Specific Characteristics		
CF (Cash Flow)	Operating Cash Flow/ Liabilities	Gu, 2002
Liq (Liquidity)	Current Assets/Current Liabilities	Fernández-Gámez et al., 2016; Abidin et al., 2021; Wieprow & Gawlik, 2021
Prof (Profitability)	Net profit margin: Net Income/ Sales	Gu & Gao, 2000; Gu, 2002; Lee et al., 2011; Fernández-Gámez et al., 2016; Gémar et al., 2016
Lev (Leverage)	Liabilities/Assets	Gu & Gao, 2000; Gu, 2002; Fernández-Gámez et al., 2016; Vivel-Búa et al., 2018; Abidin et al., 2021; García & Miguélez, 2021; Wieprow & Gawlik, 2021
Effic (Efficiency)	Cost employee/Sales	Gémar et al., 2016; Gemar et al., 2018
A. Str. (Asset Structure)	Fixed Assets/Assets	Lee et al., 2011
Size	ln(sales)	Escribo-Navas & Gemar, 2021
Age	ln (age)	Gémar et al., 2016; Gemar et al., 2018; Abidin et al., 2021
Group	Takes the value 1 if it belongs and 0 otherwise	Nicolau, 2005; Dahlstrom et al., 2009

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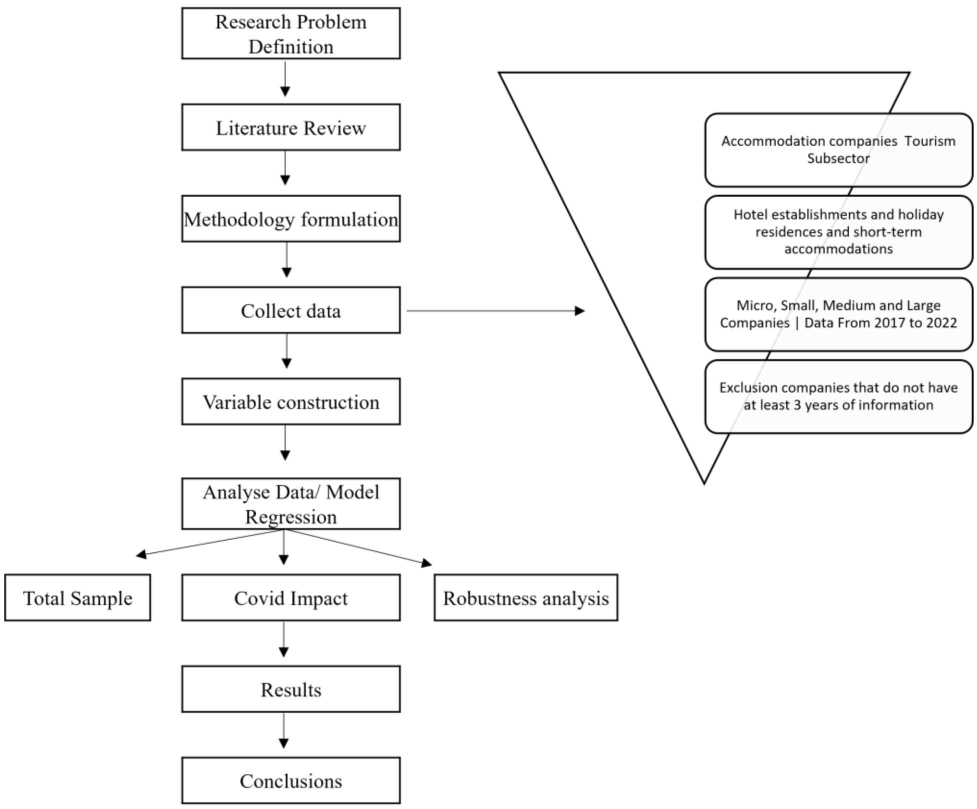
Region	1 - Nort; 2 - Centre; 3 - Lisbon; 4 - Alentejo; 5 - Algarve; 6 - Madeira; 7 – Azores	Gémar et al., 2016; Fernández-Gámez et al., 2016
Macroeconomic factors		
GDP (Gross Domestic Product)	GDP growth	Cathcart et al. 2020
Inflation	Inflation rate	Tinoco & Wilson, 2013
Covid-19	Takes the value 1 in years of Covid-19 (2020 to 2022) and 0 otherwise (2017 to 2019)	

Source: Own Elaboration

The direct impact of Covid-19 will be analyzed as well as its moderating role in the determinants.

The following figure summarizes the research steps:

Figure 2: Research steps



Source: Own Elaboration

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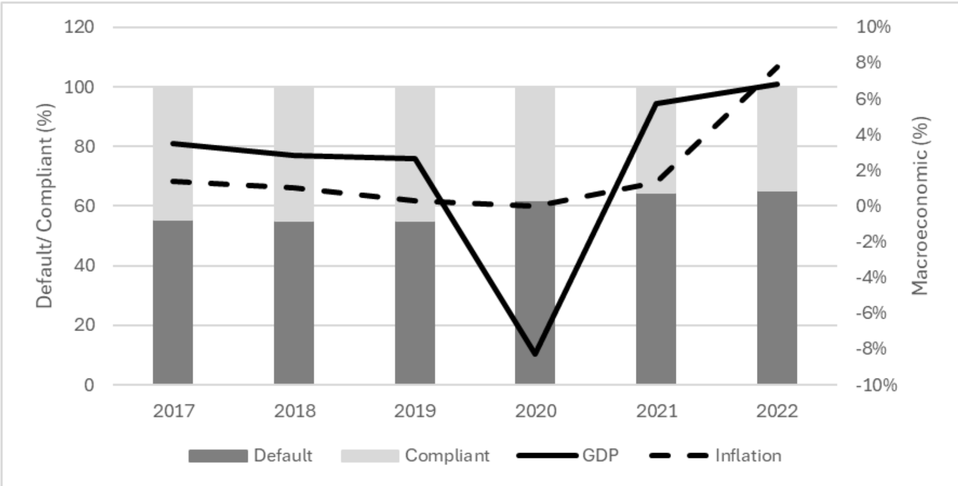
4. Results

4.1. Sample characterization

Graph 1 presents the percentage of companies classified as default and compliant per year of analysis, as well as the evolution of GDP and the inflation rate.

Graph 1: Companies Classification per year



Source: Own Elaboration

The graph shows that several Portuguese companies from the accommodation sector present signs of financial difficulties, which can be justified due to their seasonality. The percentage of default firms slightly decreased from 2017 to 2019, but afterward, it increased, suggesting that Covid-19 impacts companies' financial situation, in line with the findings of Kubickova et al. (2021). Moreover, an analysis of the macroeconomic variables (GDP and inflation) shows that the deterioration in the financial situation of companies is in line with the decline in economic growth and the fall in purchasing power (rise in inflation). Similar conclusions were found by Castro (2016) when analyzing the impact of the great recession of 2010 in the Portuguese tourism sector.

4.2. Descriptive Statistics and Correlation

The Kolmogorv-Smirnov analysis was performed showing the non-normality of variables. Table II presents the descriptive statistics of the variables and the median value of the variables for default and compliant firms, and before and during Covid-19. The Mann-Whitney nonparametric test (MW) was performed to verify whether the medians of groups are statistically equal.

Most accommodation companies present some financial difficulties (default situation). The cash flow ratio shows that companies present some difficulties in generating free cash flow. The liquidity ratio indicates that the amount the company expects to receive in the short term is adequate to pay its current debts. In median, companies are profitable. Around 73% of total assets are financed by debt. Companies are efficient (in median), as the cost paid to employees contributes to increased sales. 58% of total assets are fixed assets (asset structure). Regarding size, most companies have similar dimensions. The youngest firm in the sample is 3 years old, while the older is 125 years old. The generality of firms in the sample belongs to a group and firms are located in the seven regions of Portugal. Finally, the GDP growth and inflation rate reveal that the period analyzed includes both downturn and upward moments.

Table II also evidence that all determinants that measure firms' specific characteristics are singular to default and compliant companies. Compliant firms have more liquidity, profitability, efficiency, and fixed assets and less debt than default firms confirming the findings of Kaczmarek et al. (2021). Compliant firms are in median larger and older.

When analyzing the two subperiods, before and during Covid-19, most of the variables of the sample present singular median values (except belonging to a group) suggesting that Covid-19 caused an impact on firms' financial situation. Companies' liquidity was higher during the years of Covid-19, indicating that firms focused on increasing current assets to be prepared for uncontrollable factors. The profitability decreased as the number of guests decreased around 60.4% in 2020 (INE, 2020). Leverage increased since, even if the operational activity was closed, companies needed to maintain their fixed costs and negotiated moratoriums with banks to pay only interest (and not capital) during a specific period. The efficiency increased during Covid-19, revealing companies' resilience, as argued by Sharma et al. (2021). Asset structure slightly decreased, as well as firm size and age, which can be justified by the close of some accommodation. Finally, regarding GDP and inflation, both were high during Covid-19.

The correlation matrix and the Variance Inflation Factor (VIF) test were performed. GDP growth and inflation rate are highly correlated, and the VIF of the inflation rate is high, so this variable will be excluded from the analysis.

Table II: Descriptive Statistics

	Min.	Max.	Std. Dev.	Mean	Median						
					Total	Default	Compliant	MW P-value	Before Covid-19	During Covid-19	MW P-value
Default	0.0000	1.0000	0.4891	0.6040	1.0000	-	-	-	1.0000	1.0000	0.0000
CF	-55.4781	17.8462	0.5238	0.0147	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Liq	0.0000	1,478.1824	68.2487	13.8304	1.6007	1.4454	1.7638	0.0000	1.5751	1.6148	0.0591
Prof	-912.6627	997.2244	21.0798	-0.9501	0.0201	-0.0169	0.0533	0.0000	0.0437	0.0020	0.0000
Lev	0.0000	467.0252	7.2197	1.2104	0.7285	0.8991	0.5792	0.0000	0.6709	0.7673	0.0000
Effic	0.0000	1,111.2829	14.3358	0.8860	0.2655	0.2564	0.2742	0.0000	0.2499	0.2832	0.0000
A. Struct.	0.0000	1.0000	0.3520	0.5187	0.5848	0.5479	0.6224	0.0000	0.6061	0.5696	0.0000
Size	0.0000	18.5766	1.8904	11.6075	11.5082	10.9202	12.4037	0.0000	11.8727	11.2651	0.0000
Age	3.0000	125.0000	14.2103	14.7643	9.0000	7.0000	13.0000	0.0000	11.0000	8.0000	0.0000
Group	0.0000	1.0000	0.0570	0.9967	1.0000	1.0000	1.0000	0.0000	1.0000	1.0000	0.3219
Region	1.0000	7.0000	1.7153	3.0397	3.0000	3.0000	3.0000	0.0000	3.0000	3.0000	0.0234
GDP	-0.0830	0.0683	0.0519	0.0237	0.0351	-	-	-	0.0285	0.0574	0.0000
Inflation	0.0000	0.0780	0.0293	0.0228	0.0130	-	-	-	0.0100	0.0130	0.0000

Where: CF- Cash Flow; Liq- Liquidity; Prof- Profitability; Lev- Leverage; Effic- Efficiency; A. Struct- Asset Structure; GDP- Gross Domestic Product.

Source: Own Elaboration

4.3. Logit Regression

4.3.1. Model

Table III presents the estimation results.

Table III: Model results

	Expected sign	Total sample		Before Covid-19	During Covid-19
		Model 1	Model 2	Model 1a	Model 1b
CF	-	−0.0257	−0.0171	−0.0159	−0.0365
Liq	-	0.0016 ***	0.0020 ***	0.0019 ***	0.0014 ***

Prof	-	−0.0049 ***	−0.0043	−0.0044	−0.0050 ***
Lev	+	1.8342 ***	1.7425 ***	1.7393 ***	1.8928 ***
Effic	-	−0.0093 ***	−0.0060	−0.0070	−0.0093 ***
A. Struct.	-	−0.8311 ***	−0.7993 ***	−0.8085 ***	−0.8401 ***
Size	-	−0.4673 ***	−0.4721 ***	−0.4788 ***	−0.4568 ***
Age	-/+	−0.1786 ***	−0.0966 ***	−0.0979 ***	−0.2425 ***
Group	-	−0.8271 ***	−1.0440 ***	−1.3339 ***	−0.4145
Region		−0.0463 ***	−0.0383 ***	−0.0393 ***	−0.0520 ***
Covid19		0.0225	-	-	-
GDP	-	2.6695 ***	7.9644	5.1979	2.6183 ***
CF x Covid-19		-	−0.0185	-	-
Liq X Covid-19		-	−0.0006	-	-
Profit X Covid-19		-	−0.0007	-	-
Lev X Covid-19		-	0.1481 **	-	-
Effic X Covid-19		-	−0.0035	-	-
A. Struct.X Covid-19		-	−0.0475	-	-
Size x Covid-19		-	0.0107	-	-
Age x Covid-19		-	−0.1473 ***	-	-
Group x Covid-19		-	0.3889	-	-
Region X Covid-19		-	−0.0144	-	-
GDP x Covid-19		-	−5.3353	-	-
Adjusted R2		22.50%	22.54%	21.08%	22.79%
Success rate		71.6%	71.6%	70.5%	72.4%

Where: CF- Cash Flow; Liq- Liquidity; Prof- Profitability; Lev- Leverage; Effic- Efficiency; A. Struct- Asset Structure; GDP- Gross Domestic Product. Model 1 presents the regression results analyzing the direct effect of the Covid-19 dummy variable. Model 2 presents the regression results by inserting the Covid-19 variable as a mediating variable. Model 1a and 1b represent the regression results of the subsamples before and during Covid-19, respectively. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

Source: Own Elaboration

The results presented in Table III show that determinants are statistically significant to explain default risk, except cash flow and the dummy that measures the impact of Covid-19 (model 1).

Results show no direct impact of Covid-19 on default prediction (model 1). However, when the interaction of the dummy Covid-19 with the determinants is used (model 2) some conclusions emerge. Covid-19 had a particular impact on companies' leverage and age. Sharma et al. (2021) argued that accommodation companies tried to be resilient and to adapt the business to survive during the pandemic. Profits were not the main focus since there was a restriction on the free movement of people. To surpass the lack of profits, companies' leverage increased. According to Kaczmarek et al. (2021), companies less indebted had less financial problems since have more ability to look for financial funds when the operational activity stopped. This explains why leverage is one of the most relevant determinants in unexpected situations.

Additionally, Covid-19 causes more damage to young companies, since these companies have less self-funding and experience, so less support to surpass a decrease in sales and profits.

Regarding the explanatory variables, firms with higher liquidity are more prone to have financial difficulties, maybe because their short-term assets are less liquid (e.g., inventories or bad debts). This conclusion is singular compared with that of Abidin et al. (2020) and Srhoj et al. (2024), for example, which can be explained by the period analyzed. Less profitable firms have less financial resources to meet their obligations and to invest in the company and are less efficient, so are more likely to default. Similar results were found by Situm (2023).

Leverage increases default probability, since firms have more commitments to fulfil, as suggested by Cathcart et al. (2020). The efficiency ratio negatively impacts default. When firms are more efficient in managing their inputs and outputs, they have more profits and less financial difficulties, as also found by Gu (2002). Concerning asset structure, the results confirm Lee et al. (2011) findings, as fixed assets can be used as collateral in case of financial problems of firms, reducing the probability of default. Similar to Situm (2023), smaller firms are more prone to default since they have less experience and knowledge about the market. Moreover, large-size companies usually have more resources that can help to reduce the risk of failure. Regarding age, a negative impact is found, since as firms get older, they have more cash flow, more resources, and a competitive advantage that contributes to reducing their risk.

Belonging to a group reduces the probability of default as firms' activity is more diversified, contributing to decreased risk. Similar results were presented by Situm (2023). The region where the firm is located also impacts results, in line with the findings of Nicolau (2005) and Gémar et al. (2016). Moreover, it can explain regional disparities within the same country as not all areas have the same number of visitors, depending on the facilities surrounding a travel experience. Finally, a negative impact of GDP growth on default was expected, based on Cathcart et al. (2020), but the result was the contrary. The sample period is singular as in 2020 GDP growth had a great decrease and a recovery in the period after, which can explain the results.

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When analyzing the two subperiods separately (model 1a and 1b), results show that determinants that explain default before and during Covid-19 are singular. Before Covid-19 (model 1a), profitability, efficiency, and macroeconomic factors are not statistically significant to explain default probability, while during Covid-19 (model 1b), results are similar to those obtained from the total sample, except for the variable belonging to a group which is not statistically significant. The model's success rate is higher for the period of Covid-19 (72.4%), than before Covid-19 (70.5%) and higher than for the total sample (71.6%).

4.3.2. Robustness analysis

Additionally, as a robust analysis, we test the model per firm dimension to see if the determinants that explain default probability depend on the type of firm (table IV).

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Table IV: Model results per firm dimension

	Micro		Small		Medium		Large	
	Model 1c	**Model 2a**	**Model 1d**	**Model 2b**	**Model 1e**	**Model 2c**	**Model 1f**	**Model 2d**
CF	−0.0267	0.0042	−0.0416	−0.2666	0.4458 **	0.6673 **	−0.0983	0.6574 *
Liq	0.0015 ***	0.0017 ***	−0.0003	−0.0024	0.1002 ***	0.0977 **	0.0031 **	0.0103 ***
Prof	−0.0042 **	−0.0047	−0.0086 **	0.0043	−0.2279 ***	−0.3222	−0.0394 **	−0.0069
Lev	1.6604 ***	1.5169 ***	2.4852 ***	2.4683 ***	4.0244 ***	3.6953 ***	1.9009 ***	2.1491 ***
Effic	−0.0076 **	−0.0136	−0.0437 **	0.1584	−0.2128 **	−0.2861	−0.0439	0.0102
A. Struct	−0.7792 ***	−0.7099 ***	−0.8225 ***	−0.8986 ***	−0.6759 ***	−0.5578	−1.2233 ***	−1.4094 ***
Size	−0.5014 ***	−0.5173 ***	−0.5326 ***	−0.5388 ***	−0.2949 ***	−0.2434 **	−0.3607 ***	−0.3939 ***
Age	−0.1793 ***	−0.1054 ***	−0.1742 ***	−0.0796	−0.4017 ***	−0.3945 **	−0.0831	0.0227
Group	0.3389	0.3346	−1.5602 ***	−1.9703 ***	−2.5128 ***	−3.0368 ***	−0.2552	−0.5046
Region	−0.0493 ***	−0.0475 ***	−0.0644 ***	−0.0422	−0.1088 **	−0.1363 *	0.0094	0.0368
Covid19	0.0413	-	−0.1329 *	-	−0.0299	-	0.1197	-
GDP	2.8330 ***	4.3872	2.6467 ***	16.8860	2.5501	12.2285	2.3011 ***	6.5910
CF x Covid-19	-	−0.0624	-	0.6076 *	-	−0.2832	-	−1.1535 **
Liq x Covid-19	-	−0.0005	-	0.0044	-	0.0081	-	−0.0092 **
Prof x Covid-19	-	0.0006	-	−0.0193	-	0.1338	-	−0.0374
Lev x Covid-19	-	0.2371 ***	-	0.0329	-	0.7132	-	−0.3232
Efficx Covid-19	-	0.0073	-	−0.2149	-	0.1199	-	−0.0473
A. Struct. x Covid-19	-	−0.1127	-	0.1596	-	−0.1941	-	0.3405
Size x Covid-19	-	0.0284	-	0.0183	-	−0.0935	-	0.0495
Age x Covid-19	-	−0.1307 ***	-	−0.1862 **	-	0.0001	-	−0.2026 *
Group x Covid-19	-	−0.0150	-	0.6390	-	1.1394	-	0.3981
Region x	-	−0.0039	-	−0.0467	-	0.0484	-	−0.0444

Covid-19 GDP x Covid-19	-	−1.6103	-	−14.4421	-	−9.4799	-	−4.2150
Adj. R2	18.66%	18.68%	20.79%	20.87%	26.12%	25.11%	21.10%	21.18%
Sucess rate	70.5%	70.7%	76.2%	76.7%	83.5%	83.7%	70.4%	71.1%

Where: CF- Cash Flow; Liq- Liquidity; Prof- Profitability; Lev- Leverage; Effic- Efficiency; A. Struct- Asset Structure; GDP- Gross Domestic Product. Model 1e to model 1h represent the regression results analyzing the direct effect of the Covid-19 dummy variable of the subsamples micro, small, medium, and large dimensions, respectively. Model 2c to model 2f present the regression results by inserting the Covid-19 variable as a mediating variable of the subsamples micro, small, medium, and large dimensions, respectively. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively

Source: Own Elaboration

Analyzing Table IV, most of the determinants explain the probability of default in the same way, however, there are differences to highlight. Cash flow is a significant determinant for medium-sized enterprises although it has the opposite sign to what would be expected). Efficiency, age, belonging to a group, and the region do not determine the default probability of large companies. Belonging to a group also does not affect micro-size companies, nor does GDP growth impact medium-size companies. Interestingly, the Covid-19 period has a negative influence on the probability of default for small companies, suggesting that during Covid-19 small firms tend to improve their financial situation to survive in the market.

The interaction of the dummy Covid-19 with the determinants confirms the relevance of cash flow to explain the default probability of small and large-size firms. Although to small companies, the impact of cash flow on default probability is positive, to large-size firms the effect is the opposite. To large-size firms, results suggest that during Covid-19 firms with less free cash flows had more probability of default. The interaction of liquidity with Covid-19 is also relevant to negatively explaining default probability to large-size firms.

In line with previous results, when interacting Covid-19 with the determinants, profitability, efficiency, age, region (these last two only to medium and large-size firms), and GDP growth lose their statistical significance to explain default. Asset structure is also irrelevant to explain the default probability of medium-size firms. Finally, leverage to micro firms, and age to micro, small, and large firms are the determinants most relevant to explain default probability during Covid-19. The model has a higher success rate in medium-sized companies.

5. Conclusion

Creditors, shareholders, and managers need to understand the determinants explaining the risk of corporate failure, to make better investment decisions to avoid financial distress. The tourism sector, and the accommodation in particular, has been one of the hardest hits by the Covid-19 virus. It forced many companies to rapidly reconsider their business, due to the limitation of the free movement of people and to financial constraints.

This study aims to understand if Covid-19 directly impacts default risk, and indirectly the determinants that explain the default risk of companies in the accommodation sector. The idea is to understand whether this global phenomenon has had an impact not only on the likelihood of a business not complying, but also on what determines that likelihood. For this purpose, information from a data panel with a time horizon covering the period 2017-2022 was analyzed using a sample of 8,688 Portuguese companies in the accommodation sector.

The results allow us to conclude that the median probability of default is different before and during the Covid-19 period, as well as the explanatory determinants (firm-specific and macroeconomic characteristics). When estimating the model, the direct impact of Covid-19 is not statistically significant but caused a huge impact, especially in companies' leverage and age. Companies more indebted and younger have more probability of failure, since have less probability to look for additional financial sources to surpass the lack of earnings due to a decrease of the number of guests. Moreover, younger firms have more financial constraints as have less self-funding and experience in how to surpass macroeconomic shocks. Additionally, results show that profitability, efficiency, and economic growth have become important during the Covid-19 period. The fact that the company is protected by a group no longer has an impact on default probability. Moreover, during Covid-19 more levered and younger firms had more probability of default.

Company size influences how the determinants explain the probability of default. To large-size firms, during Covid-19 cash flow and liquidity are two relevant determinants to explain default probability, while to other firms' dimension age is the most relevant determinant to explain default probability, as well as leverage to micro-size firms.

The present work presents several contributions to literature. First, the sample focuses on a sector that is relevant to most economies, both in terms of the development of communities and the creation of wealth and employment for the country. This sector has been little explored within the scope of default risk, so this work contributes to increasing the debate in the area. Second, studies about Portuguese accommodation are scarce. Portugal is a small country, and most companies are small size, with a financial situation less stable, making Portuguese companies apart from others of larger-developed countries. This allows us to understand whether country size may affect companies' probability of default. Moreover, macroeconomic impacts can cause huge damage to companies' financial position, leading to a situation of default.

Third, the focus is not on understanding the best predictive model, as in the works of Wieprow and Gawlik (2021) and Matejić et al. (2022), or the best set of explanatory variables as in Habib et al (2020) and Lisboa et al., (2021), but rather the impact of Covid-19 on default probability and on the determinants that explain default. Thus, this paper intends to fill this gap in the literature and explore the specific impact of Covid-19. This adds new knowledge to the literature and can help managers to lead with future economic instabilities. The pandemic situation had a huge impact on companies, and it was an opportunity to focus on the most important to ensure companies' sustainability.

The results of the study may be useful for managers and shareholders, by identifying the factors that best reflect the financial health of companies. They can understand what promotes the companies' resilience to unexpected situations such as Covid-19. Companies have undergone a change with this global phenomenon, and the paper's results can be seen as a decision-making tool to predict default and avoid bankruptcy. To avoid great impacts in companies' financial situation during unexpected events, companies should focus on avoiding high levels of indebt as it causes more constraints. Moreover, younger firms should be more resilient to overcome moments with higher constraints.

For creditors, the proposed model is also relevant, as it contributes to ascertaining the company's potential to fulfil its commitments, allowing it to understand the exposure of capital to the risk of default. The Government can implement strategic policies and/or create infrastructures to promote the development of tourism and help companies to be more profitable to avoid situations of default. The bankruptcy of tourism companies has impacts not only on the surrounding companies but also on the development of local communities, employment, country wealth, and reputation.

For future works, would be interesting to analyze other countries, specifically regarding the impact of unexpected situations such as Covid-19. It could be particularly interesting to analyze countries where the tourism and accommodation sector has a strong economic impact on the country's development.

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