Financial determinants of hotel bankruptcy in Greece.

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Abstract
The aim of the study is to identify the financial determinants of firm bankruptcy in the Greek hotel sector for the period of 2010-2020. Combining legal bankruptcy events and financial data from two credible databases, an imbalanced sample occurs with five and a half thousand hotels of which thirteen were declared bankrupt, belonging solely to the economic activity "hotels and similar accommodation" corresponding to NACE code 5510. The econometric method is a multi-period logistic regression with clustered robust standard errors, an approach widely used in finance, but with most applications examining aggregated rather than segregated sectors. With the assistance of a stepwise procedure for variable selection, the main results show that the likelihood of Greek hotel bankruptcy is an increasing function of leverage and size and a decreasing function of EBITDA to total liabilities. By extending the bankruptcy horizon by two years, leverage keeps its qualities, but statistical significance for liabilities coverage and size becomes intermittent. A comparison is done also with two related studies conducted in Greece but for earlier time periods, the one for the whole economy with the same methodology and the other for hotels with multiple discriminant analysis and the traditional set of Altman's financial ratios. By loading the other studies' variables into the multi-period logit, results differ in terms of relevance and statistical significance, as also the sign for size with the whole economy model, suggesting that updated industry-specific bankruptcy modeling is more appropriate. The implications of the study offer empirical early warning indicators of hotel default and can be informative for stakeholders involved in the sustainability of the sector.

Keywords
Hotel bankruptcy, economic activity bankruptcy prediction, hotel sector, multi-period logit, financial ratios

Introduction

Firm bankruptcies have severe costs on business and society (Ang et al., 1982; Bernanke, 1981; Kim, 2018; Warner, 1977), therefore knowing early warning predictors of bankruptcy can provide useful economic inferences concerning financial sustainability. Developing though firm bankruptcy models is considered a very challenging task in the accounting and finance areas (Carmona et al., 2022; Kim, 2018).

From the inception of the genre, a very prevalent approach utilizes accounting data (Horrigan, 1968) and this inheritance holds until today (Veganzones & Severin, 2021). Although this approach excludes other possible determinants, as qualitative firm information (Keasey & Watson, 1987) or external to the firm elements, as spatial concentration (Baum & Mezias, 1992; Piacentino et al., 2021; Weterings & Marsili, 2015) or distances to transport hubs (Chen & Yeh, 2012; Gémar et al., 2016), the pure financial ratio approach is a solid treatment able to reach high predictive accuracies, allowing also some unique technical features as the extension of the bankruptcy horizon and out-of-sample validation. Therefore, it is a very informative angle researching effectively the financial clauses of business failure.

A basic tenor of bankruptcy prediction is the ability to discriminate between the two classes of failed and non-failed firms, based upon their characteristics. Under contemporary circumstances of data abundance and the capacity of methods to deal with limited numbers of bankruptcies and imbalanced samples, the opportunity to research the whole universe of an economic activity is more inviting than ever, where in the past such info was available only for large and listed firms. This becomes increasingly important, as small and private firms are not "scaled-down versions" of large and listed firms (Balios et al., 2016) and as in the European Union for example, 99% of firms are small and medium-sized enterprises.

Many discrete sectors have been investigated, as construction companies (Alaka et al., 2017), hospitals (Enumah & Chang, 2021), airlines (Gudmundsson, 2004) and the same applies to the hotel sector, which is the intention to research here. In a recent review of the relevant literature, Metaxas and Romanopoulos (2023) identified twenty-nine studies using financial variables in their final presented models, having received over 1.200 citations. So, the aim of this study is to research bankruptcy for the segregated hotel sector in Greece, a country relying almost 20% of gross domestic product formation on tourism, and accommodation is a basic part of it. Also, studies in tourism have become a discrete discipline and increasing the pool of related research is beneficial from this perspective too.

For this reason, a multi-period logit or hazard logit model is applied, which is the most common used in the default prediction literature (Beaver et al., 2019), but to the best of our knowledge this logit specification is not applied in segregated sectors. The results identified the most important financial ratios related to Greek hotel bankruptcy to be leverage as total liabilities to total assets and size as the natural logarithm of total assets with an increasing effect on bankruptcy, while the opposite holds for liabilities coverage as earnings before interest, taxes, depreciation and amortization (EBITDA) to total assets. Also, a comparison is performed with two relevant studies conducted in Greece, and the results support the development of updated economic activity-specific bankruptcy models.

Literature review

Predicting bankruptcy was inaugurated with the studies of Beaver (1966) and Altman (1968). Martin (1977) and Ohlson (1980) followed with logistic regression, Lane et al. (1986) and Luoma and Laitinen (1991) with survival analysis and Odom and Sharda (1990) introduced neural networks. For the hotel sector, there is an analogous timeline but with a time lag. It begun with Adams (1991, 1995) using multivariate discriminant analysis, followed by Baum and Mezias (1992) with survival analysis, Cho (1994) with logit, while artificial intelligence appeared with Kim (2011).

Cathcart et al. (2020) state that leverage is possibly the most influencing factor affecting default for private firms. For the hotel sector, leverage is an important factor enhancing default, while the opposite holds for revenues, earnings, profitability and size in terms of total assets (Metaxas & Romanopoulos, 2023).

Sector issues

As banking and utilities are excluded from many bankruptcy studies (Beaver et al., 2005; Mousavi & Ouenniche, 2018; Sayari & Mugan, 2017), mainly to avoid bias due to different firm regulations, many researchers have suggested sampling firms from the same sector (Adams, 1991; Altman, 1971; Giannopoulos & Sigbjørnsen, 2019; Korol, 2020; Sun et al., 2014) in order to obtain a more homogenous sample. In a similar vein, banks have their own type of rating system, the CAMEL framework based on financial information.

Regarding the hospitality industry which includes hotels and restaurants, it has been widely recorded to suffer from high failure rates (Abidin et al., 2020; Boer, 1992; Chathoth et al., 2006; Pisula, 2020; Situm, 2023; Solnet et al., 2010; Westgaard & van der Wijst, 2001), as also the determinants of failure can vary per sector (Caires et al., 2023; Chava & Jarrow, 2004; Cho, 1994; Kim, 2018; Platt & Platt, 2002).

Thus, it is derived that researching bankruptcy for firms belonging to a unique economic activity, can be considered a more objective approach, as it avoids cross-sectoral bias (Barreda et al., 2017; Caires et al., 2023; H. Li & Huang, 2012). On the other hand, some researchers claim that this may increase cost of implementation and maintainance (del Castillo García & Fernández Miguélez, 2021; Laguillo et al., 2019).

Method

Possibly the most applied econometric method in bankruptcy research is logistic regression (Beaver et al., 2019; Dastile et al., 2020; Dumitrescu et al., 2022; Jackson &

Wood, 2013; Shi & Li, 2019), though artificial intelligence models are gaining momentum, but it is generally observed they lack transparency and interpretability (Barboza et al., 2017; Carmona et al., 2022; Charalambous et al., 2023; Kim, 2011). For this reason, logistic regression is applied here and more specifically the multi-period logit, which has a relatively frequent use in wider sectors, but no applications in segregated economic activities. This specification is considered equivalent to a discrete time survival model (Shumway, 2001).

The multi-period can be applied on panel or firm-year data (Allison, 2010; Pierri & Caroni, 2017; Suresh et al., 2022) but needs the parametrization of adjusting the standard errors per firm (Charalambous et al., 2020, 2023; Filipe et al., 2016; Tomas Žiković, 2018) which accounts also for heteroscedasticity. At the Stata software level, this treatment is equivalent to the appliance of clustered robust standard errors (Rabe-Hesketh & Skrondal, 2022) or the Rogers standard errors (Petersen, 2009; Rogers, 1993).

Following the notation of Charalambakis and Garrett (2019), modified slightly for the current dataset, the probability of a hotel entering bankruptcy is:

$$P_{i,t}(Y_{i,t} = 1) = \frac{1}{1 + \exp\left(-a - \beta' X_{i,t}\right)}$$

where the dependent variable $Y_{i,t}$ takes the value of 1 at the year prior to bankruptcy or at the last year of available financial information and the value of 0 in any other case, β' is the vector of coefficients and X_{it} is the vector of the ith independent variable at time t. When extending the bankruptcy horizon, the financial ratios are lagged, thus the vector of inputs becomes $X_{i,t-1}$, and their consistency can be estimated for further periods.

Data

The dataset is comprised by official hotel bankruptcies belonging solely to the basic NACE code 5510, which is considered more homogenous to the other three codes corresponding to accommodation and were retrieved by the Hellenic Statistical Authority covering the years 2010-2020. Financial data were extracted by ICAP database, which has an ongoing presence in financial research (e.g., Niklis et al., 2014; Theodossiou, 1991), covering the years 2005-2020.

After the merge of the two sources and initial treatment in spreadsheets, the final dataset is further processed in Stata and includes thirteen bankrupt and 5.753 non-bankrupt hotels. The failed hotels contribute 87 firm-years and the total sample has 55.816 firm-years. Table 1 presents the years where the thirteen bankruptcies occur.

Table 1 Year distribution of hotel bankruptcies.

Year	Observed bankruptcies
2010	3
2011	1
2012	0
2013	1
2014	0
2015	0
2016	1
2017	2
2018	1
2019	2
2020	2
Total	13

Observing Table 1, one can see that in three years no bankruptcies take place, or there are empty intervals. Although Allison (2010) states that with empty intervals the maximization of likelihood won't converge, the estimations in this exercise were performed normally. Empty intervals are not unusual in bankruptcy studies (e.g., W. H. Beaver et al., 2005; Campbell et al., 2008; Carmona et al., 2019; Chava & Jarrow, 2004; Gupta et al., 2018; Ho et al., 2013).

It should be noted for the dataset, that there is a time delay between the year of official bankruptcy and the last available balance sheet information, averaging 3.6 years, a frequent issue in finance research (Keasey & Watson, 1991; L. Li & Faff, 2019; Pierri et al., 2016; Sensini, 2016). So, due to the data available, prediction of bankruptcy is performed with the last available financial information. Regarding the small number of bankruptcy events, many contemporary studies use a similar number of events with logistic regression structures (e.g., Chen and Yeh (2012) use ten and Ho et al. (2013) use twelve).

Variables

Fourteen financial ratios comprise the beginning set of variables, namely: return on assets (ROA) calculated as net profit to total assets multiplied to 100, return on equity (ROE) as equity to total assets multiplied to 100, return on capital employed (ROCE) as capital employed to total assets multiplied to 100, asset turnover (SATA) as sales to total assets, equity turnover (SAEQ) as sales to equity, fixed asset turnover (SAFA) as sales to fixed assets, equity to total assets (EQTA), equity to total liabilities (EQTL) working capital to total assets (WCTA), retained earnings to total assets (RETA), EBITDA to total assets (EBTA), EBITDA to total liabilities (EBTL), total liabilities to total assets (TLTA) and the natural logarithm of total assets (LnTA).

A first treatment is winsorizing the variables at the 1% and 99% levels (e.g., Altman et al., 2020; Charalambakis & Garrett, 2019) to limit the potential effect of extreme outliers. The descriptive statistics of the number of observations, the mean, median, standard deviation, minimum and maximum values, for the fourteen variables for the full sample of hotels follow in Table 2.

Table 2 Descriptive statistics for the whole sample

Variable	Obs	Mean	Std. Dev.	Min	Max
ROA	55819	-.61	8.19	-41.02	25.73
ROE	53611	-1.71	19.26	-108.86	66.8
ROCE	54586	-.46	12.17	-58.41	51.47
SATA	55813	.25	.33	0	2.22
SAEQ	46867	.73	1.58	0	12.04
SAFA	54843	.68	2.06	0	17.09
EQTA	55813	.66	.32	-.52	1
EQTL	54328	56.66	234.04	-.35	1890.29
WCTA	55813	.08	.31	-.99	.95
RETA	55812	.15	.19	0	.90
EBTA	55813	.041	.08	-.35	.33
EBTL	54328	.47	3.17	-15.25	19.16
TLTA	55813	.33	.32	0	1.51
LnTA	55813	14.08	1.45	10.23	18.03

Table 3 contains the same information, but this time for the splitted samples. The upper part has the descriptives for the non-bankrupt sample, while the lower part has info for the bankrupt part. Due to missing information, especially in the minority sample of the bankrupt hotels, the variables ROE, ROCE, SAEQ and SAFA will be removed from further consideration.

Table 3 Descriptive statistics for non-bankrupt and bankrupt hotels

Non-bankrupt hotels

Variable	Obs	Mean	Std. Dev.	Min	Max
ROA	55806	-.61	8.19	-41.02	25.73
ROE	53604	-1.70	19.26	-108.86	66.8
ROCE	54576	-.46	12.17	-58.41	51.47
SATA	55800	.25	.33	0	2.22
SAEQ	46859	.73	1.58	0	12.04
SAFA	54831	.68	2.06	0	17.09
EQTA	55800	.66	.32	-.52	1
EQTL	54315	56.67	234.06	-.35	1890.29
WCTA	55800	.08	.31	-.99	.95
RETA	55799	.15	.19	0	.90
TLTA	55800	.33	.32	0	1.5
EBTA	55800	.04	.08	-.34	.33
EBTL	54315	.47	3.17	-15.25	19.16
LnTA	55800	14.08	1.45	10.23	18.03

Bankrupt hotels

Variable	Obs	Mean	Std. Dev.	Min	Max
ROA	13	-7.01	10.80	-38.97	2.84
ROE	7	-12.32	22.96	-59.63	10.81
ROCE	10	-16.61	23.20	-58.41	5.89
SATA	13	0.27	0.44	.01	1.71
SAEQ	8	1.85	4.12	.12	12.04
SAFA	12	0.42	0.70	.02	2.58
EQTA	13	0.11	0.29	-0.52	0.60
EQTL	13	.27	.52	-.34	1.54
WCTA	13	-0.36	0.37	-.99	0.17

RETA	13	0.07	0.14	0	0.49
TLTA	13	0.88	0.29	0.39	1.51
EBTA	13	.00	0.05	-0.13	0.08
EBTL	13	.01	.07	-.13	.13
LnTA	13	15.17	1.72	11.35	17.32

Table 4 presents the t-test of the mean difference between the two classes. Statistically significant differences are estimated for ROA, EQTA, WCTA, TLTA, EBTA and LnTA.

Table 4 T-tests

Variable	t	p-value
ROA	2.81	**0.0049
SATA	-0.19	0.8423
EQTA	6.12	***0.0000
EQTL	0.86	0.3849
WCTA	5.20	***0.0000
RETA	1.43	0.1502
TLTA	-6.13	***0.0000
EBTA	1.71	*0.0868
EBTL	0.52	0.6022
LnTA	-2.70	***0.0068

The forthcoming steps will deal with variable selection. Given that no unified strategy exists (Bauweraerts, 2016; Veganzones & Severin, 2021), this study uses a mix of procedures, commencing with univariate analysis. For this reason, the main multi-period logit specification will be applied per variable, with a p-value threshold of 0.25 (Gupta et al., 2018; Hosmer et al., 2013). These results are place in Table 5, where it can be observed that SATA does not reach the given threshold and is further excluded.

Table 5 Univariate regressions

Variable	coef	p-value
ROA	-.0576022	*** .000
SATA	.1521408	**.867**
EQTA	-3.175028	*** .000
EQTL	-1.664724	*** .003
WCTA	-3.2799	*** .000
RETA	-3.349015	.226
TLTA	3.183531	*** .000
EBTA	-4.420325	*** .000
EBTL	-.0468724	*** .000
LnTA	.4728441	** .011

Table 6 contains the correlation analysis of the nine remaining variables. A high correlation is observed for the variables of ROA and EBTA as also a perfect negative correlation for EQTA and TLTA. As these two pairs of variables represent very similar accounting relations, no specific treatment is taking place until the next stage of stepwise regression.

Table 6 Correlation matrix

Variables	ROA	EQTA	EQTL	WCTA	RETA	EBTA	EBTL	TLTA	LnTA
ROA	1.000								
EQTA	0.224	1.000							
EQTL	-0.017	0.244	1.000						
WCTA	0.255	0.533	0.135	1.000					
RETA	-0.023	0.189	-0.011	0.054	1.000				
EBTA	**0.807**	0.074	-0.087	0.160	-0.028	1.000			
EBTL	0.213	0.117	-0.042	0.094	0.011	0.274	1.000		
TLTA	-0.225	**-1.000**	-0.244	-0.534	-0.190	-0.075	-0.117	1.000	
LnTA	0.128	-0.216	-0.111	-0.128	0.079	0.174	-0.011	0.214	1.000

Stepwise regression is a heuristic tool aiming to find the jointly most influential variables. More specifically, the forward stepwise method with backward elimination is applied, having as a base the multi-period logit model as in Charalambous et al. (2022). Following the suggestion of Hosmer et al. (2013) a p-value for entry is set to 0.15 and for exit to 0.20. The results are presented in Table 7, where the vertical axis has the variable names, with the estimated coefficient and the relevant statistical significance attached on the right, while standard errors are beneath in parentheses. The constant of the model follows, then the Akaike information criterion (AIC), the Bayesian information criterion (BIC), the area under the curve (AUC), the sensitivity of the model in terms of correct classification of the bankrupt sample (Cathcart et al., 2020; Zhang et al., 2015) and lastly the number of observations. The horizontal axis has on top the names of the different models estimated.

Table 7 Results of models Mstepwise, M1 and M2

	MStepwise		M1		M2	
EBTL	-.07623	***	-.07622	***	-.07636	***
	(.02226)		(.02226)		(.02216)	
TLTA	3.517	***	3.5167	***		
	(.49466)		(.4947)			
LnTA	.3729	**	.37269	**	.37015	**
	(.1506)		(.15054)		(.15024)	
EQTA					-3.5014	***
					(.49369)	
_cons	-15.931	***	-15.928	***	-12.382	***
	(2.4071)		(2.4062)		(2.2879)	
AIC	219.9802		219.9859		220.1481	
BIC	255.5913		255.597		255.7593	
AUC	0.8962		0.8962		0.8957	
sensitivity	92.31%		92.31%		92.31%	
N	54327		54328		54328	

*** p<.01, ** p<.05, * p<.1

The stepwise procedure, named MStepwise, identified as jointly significant the variables EBTL, TLTA and LnTA. EBTL has statistical significance at 1% and a negative sign, TLTA has a 1% significance with a positive sign and LnTA is significant at 5% with a positive sign. The value of AIC is 219.9802, BIC is 255.5913, AUC is

0.8962 and sensitivity captures correctly twelve out of thirteen bankruptcies, reaching 92.31%.

M1 model is estimated only with the three jointly significant variables, as it not certain that stepwise and non-stepwise specifications yield identical results. Though in column M1, the estimations are the same with minor alterations for AIC and BIC. Column M2 estimates a new model, replacing TLTA with EQTA, in order to examine robustness of the basic results and the perfect correlation of this pair of variables. The core effects for EBTL and LnTA remain while EQTA enters with a negative sign and statistical significance at 1%. Overall, the three models perform very similar and have the exact sensitivity of 92.31%.

Horizon

In order to check the stability and the information content of the estimations, the horizon of bankruptcy is going to be extended further by one and two years. This is a widely applied technique in the literature (e.g., Korol, 2020; Mossman et al., 1998) and usually the effects of the predictions become weaker. These results are seen in Table 8, where the base model M1 is placed first, as in contrast to M2 has better AIC and BIC values, followed by the one and two-lag models, named M1_lag and M1_2lag respectively. Although every model is estimated with the appropriate lagged covariates, for reasons of table compactness, the results are placed in the same line.

Table 8 Results of M1, M1_lag and M1_2lag

	M1		M1_lag		M1_2lag	
EBTL	-.07621	***	-.07036	**	-.05763	
	(.02225)		(.03285)		(.04264)	
TLTA	3.51671	***	3.29178	***	3.57382	***
	(.49470)		(.45911)		(.65437)	
LnTA	.37269	**	.26143		.36292	**
	(.15054)		(.16806)		(.162738)	
_cons	-15.92777	***	-13.89964	***	-15.86062	***
	(2.40616)		(2.65313)		(2.63914)	
AIC	219.9859		222.6047		157.7839	
BIC	255.597		257.7818		192.4837	
Sensitivity	92.31%		84.62%		77.78%	
N	54328		48742		43259	

*** p<.01, ** p<.05, * p<.1

EBTL in the M1_lag model retains the negative sign and reduces its statistical significance to 5%, while loses significance in the M2_lag version. TLTA retains magnitude and significance across all models. LnTA becomes insignificant in the one lag but re-enters in the two-lag model, thus has an intermittent effect to bankruptcy across the three horizons. Regarding sensitivity, by extending the horizon, this metric is reduced to 84.62 and 77.78% respectively, thus capturing eleven and ten out of the thirteen events respectively.

Comparisons

In this section, a comparison with two relevant studies that were conducted in Greece will take place, in terms of loading the input variables of the two studies into the multi-period logit specification (e.g., Grice & Dugan, 2003; Grice & Ingram, 2001; Shumway, 2001). The results of this exercise are placed in Table 9, where at column one, the results of M1 model are replicated.

Table 9 Results of models M1, CG19 and D12

	M1		CG19		D12	
EBTL	-.07622	***				
	(.02226)					
TLTA	3.5167	***	2.1655	**		
	(.4947)		(.95541)			
LnTA	.37269	**	.46862	***		
	(.15054)		(.17973)			
WCTA			-1.7569		-1.3334	*
			(1.2157)		(.70347)	
EBTA			-.9819		.11988	
			(.97695)		(1.3207)	
RETA			-2.0021		-.7019	
			(2.195)		(1.6736)	
EQTL					-1.2317	***
					(.45833)	
SATA					-.66584	
					(.76359)	
_cons	-15.928	***	-16.496	***	-6.8957	***
	(2.4062)		(2.5285)		(.51112)	
AIC	219.9859		219.3802		219.5989	
BIC	255.597		272.9587		273.0156	
AUC	0.8962		0.8878		0.9086	
Sensitivity	92.31%		76.92%		84.62%	
N	54328		55812		54327	

*** p<.01, ** p<.05, * p<.1

The first such study of Charalambakis and Garrett (2019), named here CG19, examined bankruptcy and financial distress for the Greek private sector for years 2003-2011 with the same econometric specification, but with a different set of variables. In the second column of Table 9, the results show that TLTA has a positive effect to bankruptcy though at 5%. LnTA remains positive too, though at 1%, while the rest of the variables WCTA, EBTA and RETA do not exert statistical significance. This is an interesting result for size, as in the original study, this variable has a negative effect to failure. Regarding sensitivity, it is reduced to 76.92% with ten correct classifications.

The second study of Diakomihalis (2012), named as D12, examined bankruptcy for Greek hotels for the period 2007-2008, with the original set of Altman's (1968) variables and multivariate discriminant analysis. The insertion of the ratios of WCTA, EBTA[1], RETA, EQTL and SATA showed that only WCTA and EQTL have a negative effect to bankruptcy and hold statistical significance at the 10 and 1% level respectively. From the descriptive statistics section, as EQTL had after winsorization an extreme value, different incremental levels of winsorization until 10% were used, and the results did not differ. The sensitivity of this specification reached 84.62% classifying correctly eleven cases.

Discussion

As contemporary circumstances allow bankruptcy research at the economic activity level, this study attempted to investigate the hotel sector in Greece from the financial perspective, as one model may not fit necessarily all sectors. With a bankruptcy dataset representing balance sheet information of over 5.500 hotels from NACE code 5510 for the years 2005-2020 and with thirteen bankruptcies, the application of a multi-period logit showed that TLTA representing leverage, appeared as the most stable covariate with a positive effect on bankruptcy and statistical siginificance at 1% across all three horizons. This result is in full accordance with the literature, and more specifically with the Greek economy (Axioglou & Christodoulakis, 2021; Charalambakis & Garrett, 2019), the broader literature (Cathcart et al., 2020) as well as the hotel bankruptcy literature (Vivel-Búa et al., 2016, 2019).

The next ratio found significant, EBTL or liabilities coverage, constructed by EBITDA to total liabilities, exhibited a statistically significant negative effect to failure for the base and the one further lag models, but not in the two-lag model. This variable has participated in similar hotel bankruptcy studies (del Castillo García & Fernández Miguélez, 2021; Fernández-Gámez et al., 2016; Gu & Gao, 2000; Youn & Gu, 2010) but due to the methodologies used, a positive or a negative sign was not possible to be provided.

The third ratio of LnTA to capture size, has a positive coefficient significant at the 5% level for the base and the two-lag models, except for the one lag model, thus has an intermittent effect regarding statistical significance, but bears a stable sign. This result is in line with Vivel-Búa et al. (2019) for Spanish hotels, though in a non-logarithmic form. The absolute value measure of total assets as of Vivel-Búa et al. (2019) was tested also in the multi-period logit model and gave the same results. This result regarding size, contrasts also a set of hotel bankruptcy studies that found a protective effect of size in total assets (Lado-Sestayo et al., 2016; Maté-Sánchez-Val, 2021; Situm, 2023; Vivel-Búa et al., 2016; Vivel-Búa & Lado-Sestayo, 2023) as also the study of Belda and Cabrer-Borrás (2020) for the hospitality sector in Spain. Further it

[1] In the study of Diakomihalis (2012), earnings before interest and taxes (EBIT) are used to construct EBTA, but since it was not available, EBITDA is used instead.

contradicts a series of studies from various countries, using though broader sector samples, as for Belgium (Bauweraerts, 2016; Cultrera & Brédart, 2016) and France (Mselmi et al., 2017), but only for the two-lag model in this case.

Regarding the comparisons made with the study of Charalambakis and Garrett (2019) for the Greek economy and the study of Diakomihalis (2012) for the Greek hotel sector, the differentiated results show that sectoral bankruptcy research may pinpoint different financial ratios, but more importantly may signify opposite relations, as in the case for size, leading to opposite economic interpretations. Thus, the comparisons imply that bankruptcy models need to be updated to better reflect the financial conditions of firms (Grice & Dugan, 2003), and support the argument of researching firm bankruptcy per economic activity as roundly affirmative.

Implications, limitations and further research

Based on the empirical results, some implications can be derived. Initially, hotel management should be conservative about the level of total assets, as by increasing their value, may not lead to the desired economies of scale, but instead can enhance bankruptcy. Similarly, leverage should be retained at low levels, as its increase has the biggest influence on bankruptcy. Regarding liabilities coverage, this metric should have an increased nominator as it has a protective effect to bankruptcy.

Policies towards the direction of the sector's financial sustainability can be the establishment of support programs targeted specifically to relieve specific hotel balance sheet items, as the partial coverage of employment costs and renovation schemes.

A limitation of the study can be considered the small number of hotel bankruptcies with available financial data. Future research can augment such financial models by covering non-financial aspects as economic and corporate governance indicators, can consider external to the firm variables, as also focus on economic activities within a region. In a technical aspect, out-of-sample predictions can be performed as also employ more advanced variable selection techniques as LASSO.

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