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Doctoral Thesis

Athanasios Romanopoulos

FINANCIAL DETERMINANTS OF BANKRUPTCY IN THE GREEK HOTEL SECTOR

Supervisor

Theodore Metaxas, Professor

Members

Stephanos Papadamou, Professor

Dimitrios Lagos, Professor Emeritus

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Financial determinants of bankruptcy in the Greek hotel sector

Abstract

Aim of the thesis is to investigate the financial determinants of hotel bankruptcies in Greece. For this reason, the study is separated in two parts. The first consists of the theoretical part, where the relevant literature is thoroughly searched. By defining the conceptual framework, the main positions and basic features of this strand are discussed. The main point is that sectors differ and by performing sectoral research better results might be extracted. A systematic literature review is conducted also in order to assess the state of the literature in terms of the relationship of financial ratios and hotel failure. The second part of the thesis sets the methodological background. The multi-period logistic regression is the selected quantitative tool, and the available 5,500 hotels of which 13 went bankrupt are analyzed in Stata. The main results showed that leverage and size in terms of total assets increase the probability of bankruptcy while liabilities coverage with EBITDA reduce it. These results were further checked through a specification and longer horizon analysis and appeared robust. Efficiency comparisons were performed with two relevant Greek studies and the base model proved better in terms of sensitivity and variable relevance. One important artifact of the analysis is the positive sign for size, that contradicts the negative sign found usually in the literature and in the one comparison study performed for the whole economy, providing evidence firstly that the "too big to fail" principle does not hold in this sample and secondly for the development of sectoral models, as one model may not be equally efficient under different circumstances.

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

JEL Classification G33, Z33

Χρηματοοικονομικοί παράγοντες πτώχευσης στον ελληνικό ξενοδοχειακό κλάδο

Περίληψη

Σκοπός της διατριβής είναι να διερευνήσει τους χρηματοοικονομικούς παράγοντες πτώχευσης ελληνικών ξενοδοχειακών επιχειρήσεων. Για το λόγο αυτό, η εργασία χωρίζεται σε δύο μέρη. Το πρώτο περιλαμβάνει το θεωρητικό σκέλος, όπου η σχετική βιβλιογραφία μελετήθηκε ενδελεχώς. Καθορίζοντας το εννοιολογικό πλαίσιο, οι βασικές θέσεις αυτής της διόδου έρευνας συζητούνται. Το βασικό επιχείρημα είναι ότι οι κλάδοι διαφέρουν και η κλαδική έρευνα πιθανόν να φέρει καλύτερα αποτελέσματα. Μία συστηματική ανασκόπηση διεξάγεται επίσης, με σκοπό να δοθεί η κατάσταση της βιβλιογραφίας αναφορικά με τη σχέση αριθμοδεικτών και εταιρικής αποτυχίας ξενοδοχείων. Το δεύτερο μέρος της διατριβής, θέτει το μεθοδολογικό υπόβαθρο. Σαν ποσοτικό εργαλείο επιλέγεται η λογιστική παλινδρόμηση πολλαπλών περιόδων, και τα διαθέσιμα 5,500 ξενοδοχεία εκ των οποίων 13 πτωχεύσανε, αναλύονται στο λογισμικό Stata. Τα βασικά αποτελέσματα δείξανε ότι η μόχλευση και το μέγεθος σε όρους ενεργητικού αυξάνουν την πιθανότητα πτώχευσης ενώ η κάλυψη υποχρεώσεων με κέρδη προ φόρων, τόκων και αποσβέσεων τη μειώνει. Στα αποτελέσματα έγινε έλεγχος εξειδίκευσης και μεγαλύτερου χρονικού ορίζοντα και παρέμειναν ανθεκτικά. Πραγματοποιήθηκαν συγκρίσεις με δύο σχετικές ελληνικές εργασίες, με το βασικό μοντέλο να αποδεικνύεται καλύτερο σε όρους ευαισθησίας και συνάφειας μεταβλητών. Ένα σημαντικό εύρημα της ανάλυσης είναι η θετική επίδραση του μεγέθους, που έρχεται σε αντίθεση με το αρνητικό πρόσημο που συνήθως απαντάται στη βιβλιογραφία και στη μία εργασία σύγκρισης που εξέτασε όλη την οικονομία, δίνοντας στοιχεία αφενός ότι η αρχή του “πολύ μεγάλο για να αποτύχει” δεν ισχύει στο συγκεκριμένο δείγμα και αφετέρου για την ανάπτυξη κλαδικών μοντέλων, καθώς ένα μοντέλο μπορεί να μην είναι εξίσου αποδοτικό υπό διαφορετικές συνθήκες.

Λέξεις κλειδιά: ξενοδοχειακή πτώχευση, πρόβλεψη πτώχευσης οικονομικής δραστηριότητας, λογιστική παλινδρόμηση πολλαπλών περιόδων, χρηματοοικονομικοί δείκτες

Υπεύθυνη Δήλωση

Δηλώνω υπεύθυνα ότι είμαι ο δημιουργός αυτής της διατριβής και νόμιμος κάτοχος των πνευματικών δικαιωμάτων της. Η διατριβή διατίθεται υπό το πρότυπο “Αναφοράς Δημιουργού 4.0 Διεθνές”.

ΑΡωμανόπουλος

Ευχαριστίες

Αρχικά θέλω να ευχαριστήσω την οικογένεια μου που με υποστήριξε σε αυτή μου την απόφαση, καθώς και το οικείο μου περιβάλλον.

Να ευχαριστήσω τον Καθηγητή Στέφανο Παπαδάμου, για την εξ'αρχής ενθαρρυντική του στάση και τις οικονομετρικές γνώσεις που μοιράστηκε.

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Θερμές ευχαριστίες προς τον Επιβλέποντα Καθηγητή Θεόδωρο Μεταξά, που με ανέλαβε αρχικά, και ήταν βασικός καθοδηγητικός παράγοντας για να ολοκληρωθεί η διατριβή. Όπως τον είχα χαρακτηρίσει σε κάποια από τις συναντήσεις μας, είναι ο "καλύτερος προπονητής" που είχα ποτέ.

Δεν θα ήταν δυνατή η ολοκλήρωση της διατριβής χωρίς τη συνεισφορά των μελών της Εξεταστικής Επιτροπής, που αποτελείται από τον Καθηγητή Ευστάθιο Βελισσαρίου, τον Καθηγητή Θεμιστοκλή Λαζαρίδη, τον Επίκουρο Καθηγητή Νικόλαο-Γεώργιο Καραχάλη και την Επίκουρη Καθηγήτρια Γεωργία Ζούνη.

Ευχαριστίες οφείλω και στο σύνολο της Σχολής Οικονομικών Επιστημών, που προσέφερε ένα ιδανικό και φιλόξενο πλαίσιο για την περίοδο που διήρκησε η διατριβή.

Ευχαριστίες και προς το Ίδρυμα Κρατικών Υποτροφιών για το πρόγραμμα χρηματοδότησης και την ομαλή συνεργασία.

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CHAPTER 1: Introduction and objective of the thesis

In this doctoral dissertation, a theoretical and empirical assessment of hotel default is performed. Firm failure is a phenomenon on the opposite side of firm profitability, which has gathered bigger attention in economics. Having information though about the numbers of firms that fail every year across the spectrum of economic activities, as well as the conceptually and technically challenging literature that researches this phenomenon, a road is paved towards the investigation of this issue. Studying this issue becomes more useful, as firm bankruptcies tend to have consequences for a big number of stakeholders involved and impose huge economic costs and loss of welfare, and by researching firm failure may assist to reach inferences that may tackle failure. Nowadays, with the plethora of available secondary data that reach even at the micro-firm level and the methodological advancements, the conditions to conduct bankruptcy research are better than ever before, as in contrast to the relatively immediate past, such info was available only for large and usually listed companies in stock markets.

While there is a big number of studies examining firm failure with financial information for wide parts of the economy, when focusing on specific sectors and segregated economic activities, the available studies become naturally smaller. One such economic activity is the accommodation sector, where the relevant studies are more limited. For this reason, the economic activity of hotels in Greece is selected, to check empirically the financial factors that are related to bankruptcy. The selection of this economic activity, besides its important contribution to the country’s tourism product, contains an aspect which is reflected on the financial statements, as the sector is capital-intensive and hotels tend to have a high portion of fixed assets. This fact makes accommodation firms potentially more differentiated to the rest of the economy.

Focusing on a specific sector or economic activity, besides that it can be seen as advantageous, is usually accompanied with the disadvantage of a potential smaller available sample of bankrupt firms, as also with the further imperfect information on firms due to anonymized and confidential information that can reduce even further the sample. These issues, i.e., a small sample and a possible selection-bias, are limitations of the thesis, but these do not necessarily hinder research, as there are numerous examples of quality peer reviewed studies with an equal or analogous number of bankrupt firms as the one used here.

The first step in this course is the setting of the theoretical underpinnings of firm failure. More specifically an extensive discussion takes place regarding the basic research approaches that exist, the issue of firm failure definition and the discourses around developing sectoral models. The second step is to systematically collect and analyze the studies in the field of the hotel sector, that have investigated the relationship of hotel failure with the use of financial variables. These steps pertain the theoretical objectives of the thesis.

The empirical part of this thesis shifts towards the quantitative objectives**.** The hotel sector is selected as an important sector in the Greek economy, that is differentiated to the rest in terms of balance sheet structure and suffers different rates of bankruptcies to other sectors. The financial ratio approach is selected due to its popularity, and the use of the bankruptcy definition is followed because it is the most objective criterion. As a quantitative tool, the multi-period logistic regression is selected, which is quite spread in finance studies for broader sectors, has a better interpretability to artificial intelligence models and has an appearance in high quality peer reviewed journals. The available sample of over 5,500 hotels of which 13 officially bankrupted for the period of 2010 to 2020 is processed then in Stata software. The main research questions are related to the identification of the financial determinants related to bankruptcy and the efficiency comparison of the main specification results with two Greek studies.

The contribution of this dissertation is multifaceted. Initially, a published literature review article regarding the financial determinants of hotel default is offered (Metaxas & Romanopoulos, 2023), as such a systematic review was absent. The conference paper of Romanopoulos and Metaxas (2023) and its forthcoming formal publication which investigate the financial determinants of hotel bankruptcy for Greece with multi-period logit, enriches the pool of relevant hotel default studies with a contemporary estimation methodology in Stata**,** where to the best of our knowledge, this exact version is not used before for the hotel industry. By this way, a competent methodology is extracted from finance and specifically the JEL code G33 related to bankruptcy under the umbrella of financial economics and creates a link with code Z33 that represent the finance section of tourism economics. In addition, the empirical part, renews the interest in bankruptcy studies for the Greek hotel sector after almost a decade. Another minor technical contribution is the application of the user-written command for rare events, which has a limited use besides the international affairs context and can become a specification of wider use in empirical firm bankruptcy studies, especially due to its inherent structure to handle severely imbalanced datasets. Regarding the econometric results, the estimations provide sufficiently robust evidence that: the "too big to fail" principle does not hold for the hotel sample examined, it is more appropriate developing sectoral models as one model does not fit all circumstances, and size in terms of total assets and fixed assets should be included as potential covariates. Finally, the last contributions lie in the proposed research paths inspired by combining elements of the literature.

The thesis consists of a total of eight chapters. Briefly, the presentation of the individual chapters is as follows:

CHAPTER 1: Introduction and objective of the thesis

The abovementioned part of current chapter provided a broad introduction to the framework within the thesis will operate, in the form of an extended abstract. Next, a brief overview of the individual chapters is given, covering the chapters of the conceptual underpinnings of firm failure (Chapter 2), a review of the previous research (Chapter 3) and the hotel sector and bankruptcies in Greece (Chapter 4). These four chapters conclude the theoretical part of the thesis. The quantitative part follows, regarding the methodological framework (Chapter 5), the econometric analysis (Chapter 6), the discussion of results (Chapter 7) and conclusions (Chapter 8). Every chapter begins with an introductory note and concludes with a short summary.

CHAPTER 2: Conceptual underpinnings of firm failure

In Chapter 2, a discussion on the basic components of the broader conceptual framework takes place. Initially, the firm failure problem is set, with the ways researchers have addressed this problem, mainly with the use of the internal and external variables paradigms. The focus then shifts to the approach that uses financial indicators, as it is the most common in the literature, and a further discussion is made about research performed at a segregated or aggregated level. Various definitions of corporate failure are presented, mainly bankruptcy and financial distress, along with some rarer examples from the literature. The chapter closes with the variety of methodologies employed and the technique of extending the observed failure horizon.

CHAPTER 3: Review of the previous research

Chapter 3 involves a review of the literature. Initially, it focuses on some milestone works in the field of corporate failure prediction. Then, it turns to studies that have examined the failure of hotel businesses. To achieve this, a systematic literature review regarding the financial determinants related to the failure of hotel businesses is conducted, leading to 29 studies. The studies are narrated in detail and the financial variables and their effect to default are recorded in a summary table.

CHAPTER 4: The hotel sector and bankruptcies in Greece

Chapter 4 provides initially a brief overview of the contribution of the accommodation economic activity of hotels in the economy. Also, a breakdown and a description of the four NACE (Statistical Classification of Economic Activities in the European Community) codes designated to the accommodation sector is done, that assists to better comprehend the differences of firms within an economic activity and its possible implication on sample homogeneity when researching economy-wide models. Additionally, cumulative data on bankruptcies by year and industries are presented, as also separately for the hospitality sector.

CHAPTER 5: Methodological framework

Chapter 5 establishes the methodological foundations of the forthcoming analysis, starting with the presentation of the research objectives and research questions. The econometric specification of multi-period logistic regression is articulated, which is conceptually and statistically interwoven to a discrete-time hazard model capable of processing panel data. The appropriateness of the methodology is discussed with reference to studies that have applied it. The complete dataset is presented, with the financial ratios of over 5,500 Greek hotels and the 13 available bankrupt hotels. Various data curation routines are employed at this point, including winsorization, descriptive statistics, correlation analysis, t-tests and an initial univariate analysis with the primary specification.

CHAPTER 6: Econometric analysis and results

Chapter 6 reports the results of the econometric analysis. To answer the first research question regarding the financial determinants of hotel bankruptcy, initially, a stepwise logistic regression procedure leads to a three-variable model. Then, the bankruptcy horizon is extended by one and two years to assess the stability of coefficients over time. Sensitivity analyses are also conducted concerning the econometric method by using four additional close related models. Regarding the second research question, the multi-period logit model is loaded with the variables of two previous Greek studies, to evaluate efficiency in terms of model sensitivity and statistical relevance and significance of the variables. The chapter concludes with a sensitivity check for the size variable using alternative measures.

CHAPTER 7: Discussion of results

In Chapter 7, the estimated econometric evidence is further discussed and contrasted with the relevant hotel literature that resulted from the systematic review as also with the broader literature, in terms of statistically significant variables and their effects. Based on the main results, economic inferences arising from theory are discussed, as also the discrepancies that arose from the comparison studies. Finally, suggestions are made at a management, policy and research level, the limitations of the study are re-stated and some future research directions are proposed.

CHAPTER 8: Conclusions

The final chapter summarizes the most important points from the theoretical and empirical parts and concludes the thesis.

CHAPTER 2: Conceptual underpinnings of firm failure

This chapter will discuss the main conceptual underpinnings of the corporate failure literature. Initially, the firm failure problem is posited and the main approaches that research has followed, in terms of the use of external, internal and financial variables are set. Then, the discussion evolves towards the financial ratio approach as the most frequent sub-strand, and evidence is given regarding research conducted in a sectoral and a wider scale level. The last three sections review the various definitions of firm failure that can be met in the literature, the variety of the methodologies applied and the technique of extending the bankruptcy horizon.

2.1 The firm failure problem

Firm failures, though considered rare events (Cramer, 1999; Veganzones & Severin, 2021), are a real-world phenomenon and nevertheless exist. Although a bigger part of economic science is involved with firm profitability and organizational growth (Solnet, Paulsen & Cooper, 2010), another smaller strand of the literature explores firms that fail. Besides the fact that this path of research is growing exponentially (Ciampi et al., 2021) due to micro-firm data dissemination and computational methods availability (Sensini, 2016) and can be technically challenging (Carmona, Dwekat & Mardawi, 2022), it addresses some practical issues of wide interest. Firstly, many companies across various sectors fail every year. One may recall the large bankruptcies of Enron and Thomas Cook. Secondly, these failures have a heavy impact on the economy in terms of high administrative and social costs (Crutzen & Van Caillie, 2008; Dimitras et al., 1996; Jayasekera, 2018; S. Y. Kim, 2018; LeClere, 2006; Lensberg et al., 2006; Park & Hancer, 2012; Situm, 2015; Warner, 1977) and can be seen as a threat (Charitou, Neophytou & Charalambous, 2004). So, firm failure research may interest a variety of stakeholders, as governments, regulators, creditors and professionals within the field, to better apprehend this phenomenon and the possible reasons of failures.

A firm may fail for various reasons, as for economic reasons, as fraud, increased debt, due to the pension of the owner (Asimakopoulos et al., 2008; Everett & Watson, 1998), or the market forces as increased competition, changing regulations (Charitou et al., 2004) or natural disasters. To face this “problem”, and despite the argument of Schumpeterian cleansing (Dörr, Licht & Murmann, 2022) that extinguishing firms are a part of natural process that reallocates resources, researchers have pondered how this phenomenon can be treated, thus to find the factors, variables, methods, and generally approaches to investigate appropriately.

One ongoing issue though, is that there is no unifying framework of firm failure (Crutzen & Van Caillie, 2008; Dimitras, Zanakis & Zopounidis, 1996; Jayasekera, 2018; LeClere, 2006; Situm, 2015) and more specifically, Charitou et al. (2004) state the lack of a theory to select the best possible set of variables. Varetto (1998) expresses the view that it is easier to produce empirical results than work on developing a theory, for example a theory of financial signals related to bankruptcy. Usually, reality is far too complex and there no single factor or cause that may forward a failure, as these factors can overlap (Levratto, 2013). In any case, to apprehend in full such phenomenon, a big array of info needs to be collected, that may become expensive and that may fail to happen also due to restricted resources and data confidentiality.

2.2 The internal, external and financial ratio approaches

In this quest to investigate the failure phenomenon, researchers have followed some broad frameworks. Mellahi and Wilkinson (2004) and Amankwah-Amoah, Khan and Wood (2021) classify corporate failure research on the spectrum of two approaches. On the one side lies the voluntaristic approach, which assumes that causes of failure are rooted within the firm and take the form of internal factors as capabilities, resources, strategy and leadership (Heracleous & Werres, 2016) and practiced in organizational studies and by the organizational psychology school of thought.

On the other side, lies the deterministic perspective which assume that failure causes are external to the firm, related to industry and the environment and is practiced by industrial organization and organizational ecology (Heracleous & Werres, 2016), where uncertainty and non-adaptation are the main reasons for firms to fail and firms have no control over these factors. Organizational ecology assumes population density, product life cycle, age and size of firm to be crucial, with more weight though placed in the external factors (Madrid-Guijarro, García-Pérez-de-Lema & van Auken, 2011). Of course, there exists the combination of the internal and external factors, the integrative approach (Heracleous & Werres, 2016; Ropega, 2011; Vivel-Búa, Lado-Sestayo & Otero-González, 2019).

These approaches find their expression in terms of variables too. Some brief and non-exhaustive examples in the tourism literature for internal firm variables are age, size as room capacity and price as the average advertised daily room rate and can be found in Baum and Mezias (1992) and Ingram and Baum (1997). Examples of exogenous variables are market concentration (Kaniovski, Peneder & Smeral, 2008), population density and localization (Baum & Mezias, 1992; Piacentino, Aronica, Giuliani, Mazzitelli & Cracolici, 2021), seasonality (Kaniovski et al., 2008; D. Zhang & Xie, 2023), distance from the coast (Piacentino et al., 2021), distance to transport hubs (Chen & Yeh, 2012; Gémar, Moniche &

Morales, 2016; Gemar, Soler & Guzman-Parra, 2019; Vivel-Búa et al., 2019), and macroeconomic factors as gross national product (Baum & Mezias, 1992), political instability (Türkcan & Erkuş-Öztürk, 2020) or the 2008 credit crunch (Gémar et al., 2016).

In another taxonomy of variables related to failure, Berryman (1983) acknowledges entrepreneurial information. Regarding this angle in tourism firms, Brouder and Eriksson (2013) researched tourism firm survival in Sweden with questionnaires interested in entrepreneurial experience and education. Kalnins and Chung (2006) researched the dimension of social capital networks of ethnic groups in relation to hotel survival in the US.

Despite these theory-based approaches and their relevant variables, the financial ratio approach exists, which although atheoretical (Jayasekera, 2018), can claim to be situated within the voluntaristic paradigm relevant to firm resources. A bridging rationale for this position, is that as firms enter the last stages of their life, the deterioration of the entity can be traced and mirrored in financial statements (Crutzen & Van Caillie, 2008; Moncarz & Kron, 1993; Veganzones & Severin, 2021), which can as well include shrinking financial resources as negative profitability (Mellahi & Wilkinson, 2004) increased debt and payment defaults. Dioko and Guo (2024) mention that eventually firm failures are triggered by financial distress and Veganzones and Severin (2021) comment that such internal financial factors are predictable, in contrast to the exogenous and deterministic ones.

Argenti (1976) argued though, that financial information may be relevant to failure, but is just a sign or symptom of organizational decline (Stokes & Blackburn, 2002) and not the true causes. Indeed, the organizational and financial deterioration can be seen as the financial antecedents or the financial clauses of failure and not the real causes (Z. Li, Crook, Andreeva & Tang, 2021), as from the voluntaristic view, failure causes are rooted within aspects of management and transmitted via the corporate governance channel (Almaskati, Bird, Yeung & Lu., 2021; Z. Li et al., 2021).

As per Mellahi and Wilkinson (2004) attempts to explain organizational and firm failure are non-holistic unless considering internal and external factors. Also, both these factors, can still be considered incomplete if missing in-depth qualitative information that can be gained from case studies, interviews, or questionnaires (Carter & Van Auken, 2006; Laitinen & Gin Chong, 1999; Madrid-Guijarro et al., 2011; Mellahi & Wilkinson, 2004). Thus, it is believed that to comprehend in full the failure phenomenon, these approaches should not be necessary seen as substitutive but complementary, as all have their distinct merits. Many studies have demonstrated for example, that by augmenting or combining a specific type of variables, as accounting metrics, with other types, as external variables, the models increase incrementally their explanatory power (e.g., Lado-Sestayo et al., 2016). In all cases, every little step made from the above approaches helps towards a future theory development (Situm, 2015).

Despite this broad discourse, the financial approach gained popularity in early days (Horrigan, 1968) and still remains the most frequent (Cultrera & Brédart, 2016; Veganzones & Severin, 2021). It is further so-called bankruptcy prediction, where two basic trends exist: the investigation of failure to identify the symptoms or the best predictors, and the performance comparison of different methods (S. Y. Kim, 2011; Tseng & Hu, 2010). Pure financial models are relatively cheap to construct, as they combine secondary data which in many cases are provided in the same source. The financial approach, depending on the methodology applied, can provide comprehensive information about the participation, importance and the effect of financial inputs and can reach very high accuracies. This is usually performed on a methodological structure that best discriminates and classifies the sample of the failed and non-failed firms based on their financial characteristics. As such, this type of modeling can act as a canary in a coal mine, a metaphor for the practice of coal miners in the past who used to let a canary fly into a mine to check air quality, able to offer the early warning or prognostic indicators of firm default by highlighting the role of the specific accounting items, which in turn can lead to useful economic inferences and preventive actions. This early warning aspect, which can be enhanced by the possible extension of the failure horizon that allows to investigate variable stability and the information content over longer periods, is a distinctive trait of bankruptcy prediction with financial ratios, not practiced by the other approaches and will be further discussed and applied later in the analysis.

Another advancement of the bankruptcy prediction part with financial information, is the increased efficiency these attempts demonstrate, where in many cases, have a marginal difference from reaching 100% in predictive accuracy. And such accuracies are important, as for example there are capturing statistical quantities as type I and II errors, where type I is more expensive (Altman, Haldeman & Narayanan, 1977; Charitou et al., 2004) as it represents the value of firms that actually failed but classified incorrectly.

2.3 Aggregated and segregated sectoral research

The first studies focused on very specific niches or types of firms, as listed firms to stock markets or manufacturing firms. A starting point was the fact that more data were publicly available and more accessible for such firms. With the passage of time and the domain's advancements in data and methods, there is much accumulated empirical evidence that focusing on specific economic activities, can provide a more detailed look on the determinants of failure i.e. sector-specific determinants or improved model accuracy. To support this argument as a motivational factor to conduct such research, various arguments will be used from the acquainted literature.

As just mentioned, the first studies in bankruptcy research sampled listed manufacturing firms (Altman, 1968; Beaver, 1966). Edmister (1972) is considered the first author that departed from this norm and sampled small and medium-sized enterprises (SMEs) (Abidin, Abdullah & Khaw 2021; Ciampi, Cillo & Fiano, 2020), thus segmenting firms by size. In their recent review of the literature, Veganzones and Severin (2021) identified that the proportion of studies researching SMEs was significantly lower compared to studies involving listed firms and indeed, the SME angle is practiced by the minority of researchers (Altman, Balzano, Giannozzi & Srhoj, 2022; Altman & Sabato, 2007; Altman, Sabato & Wilson, 2010; Ciampi, 2015; Cultrera & Brédart, 2016; El Kalak & Hudson, 2016; J. Gupta, Barzotto & Khorasgani, 2018; Laitinen & Gin Chong, 1999; Maté-Sánchez-Val, López-Hernandez & Rodriguez Fuentes, 2018; Mselmi, Lahiani & Hamza, 2017; Pierri & Caroni, 2017). These deviations though, are considered of high value and of wider interest, as SMEs represent the majority of firms, as for example in Europe 99% are SMEs, contributing two-thirds of employment of the private sector (Balios, Daskalakis, Eriotis & Vasiliou, 2016; Calabrese, 2023). Besides SMEs constituting the majority, private firm failure rates are much higher to listed firms (Jones & Wang, 2019) and there is the argument that small firms should not be viewed simply as scaled-down versions of large firms (Balios et al., 2016) but as distinct samples.

2.3.1 Research in various sectors

In the route of progress, bankruptcy research with financial data begins to focus on various segregated economic activities, as for construction (Abidali & Harris, 1995; Acosta-González & Fernández-Rodríguez, 2014; Alaka et al., 2017; Amendola, Restaino & Sensini, 2015; H. Choi, Son & Kim, 2018; Mason & Harris, 1979; Toudas, Archontakis & Boufounou, 2024), banking (Cole & Gunther, 1995; Lane, Looney & Wansley, 1986), airlines (Davalos, Gritta & Chow, 1999; Espahbodi & Espahbodi, 1984; Gudmundsson, 1999), football clubs (Alaminos & Fernández, 2019; Oberhofer, Philippovich & Winner, 2015), the salmon industry in Norway (Misund, 2017; D. Zhang & Tveterås, 2022), even for non-profit economic entities, as hospitals (Enumah & Chang, 2021; Wertheim & Lynn, 1993) and municipalities (Cohen, Doumpos, Neofytou & Zopounidis, 2012; Jones & Walker, 2008).

2.3.2 Differences in ratios among sectors

One of the first observations that ratios are clustered within specific dimensions as sector, size or profitability bands, can be found in Chudson's (1945) study (Bellovary, Giacomino & Akers, 2007). Nowadays, it is more common ground that firms differ in their financial characteristics. For example, Arnis, Chytis and Kolias (2018) commented that credit rating agencies have long acknowledged sectoral variations in financial indicators, due to the nature of inventories, credit policy, capital structure and structure of assets. Altman and Sabato (2007) have noted wide differences in the accounting ratios in real estate and agriculture sectors in the US.

For the hospitality industry, which based on industry standard classification systems contain hotels and the food and beverage sectors, Singal (2015) and Kim (2018) have reported wide differences in debt levels between hospitality and the rest industries in the US. Similarly, Crespí-Cladera, Martín-Oliver and Pascual-Fuster (2021) in Spain and Caires, Reis and Rodrigues (2023) in Portugal, identified higher debt for hotels to other sectors. Dimitrić, Tomas Žiković and Arbula Blecich (2019) found different profitability determinants of the hotel sectors for Croatia, Greece, Portugal and Spain. The hospitality industry is also characterized by high sunk costs (Kalnins, 2016; Kaniovski et al., 2008), high and long-lived fixed assets that verify the capital-intensivity of the sector (Akron, Demir, Díez-Estebanet & García-Gómez, 2020; Dalbor & Upneja, 2004; Devesa & Esteban, 2011), and require regular investment (Akron et al., 2020). This type of economic standards also leads to a higher break-even point (Adams, 1995; Boer, 1992; Moncarz & Kron, 1993).

2.3.3 Hospitality as a high-risk sector

A point of consensus among hospitality researchers, is that the sector is acknowledged to be a high-risk sector (Chathoth, Tse & Olsen, 2006; Dioko & Guo, 2024; Solnet, Paulsen & Cooper, 2010) with a rich history of failures. For example, Abidin, Abdullah and Khaw (2020) use official data to depict this situation in the UK and Malaysia. For the UK, Boer (1992) provided figures showing that the same industry from 1983 to 1989, had persistently the second highest failure rates, only after the construction sector. For the UK again, Smith and Liou (2007) report that in London stock market, the leisure and hotel industry for the period 1973-2002 faced 136 failures, placed eighth out of 35 industries. Westgaard and Van Der Wijst (2001) reported that the hotel and restaurant sector in Norway for years 1995 to 1998 had a 7% default frequency, 5% more than the rest sectors.

This pattern seems to persist in more recent studies too. Filipe, Grammatikos and Michala (2016) found that SMEs in the accommodation and restaurant industry in eight European countries for the period of 2000 to 2009, to be the most distressed from six wide sectors with 2.88%, while transport, communication and utility sectors had the lowest rate. Dörr et al. (2022) reported that accommodation and catering SMEs, were the most affected sectors in Germany after COVID-19 in terms of insolvency rates. Caires et al. (2023) observed increased risk for Portuguese tourism firms in first years of operation. Crosato, Domenech and Liberati (2023) in Spain for the period of 2013-2015, found that default rates remained low also within sectors, ranging from 1.1% in agriculture, forestry and fishing, to 2.8% in food and accommodation service activities. For Austria, Situm (2023) estimated that bankruptcy rates for hotels and restaurants for the period 2009-2020 were constantly higher than the average. In addition, a number of recent studies projected that hotel bankruptcy risk was on the rise due to COVID-19 (Crespí-Cladera et al., 2021; Matejić et al., 2022; Špiler et al., 2022; Tran, Nguyen, Le, Thanh Vu & Vo, 2023) and this could possibly enhance by the ongoing crises.

2.3.4 Cross-sectoral bias

Besides the evidence that the hospitality sector embeds high risk, many studies have shown that different failure determinants may apply per sector (Chava & Jarrow, 2004; Du Jardin, 2015; Izan, 1984; H. D. Platt & Platt, 1990, 2002; Rikkers & Thibeault, 2011; Sayari & Mugan, 2017) and by considering industry effects prediction results ameliorate (Christidis & Gregory, 2010). Put in other words, there may be a differential impact of financial ratios on survival among sectors (Caires et al., 2023), either in magnitude or sign. This fact was shown recently for the tourism sector, as four predictors exhibited differing importance in tourism firms compared to other sectors (Srhoj, Vitezić, Giannozzi & Mikulić, 2024).

Another basic argument for further sectoral concentration, is that by examining together hospitality firms or firms from broader industries, can lead to cross-sectoral influence (Barreda, Kageyama, Singh & Zubieta, 2017; Caires et al., 2023; H. Li & Huang, 2012) which may introduce bias due to contaminated samples. This is empirically proven also in hospitality studies, as Cho (1994) identified different predictors for the hotel and restaurant sample, as also in Kim (2018) for the hotel, restaurant and amusement industry subsamples.

This type of bias is the reason why economy-wide studies exclude from their samples, due also to regulation and accounting conventions, banks and utilities (e.g., Abid, Mkaouar & Kaabia, 2018; Beaver, Cascino, Correia & McNichols, 2019; Charalambakis & Garrett, 2019; Löffler & Maurer, 2011; LoPucki & Doherty, 2015; Mousavi & Ouenniche, 2018; Sayari & Mugan, 2017). Also, it is not uncommon for sub-industries within a main industry, to exhibit variations regarding bankruptcy determinants, as for example the study of Topaloğlu (2012) for listed manufacturing companies in the US.

For all the above reasons, many researchers suggest bankruptcy research with a sectoral focus (Adams, 1991, 1995; Altman, 1971; Cultrera & Brédart, 2016; G. Giannopoulos & Sigbjørnsen, 2019; Korol, 2020; McGurr & DeVaney, 1998; Sun, Li, Huang & He, 2014; Vivel-Búa, Lado-Sestayo & Otero-González, 2016), as it can provide a more detailed and objective examination of firm failure calibrated on a specific sector. Ciampi, Giannozzi, Marzi and Altman (2021) consider that industry models show better accuracy to generic models and models per size band for SMEs are superior.

The basic argument here is that the nature of the business sector can alter the balance sheet and financial statements of firms in both a qualitative and a quantitative manner, and since this is the primary source of data in bankruptcy prediction, this variability of ratios might denote also differences in the determinants of failure. Sayari and Mugan (2017) discuss about this issue, having as examples the manufacturing and the utility sectors, that depending the industry and its economic nature, ratios may even have an opposite effect on financial distress. A similar type of bias can persist for countries too. Charalambakis and Garrett (2016) examined accounting and market determinants of default for listed corporations in the UK and India with a multi-period logit and found that for India the market variables did not have an effect. This type of evidence confirms the general notion that models calibrated elsewhere, may lead to misleading conclusions (Khoja, Chipulu & Jayasekera, 2019) or diminished efficiency (Allen, Powell & Singhal, 2015; McGurr & DeVaney, 1998; H. Platt & Platt, 2008).

2.3.5 Counter-arguments for sectoral focus

Although examining a unique homogenous economic activity may be an ideal research design, some shortcomings still can exist. One such shortcoming is the fact that firm failures are generally rare events (Cramer, 1999; Veganzones & Severin, 2021) and naturally will pertain to smaller samples with a small number of events of interest, which can lead possibly to reduced robustness (Rikkers & Thibeault, 2011).

Another angle of this issue is related to studies that dealt in parallel with wider models, so-called global models and separate sector models and did not gain an increased accuracy. Laguillo, del Castillo, Fernández and Becerra (2019) for example showed that centered models were less efficient to broader or off-centered models in the period closer to default for five sectors in Spain. Del Castillo García and Fernández Miguélez (2021) examined three sectoral tourism firm models for hotels, restaurants and travel agencies but found the broader tourism model to be more efficient. In a similar vein, Alaminos, del Castillo and Fernández (2016) found that global models involving firms from three continents were better in detecting failure to separate regional models. Gaganis, Pasiouras, Spathis and Zopounidis (2007) also found mixed results regarding the efficiency of sector models to broader ones for the listed manufacturing and trade sectors in the UK. A final counter-argument for developing sectoral models is that such model development may come with a costly application and maintenance (Alaminos et al., 2016; Del Castillo García & Fernández Miguélez, 2021; Laguillo et al., 2019).

2.4 Definitions of firm failure

In this section, the definitions of firm failure will be discussed, as a variety of definitions exist which are quite diversified. As the core of the problem is classification, the designation of the criterion of failure is of high importance as it affects the dependent variable and have implications on results (Balcaen & Ooghe, 2006; Pretorius, 2009).

As Ohlson (1980) and Veganzones and Severin (2021) have stated, there is no consensus about the definition of business failure in empirical studies, no single definition (Sun et al., 2014) and this variety render firm failures not directly comparable (Kücher, Mayr, Mitter, Duller & Feldbauer-Durstmüller, 2020). Tavlin, Moncarz and Dumont (1989) distinguish between three basic types of firm failure: economic failure, technical insolvency and bankruptcy. While the two first are related to financial distress conditions, bankruptcy is related to the official legal process. Balcaen and Ooghe (2006) discuss too the arbitrary nature of the definitions of corporate failure, that fall mainly to bankruptcy and financial distress.

Attention must be given to the definition adopted, as besides it defines the dependent variable, it can shape different samples. As Cole and White (2012, p.7) comment for the study of Torna (2010), "*Torna finds that the influences on a healthy bank's becoming troubled are somewhat different from those that cause a troubled bank to fail"*. This statement can be easily adjusted for any type of economic entity in the frame of corporate failure and can be narrowed down to convey that the determinants of influencing a firm to enter financial distress can be different to those for a firm entering bankruptcy. In this range, Galil and Gilat (2019) add that different distress definitions should be seen as different types of distress events that may carry their own unique features. Amendola et al. (2015) in a competing risks setting for Italy used three firm outcomes, namely, bankruptcy, inactivity and liquidation. The differences found, imply that a certain path of failure may be influenced in another way by the respectable covariates.

From the above arguments, it can be derived that every firm failure definition should be assumed to estimate the exact phenomenon it is accounted for. The definitions further presented, are extracted from the wider firm bankruptcy literature, as also from the tourism, hospitality and hotel literature.

2.4.1 Bankruptcy

Bankruptcy is the legal procedure that designates the status of an economic entity as bankrupt. The judicial or *de jure* bankruptcy (Lukason & Andresson, 2019) is the most official, as it is extracted from official authorities and allows also the exact date of the event to be dated (Appiah, Chizema & Arthur, 2015; Beade, Rodríguez & Santos, 2023).

The term though may be different in various countries. For example, in the US, bankruptcy is divided in chapters 7 and 11, with different legal and economic consequences for the firm. Chapter 7 is linked to liquidation and business cessation, while chapter 11 is relevant to protection, restructuring of debt and the continuation of business activity (Altman & Hotchkiss, 2005). Thus, in studies conducted in the US, it is observed that research may focus on one specific chapter only (Ho, McCarthy, Yang & Ye, 2013), or can include both by proceeding to a bankruptcy petition. It can be noted, that in the UK, the term bankruptcy applies only for individuals not firms (Cook, Pandit & Milman, 2012) and the relevant UK term is insolvency. Nevertheless, it is most prevalent definition in the hotel failure literature (Metaxas & Romanopoulos, 2023) and possibly the widest used too in the wider corporate failure literature.

2.4.2 Financial distress

Another definition for business failure is that of financial distress. Here the definition becomes more vague, as it usually follows a finance-based condition. This approach is widely used too, it is more of a quantitative artificial construct (Allison, 2010; Jaggia & Thosar, 2005). In such cases, the dependent variable can be the observance of a fundamental accounting item having a negative course for two consecutive years. For example, from the hotel literature, Cho (1994), Youn and Gu (2010) and Li and Sun (2012, 2013) have considered as failed, hotels that had negative net income for two or three consecutive years.

Similarly, Maté-Sánchez-Val (2021) accounted as failed, hotels with negative shareholder equity for the same period.

From the wider finance literature, Pindado, Rodrigues and De La Torre, (2008), Tinoco and Wilson (2013) and Yazdanfar and Öhman (2020) used a similar but more complicated condition, as they set a firm in distress if EBITDA is lower to interest expenses for two consecutive years or there is a fall in market value for two years. Very similar conditions are met in a variety of finance studies examining firm distress (e.g., Christopoulos, Dokas, Kalantonis & Koukkou, 2019; Gupta & Gregoriou, 2018; Keasey et al., 2015). This condition may seem more arbitrary to an official bankruptcy, but there is an incentive, as for example it coincides with a listed firm in Chinese stock markets been signaled as a "special treatment" and may be of use from an investing angle as it may signify factors affecting a potentially successful or unsuccessful course in a stock market, providing an appropriate signal to investors (Zhou, Fu, Li & Xu, 2022).

2.4.3 Other definitions

Some other definition examples are delisting from a stock market (Adams, 1995; Charalambakis, 2015), the going concern assumption (Fernández, Sánchez, Alaminos & Casado, 2018; Zhai, Choi & Kwansa, 2015), a sharp fall or a drawdown in stock price (Galil & Gilat, 2019), the estimation outcome based on a logit or a probit model (S. Y. Kim, 2018; Süsi & Lukason, 2019), no dividend payment (Lau, 1987), or a broader mix of definitions including bankruptcy and financial distress together (Beaver, Cascino, Correia & McNichols, 2023; Charalambakis & Garrett, 2019; S. Y. Kim, 2011; Löffler & Maurer, 2011). Default is another term used, which involves bankruptcy, a distressed exchange or a delay in payment (Löffler & Maurer, 2011) and is applied by credit rating agencies.

Other less frequent examples are having no data for two years in a financial database (Fotopoulos & Louri, 2000), removal from telephone catalogues and inability to contact the firm for a period of two years (Saridakis, Mole & Storey, 2008), discontinuation from appearance in commercial brochures (Baum & Mezias, 1992) and the deletion from government databases (Falk & Hagsten, 2018; Lin & Kim, 2020; Piacentino et al., 2021; Türkcan & Erkuş-Öztürk, 2020).

A swift comment for the basic definitions, is that bankruptcy is considered more objective (Appiah et al., 2015; Balcaen & Ooghe, 2006; Charitou et al., 2004; Papana & Spyridou, 2020; Veganzones & Severin, 2021), while financial distress or special treatment may not lead always to bankruptcy (Carmona et al., 2022; Jayasekera, 2018; X. Zhang, Zhao & Yao, 2022), but can be considered a pre-stage of legal events commencing (H. Choi et al., 2018). The selection of the failure definition may rely though on the purpose of research as also on the nature of available data (Ropega, 2011).

2.5 Variety of methodologies

This section will provide an overview of the methods used in the field of corporate failure research. Aziz and Dar (2006) categorize broadly the methodologies into three broad teams, to statistical methods, artificial intelligent expert system models and theoretical models. Statistical models were the most popular, employed in 64% of their sample, artificial intelligence represented 25% and theoretical approaches 11%. Overall, the most used standalone methods were multiple discriminant analysis (MDA) (30.3%), logit (21.3%) and neural networks (9%). The overall predictive accuracy was found to be the highest for artificial intelligence at 88%, followed by 85% for theoretical models and 84% for statistical models.

Jackson and Wood (2013) provided an update on this issue with a bigger sample and made the same division with Aziz and Dar (2006) on model categories. The relative frequency of model use was similar, with MDA and logit being the most used, followed by neural networks. In a slightly different fashion, Veganzones and Severin (2021) classified the methods in three groups: statistical, artificial intelligence and the more recent ensemble methods that combine several classifiers together. In the course of the strand, logistic regression seems to have become the most applied technique, as found also in the study of Shi and Li (2019) with a rate of 38%. Logit is also very popular in the close field of credit risk (Dastile, Celik & Potsane, 2020; Dumitrescu, Hué, Hurlin & Tokpavi, 2022).

A small commentary on methods, is that the more artificially sophisticated the methodologies get, the better accuracy they reach (Barboza, Kimura & Altman, 2017). This stems from the ability to overcome shortcomings of older methods regarding specific statistical properties of the data as also being highly effective in capturing non-linear variable relationships (V. Giannopoulos & Aggelopoulos, 2019; Thammasiri, Delen, Meesad & Kasap, 2014). Though, better accuracy comes with a reduction in interpretation (Carmona et al., 2022; Sigrist & Hirnschall, 2019; Suresh, Severn & Ghosh, 2022). Neural networks for example are described in many instances as black boxes (Altman, Marco & Varetto, 1994; Cybinski, 2001; Gaganis et al., 2007; Khoja et al., 2019; Levratto, 2013; S. Li & Wang, 2014; Olson, Delen & Meng, 2012; Papana & Spyridou, 2020; Park & Hancer, 2012). If accuracy is the main interest, as it may be in credit card fraud (Park & Hancer, 2012) and not necessary explainability, artificial intelligence and machine learning methods are most suitable (Barboza et al., 2017; S. Y. Kim, 2018). But this has an effect as mentioned in a meaningful and meticulous interpretability, which in turn affects economic inferences too and eventual strategies to improve business (H. Kim et al., 2020).

Some newer models, as decision trees and extreme gradient boosting are considered more transparent, but still are not completely straightforward, as the former has many classification rules (Olson et al., 2012) and the latter, with a closer look, require some additional postestimation processes to be able to reach more neat interpretations (Carmona et al., 2022). This is probably the reason why logit is popular, as the more advanced techniques are not compatible to the explainability requirements of regulators (Dumitrescu et al., 2022).

In any case, all models, including artificial intelligence, share a common statistical background and heritage (Aziz & Dar, 2006) and no single category of methods is stably predominant over the others (Alaka et al., 2018). The example of the study of Papana and Spyridou (2020) who examined firm failure in Greece with four methods, namely, MDA, logit, decision trees and neural networks, found the first to be best in classification, demonstrating that an older technology can be more efficient to newer.

Another issue with artificial intelligence is the extraction of results in terms of relative importance, which hinders possible misinterpretations. Although some authors mention that the positive or negative relationship on the dependent variable can be inferred in neural networks backed on theoretical arguments and prior literature (Abidin et al., 2020), it is not always the case, and this will be illustrated with an example for the variable of size. Size of a firm can be measured in many ways. Carmona et al. (2022) find size in terms of number of employees to be the most important variable affecting bank distress. This could imply a possible presence of diseconomies of scale and problems due to aggressive growth. Size proxied by total assets also is found to be a significant variable in six hotel failure studies which use econometric methods (Lado-Sestayo et al., 2016; Maté-Sánchez-Val, 2021; Situm, 2023; Vivel-Búa et al., 2016, 2019; Vivel-Búa & Lado-Sestayo, 2023). In only one study, size was related positively with default (Vivel-Búa et al., 2019) and in the rest negatively. If size or any variable, is not accompanied with a corresponding sign marking the effect, different empirical notions can be derived, but also different economic inferences can be made. If size is positively signed, this could indicate possible diseconomies of scale, and if negatively, a protective effect holds that can be related to economies of scale. These two examples of size, where in the personnel case the economic inference may be more profound, but in the second case of assets is less straightforward, shows the necessity for increased detail, as one cannot preclude unexpected and ambiguous results. As Altman et al. (1994) concluded, neural networks and artificial intelligence by logical extension, do not allow precise interpretation as econometric and statistical methods.

2.6 Longer prediction horizons

One feature of bankruptcy prediction with financial ratios not practiced in the other approaches is the technique of extending further the failure horizon. This technique allows to check the stability of the results and the information content for a wider time window and is performed by applying appropriate lags of the covariates. It dates back to the first bankruptcy studies (Altman, 1968; Beaver, 1966)[1] and it is widely used till today as an optional and complementary methodology tool (e.g., Altman, Iwanicz-Drozdowska, Laitinen & Suvas, 2020; Tian, Yu & Guo, 2015). The most common frame is one year (Beade et al., 2023; Tian et al., 2015) and some researchers call for bigger horizons (Veganzones & Severin, 2021), as the one-year window may not be enough for preventive actions (Youn & Gu, 2010) and managerial decisions at an earlier stage (Tian & Yu, 2017).

Hospitality examples are Cho (1994) and Fernández-Gámez, Cisneros-Ruiz & Callejón-Gil (2016) who calculated one to three-year windows. There is a tendency though of models to reduce general performance (Acosta-González, Fernández-Rodríguez & Ganga, 2019; Campbell, Hilscher & Szilagyi, 2008; Ciampi et al., 2020; Tinoco, Holmes & Wilson, 2018; Tinoco & Wilson, 2013). Also, altering the horizon may change the significance or importance of the relevant variables, as for example Mselmi et al. (2017) estimated a logit model for French firms and found a solvency ratio to be the most discriminant predictor for the one-year model but size proxied by total assets in the two-year model. Fernández-Gámez et al. (2016) estimated with neural networks hotel failure and found for the one and two-year horizons EBITDA to total assets as the most important predictor and for the third year return on assets.

Based on the above fact, i.e., the possibility that variables may change their attributes during time, this may be meaningful for the relative importance of specific groups of variables. For example, Lukason and Andresson (2019) assess that different types of variables are more beneficial for the short or the long-run, as the recent paid amount of taxes can be a better indicator in the short-run. Also, market variables tend to be better predictors close to failure as

[1] Charitou et al. (2004, p.469-471) provide a table with studies that applied the technique.

they incorporate more forward-looking information in relation to historical backward-looking accounting variables (Tian et al., 2015). Similarly, for large banks who negotiate credit default swap spreads, Flannery and Giacomini (2015, p.239) showed that this metric for the 25 largest European banks spiked during the 2007 credit crunch, having an opposite movement to market value, exhibiting an abstract example where extending the horizon prior to the event of interest may offer useful insights regarding the effect of certain groups of variables.

Conclusions

This chapter presented the main conceptual framework of business failure research. Initially, the firm failure problem and the different approaches that research follows were exhibited, with the financial ratio approach been recognized as the most applied despite the fact it is atheoretical. A focus was further placed on sectoral issues and much evidence regarding this and the differences that may exist in firms of different sectors. Then, the main definitions used to designate a firm as failed, which define also the dependent variable was addressed, and the chapter closed with the broad categories of methodologies applied and the feature of predicting failure over longer time periods.

CHAPTER 3: Review of the previous research

This chapter will move towards the literature review part of the thesis. Initially, some milestone studies regarding methodology usage will be presented. Then, the interest shifts to the literature that investigated hotel failure with financial variables. A systematic review is conducted for this reason, including a research protocol for study filtering, the narration of the selected studies, the recording of the financial ratios in a cumulative table and a final discussion section.

3.1 Significant studies in bankruptcy research

The strand of default prediction covers disciplines as accounting, finance, management and statistics, and especially after the 2007-2009 credit crunch, involves more SMEs samples and has grown exponentially (Ciampi et al., 2021). By searching in Google Scholar the terms “bankruptcy” and “financial ratios” 44,300 studies immediately come up. The terms “default” and “financial ratios” provide 33,800, showing the immense number of available material. This first part is devoted to some milestone studies in the broad field, with an attention in the appearance of specific types of methods.

The strand of firm default prediction opened up in the decade of 1930, with some references hard to find. Beaver (1966) is considered to be the first modern study, that sampled 79 bankruptcies of large US firms and with univariate analysis found that the ratio cash of flow to total debt was the best discriminatory factor for a five-year period. Beaver (1968) in a similar study, included also market metrics in terms of stock prices. Altman (1968) is another milestone study, that used MDA for the first time in such frame, again for 66 listed manufacturing firms in the US and found that a specific set of five ratios discriminated at 95% one year prior bankruptcy and 72% in the two-year period.

Martin (1977) is the first study to apply logistic regression in the banking sector. With 58 commercial banks that failed in the US from a sample of over 5,500 banks, logit with linear and quadratic discriminant analysis were compared over a six-year period and similar accuracies were attained. Ohlson (1980) was the first to apply logit to firms. In a study that coined the name for O-Score models, financial ratios were used to evaluate 105 bankrupt and 2,058 non-bankrupt listed industrial US firms and reached an accuracy of 96.12% for one and 95.55% for two years to bankruptcy. Zmijewski (1984) introduced probit with 81 bankrupt firms and three financial ratios, while Lane et al. (1986) and Luoma and Laitinen (1991) used survival analysis based on the work of Cox (1972) for US banking and Finnish firms respectively. Finally, Odom and Sharda (1990) moved the field towards the artificial intelligence and machine learning era with neural networks.

3.2 Motivation for a literature review on hotel default

Regarding the state of literature reviews on firm failure, at least 24 can be found (Alaka et al., 2017, 2018; Appiah et al., 2015; Aziz & Dar, 2006; Balcaen & Ooghe, 2006; Bellovary et al., 2007; Ciampi et al., 2021; Dimitras et al., 1996; F. T. Garcia, Ten Caten, De Campos, Callegaro & De Jesus Pacheco, 2022; Habib, Costa, Huang, Bhuiyan & Sun, 2020; Hernández et al., 2021; Jones, 2023; Keasey & Watson, 1991; H. Kim et al., 2020; Kirkos, 2015; Kristóf & Virág, 2020; Matenda, Sibanda, Chikodza & Gumbo, 2021; Nguyen & Zhou, 2023; Pretorius, 2008; Prusak, 2018; Ravi Kumar & Ravi, 2007; Shi & Li, 2019; Sun et al., 2014; Veganzones & Severin, 2021) that discuss different dimensions but generally tend not to adopt a sectoral stance and focus. An exception here is the review of Alaka et al. (2017) that focus on both quantitative factors as financial metrics and qualitative factors for the construction industry. This can be seen as a first gap of sectoral reviews in the broader strand of corporate failure.

Though the first attempts to examine hospitality and tourism firm failures with financial information can be first seen in the 90s with Adams (1991) and Moncarz and Kron (1993), Thomas, Shaw and Page (2011) mentioned that at the time failure studies were generally missing for small tourism firms. The recent reviews on hospitality financial management of Jang and Park (2011) and Tsai, Pan and Lee (2011) dedicate sections to firm failure, but indeed the studies were then more limited. More recently, Lado-Sestayo et al. (2016), Vivel-Búa et al. (2016), Falk and Hagsten (2018), Caires et al. (2023) and Situm (2023) included literature review parts in their studies on hotel default and even included aggregated evidence in terms of cumulative tables with relevant studies, as also Spyridou (2019) provided a conceptual framework regarding the tourism firm failure issue. The scope though of presenting and discussing the theme in these six abovementioned studies was not exhaustive on the nexus of financial ratios and hotel default, rather included all broader factors affecting failure for tourism and hospitality firms. The current state though of hotel default studies with financial covariates have received over 1,000 citations and no previous systematic attempt to accumulate the specific sector's financial evidence existed. This derivation is seen as another gap in the tourism firm failure sub-strand and more specifically in the hotel sub-strand.

Having set the underpinnings of a general-specific deficit in sector reviews and under the light that the financial ratio investigation is most common for the hotel sector too, this deficit becomes the motivation to perform such a systematic review. So, this section's research question is postulated as: which are the financial ratios that are been recorded in the hotel failure literature and how they effect on failure?

3.3 Materials and methods of literature review

This section will describe the procedures followed, with the aim to reach the final collection of hotel studies that have used as covariates financial ratios and to further isolate their participation and where possible their effect on default. The procedure followed here, adheres to a high degree on the protocol of the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) by Liberati et al. (2009) and its update (Page et al., 2021).

To provide a systematic literature review of the subject, initially Google Scholar is used, a database with wide coverage. An advanced search is conducted, with relevant keywords and phrases, which are based on the jargon met in the literature. This term search is not limited to the title and is performed for the whole text, with no year restriction to capture even newly published work and written in the English language. The intention is to keep and process, quality peer reviewed full papers, book chapters and doctoral theses and at the same time exclude extended abstracts, conference and working papers.

Three term combinations are used in order to flank the needed content in a most efficient manner. The rationale behind this approach, is to safeguard against missed content and term overlapping across the literature due to the use of a single algorithm[2]. Each combination of keywords is divided to two technical components. The first, is one of the three phrases “hotel bankruptcy”, “hotel failure” and “hotel survival”, which are expected to be included in the candidate studies. These three phrases become the cornerstone where the second component is attached. This part involves a search for at least one alternative word related to the hotel industry, namely accommodation, lodging, hospitality, and tourism, as also a search for terms

[2] For example, the two studies of Li and Sun (2013) and Caires et al. (2023) which are included in the final analysis, were identified only by the second and third algorithm respectively.

proxying the financial aspects of firm failure, namely default, distress, insolvency, survival and risk. These three keyword combinations are:

1. “hotel bankruptcy” accommodation OR lodging OR hospitality OR tourism OR default OR distress OR insolvency OR survival OR risk.
2. “hotel failure” accommodation OR lodging OR hospitality OR tourism OR bankruptcy OR default OR distress OR insolvency OR survival OR risk.
3. “hotel survival” accommodation OR lodging OR hospitality OR tourism OR bankruptcy OR default OR distress OR insolvency OR risk.

Table 3.1 depicts the path for the research protocol of this systematic literature review, where the first column encapsulates the various steps, column 2 to 4 depict the total number of studies added or subtracted per each term combination and column N represents the sum of the remaining studies after each step.

Table 3.1 Research framework of study

Steps of the process	Combination 1	Combination 2	Combination 3	N
Studies retrieved	208	194	222	624
Initial screening	-178	-168	-204	74
Duplicates and abstracts	-2	-9	-15	48*
In-depth screening		-25		23
WoS & Scopus		-3		20
Subjective inclusion		+9		29

* From this step on, all studies are merged.

The three combinations are entered in Google Scholar and retrieved 208, 194 and 222 studies respectively[3], thus in total 624 studies and the sum is placed in column N. After the first step, various exclusion criteria are applied. The first filter involves the initial screening of the

[3] Based on the results from the last search conducted on the 12th of June 2023.

abstract and introduction for a relevance match at a generic level. In this stage, from combination 1 178 studies are removed, from combination 2 168 and from combination 3 204, in total 550. These numbers are represented with the sign of subtraction. The items removed, were mainly related to themes regarding service failure, business strategy, law or were irrelevant to the topic. The remaining 74 articles are extracted to spreadsheets for further data manipulation.

It should be noted, that during the time of conducting this review, another useful Google Scholar function was used, that of alerts. With this function, the above used strings of terms were applied to set alerts, so whenever a new article was enlisted in the database, an email notification was received. This procedure entailed in the addition of the last article included in the analysis. The next step removes 25 duplicates and one extended abstract (Álvarez-Ferrer & Campa-Planas, 2020) leading to 48 unique entries, which are merged into one spreadsheet to simplify data management and appear further in the third column of Table 3.1.

The next phase involves an in-depth screening of the works. As the prime interest of this review is to extract the financial variables related to hotel failure and where possible their effect, studies adhering to the strands of industrial organization, organizational psychology and organizational ecology, after been scrutinized were inevitably excluded (Baum, 1995; Baum & Haveman, 1997; Baum & Ingram, 1998; Baum & Lant, 2003; Baum & Mezias, 1992; Ingram & Baum, 1997a; Ingram & Inman, 1996; Kalnins, 2016; Urtasun & Gutiérrez, 2006), as such studies examine failure with few hotel-specific metrics that involve age and size, with the latter measured in terms of room capacity, thus being consistent with the tradition and norms of this specific strands (Mellahi & Wilkinson, 2004; Ropega, 2011). At this point, the qualitative study of Lowe (1988) is eliminated also.

Another sub step of the broader in-depth filtering step is the provision to keep studies that provide clear-cut hotel results. So, studies that have used broad tourism and hospitality firm samples in an indistinguishable way and inseparably are excluded (Abidin et al., 2020, 2021; Barreda et al., 2017; Laguillo et al., 2019; Li et al., 2017, 2019; Park & Hancer, 2012; Pisula, 2020). An additional filter regarding study relevance, is the non-inclusion of ex-ante bankruptcy risk assessments that their aim is to project a future potential credit profile for hotels but do not examine actual bankruptcies or a measure of financial distress (Gallo, Timková, Šenková & Karahuta, 2018; Matejić et al., 2022; Špiler et al., 2022; Vivel-Búa, Lado-Sestayo & Otero-González, 2018). Also, studies that deal with going concern assumption explicitly (Fernández et al., 2018; Zhai et al., 2015) and the study of Yuan, Li, Liang & Chen (2023) where the initial injected capital, which corresponds to an accounting item, but was not found significant, are not included. As it can be seen in the fourth line of the second column of Table 3.1, these studies sum up to 25, leaving 23 for further consideration.

The next filter is to apply a criterion that ensures the quality of the remaining sample of works. So, the 23 studies are further cross-checked in the Core Collection of Web of Science and Scopus databases, looking for their presence in at least one database. With this filter three more studies are removed (S.-J. Choi & Lee, 2014; Nagendrakumar, Madhavika, Weerawardhana, Vishwadeepa, Anushani & Alahakoon, 2020; Waikar & Fernandes, 2020).

The last filter involves a subjective inclusion of a certain number of studies that were not captured by the keyword algorithms. Nine articles are added (Adams, 1995; Cho, 1994; Correia et al., 2022; Fernández-Gámez et al., 2016; Gu & Gao, 2000; Piacentino et al., 2021; Türkcan & Erkuş-Öztürk, 2020; Vivel-Búa et al., 2016; Youn & Gu, 2010), which were collected during the period of research from sources as the previous literature, database suggestions as Mendeley and Science Direct and from extended research. Seven of these studies belong to peer-reviewed journals and are in accordance with the inclusion standards. For the study of Correia et al. (2022), although it does not sample hotel firms in the close sense of the 5510 subcode of NACE, which is the most populated and representative of the whole accommodation code, but the remaining three subcodes, still is retained. The thesis of Cho (1994) and the book chapter of Adams (1995) are retained too, despite not been included in Web of Science or Scopus, because of their historical importance and pivotal role in this sub-strand.

Regarding the subjective inclusion filter, it can be noted that such measures i.e., the inclusion of studies into literature reviews that are not captured by a well-developed and prespecified algorithm, are not unusual in the literature. For example, Nguyen and Zhou (2023) in their literature review for reduced-form models of correlated default timing, added at the synthesis stage 15 articles based on cross-referencing and expert recommendations. Song, Qiu and Park (2019) in a review of demand forecasting, invited a panel of experts to evaluate the process and included nine more studies. The review of bankruptcy prediction with artificial intelligence methods of Kirkos (2015) used a second complementary keyword to augment the initial set of studies. With the main filters applied, the final number of studies narrowed down to 29[4], which had received by the 12th of June 2023 1,211 citations in Google Scholar, exhibiting a significant impact of research activity. Besides the thesis of Cho (1994) and the

[4] For the interested reader, more relevant references related to hotel and tourism firm failure are provided, that did not meet entirely the criteria, which taken together with the rest of the material of this chapter represent almost an exhaustive list of the relationship of hotels and default: (Adams, 1991; Belda & Cabrer-Borrás, 2020; Brouder & Eriksson, 2013; Crespí-Cladera et al., 2021; Diakomihalis, 2011; Horváthová & Mokrišová, 2018; Ingram & Baum, 1997b; Kalnins & Chung, 2006; Kaniovski et al., 2008; H. Kim & Gu, 2006; Laguillo et al., 2019; Lee & Thong, 2023; Li et al., 2013; Li & Huang, 2012; Milašinović et al., 2019; Moncarz & Kron, 1993; Pacheco, 2015; Pereira, Basto & da Silva, 2016, 2017; Santarelli, 1998; Tavlin et al., 1989; Wieprow & Gawlik, 2021; Zheng et al., 2022).

book chapter of Adams (1995), the 27 publications have been published in 15 journals and appear in Table 3.2.

Table 3.2 Frequency of publications per journal

Journal	Counts
Applied Economics	1
European Journal of Tourism Research	1
International Journal of Accounting and Financial Reporting	1
International Journal of Contemporary Hospitality Management	1
International Journal of Hospitality Management	4
International Journal of Tourism Cities	1
Journal of Forecasting	1
Journal of Hospitality and Tourism Research	3
Services Business	1
Spatial Economic Analysis	1
Sustainability	2
The Services Industries Journal	1
Tourism and Hospitality Research	1
Tourism Economics	2
Tourism Management	4
Tourism and Management Studies	2
Total	27

The most publications are hosted by the International Journal of Hospitality Management and Tourism Management journals. Three studies appear in Journal of Hospitality and Tourism Research, two studies appear at Sustainability, Tourism Economics and Tourism and Management Studies, while one publication appear in Applied Economics, European Journal of Tourism Research, International Journal of Accounting and Financial Reporting, International Journal of Contemporary Hospitality Management, International Journal of Tourism Cities, Journal of Forecasting, Services Business, Spatial Economic Analysis, The

Services Industries Journal and at Tourism and Hospitality Research. Table 3.2 also displays the diversity of journals interested in the exact subject and sub-strand.

Table 3.3 presents the distribution of the 29 studies per continents and countries. Four studies come from the United States of America and six from Asia. Two from China and Korea and one for Taiwan and Turkey. Europe is the continent with most publications, counting 18. Spain with 11 studies is the country with the highest contributions and Portugal follows with two. One study originates in Austria, Greece, Italy, Norway, Sweden and the United Kingdom.

Table 3.3 Studies per continent and country

Continent	Country	No. of studies
Americas	U.S.A.	4
Asia	China	2
	Korea	2
	Taiwan	1
	Turkey	1
Europe	Austria	1
	Greece	1
	Italy	1
	Norway	1
	Portugal	2
	Spain	11
	Sweden	1
	UK	1
	Total	29

The material of the 29 studies, will be deconstructed into basic elements (Torraco, 2005) and the studies are narrated per geographical area and year and involves a broad description of the study, in terms of significant variables and study design. Close consideration is given in keeping the same financial terminology as in the original source and explaining the composition of the ratios, when fully given, as it is not uncommon for financial ratios to be phrased with different terms (Lukason & Andresson, 2019). This approach assists to assure clarity and intelligibility, an issue that needs attention also in the tourism literature as discussed by Dolnicar and Chapple (2015). After the narration section, the financial variables will be recorded in a cumulative table.

3.4 Narration of studies

3.4.1 Americas

The narration will begin with the thesis of Cho (1994), who examined listed hospitality firms in the US belonging to the hotel and restaurant sectors. The logit model for the hotel sample of 15 failed and 15 non-failed firms, identified cash flow per share as the best and unique predictor with a negative, thus a protective, effect to default. The model also predicted up to a three-year horizon, reaching 92, 86 and 75% accuracies. It can be noted that for the restaurant sample, different variables were found as more influential.

The next study of Gu and Gao (2000) examined firm failure for a broad hospitality sample. From the firms participating, the hotel sample counted eight hotels, four failed and four non-failed. MDA was used and found as the most important variables to be earnings before interest and taxes (EBIT) to current liabilities, gross profit margin as gross profit to sales, the debt ratio of total liabilities to total assets, the fixed asset turnover of sales to fixed assets and long-term liabilities to total assets. The model overall reached 93% accuracy and from the hotel sample, only one hotel, namely the Prime Motor Inn, was not classified correctly.

Kim (2018) applied an ensemble method combining features of decision trees, neural networks and support vector machine for the listed hospitality firms in the US. The hotel model that included 26 distressed and 132 non-distressed hotels and motels selected the stock price trend, the accounts receivable turnover as sales to accounts receivable and debt-to-equity ratio and reached an overall accuracy of 95.6%.

Lin and Kim (2020) examined the failure rates of Texan hotels, taking account ownership structure, meaning franchised or company-operated and three diversification strategies, namely the geographic, brand and segment-wise, and showed a different effect of these strategies. For the full sample, geographic and segment diversification increased risk, while brand diversification reduced it. For franchised hotels, brand strategy reduced risk and the opposite effect was found for segment strategy, while geographic strategy was insignificant. For hotels operated by companies, the brand and geographic strategy was linked to bigger risk, while the segment strategy was insignificant. Age and size in terms of rooms, increased failure risk for all types of hotels, while the logarithm of revenues and being in a market with a high number of high-end hotels reduced risk.

3.4.2 Asia

Moving to Asia, Youn and Gu (2010) contested neural networks and logit for 204 public lodging companies in Korea, of which half were considered as failed under the definition of three years of continuous negative net income. The interest coverage ratio, measured as EBIT to interest expenses was found to be the best predictor in the one variable logit model and the four variable neural networks model. Neural networks also selected the quick ratio as quick assets to current liabilities, the current ratio as current assets to current liabilities and EBITDA to total liabilities. Overall, neural networks reached 87% accuracy in-sample and 81% out-of-sample, while logit reached 83 and 77% respectively.

Kim (2011) employed four methodologies, MDA, logit, support vector machine and artificial neural networks to assess bankruptcy analysis and classification accuracy for Korean hotel for the years 1995-2002. The sample consisted of 33 failed and 33 non-failed hotels under a broad default definition and the predictive variables came from traditional balance sheet metrics. Support vector machine scored best at 95.95% and selected as the most relative important variables to be the current ratio, return on equity, fixed asset turnover, fixed assets to long-term capital ratio, ordinary income to owner's equity ratio, growth in assets and growth in owner's equity. The rest methods accounted for different variables based on their selection procedure and neural networks reached 91.6%, logit 80% and MDA 72.6%. Different projections related to type I and II error costs were made and proved that over a 20:1 ratio, neural networks performed better to support vector machine.

Chen and Yeh (2012) after predicting demand uncertainty with an autoregressive model, calculated international hotel bankruptcy in a sample of 10 failed and 10 non-failed Taiwanese hotels for the period 1995-2008 with logit. Having as input variables hotel characteristics and environmental factors, the results showed that demand uncertainty and distance from an international airport increased failure risk, while the Herfindahl-Hirschman index to proxy market concentration, labor productivity measured as total operation revenues to the number of employees and belonging to a chain reduced failure probability.

Li and Sun (2012) investigated a sample of seven failed and 16 survived listed tourism firms operating also hotel businesses with logit, MDA, neural networks and support vector machine and having as inputs the Altman (1968) variables set. Because of the small sample size, the up-sampling technique of nearest neighbor was considered to augment artificially the initial sample and to perform simulations, as the authors argue that exact paired sampling of failed and non-failed firms is not a real-world equivalent, as failed firms are always a lesser portion of the total number of firms. The final simulations showed that the up-sampling approach indeed increase accuracy for all methods, with support vector machine performing though best.

In an exact similar vein, Li and Sun (2013) used the Altman and Hotchkiss (2005) variables, which are the same to the Altman (1968) set, and identical conclusions were drawn, as the more advanced ensemble method of case-based reasoning performed better.

Türkcan and Erkuş-Öztürk (2020) used firm-specific, regional and macro-environment variables to assess survival rates of 7,115 tourism related firms of which 2,738 did not survive, in the hotel, travel agency, restaurant and spa sectors for the province of Antalya in Turkey. A discrete-time survival model with a complementary log-log link resulted that age, market size, the legal form and size proxied by a dummy variable taking the value of one in the case of medium and large firms and zero in the case of micro-firms based on their initial capital decrease the exit hazard. Regional variables mirroring the competition level of the destination were found to increase hazard, as also the dummy variables for economic downturn and political crisis. Finally, hotels and travel agencies were found to be more prone not to survive.

3.4.3 Europe

The narration now shifts to Europe with Adams (1995) who used two MDA versions of the Altman (1968) Z-score and the accompanied variables, to classify correctly three occurred defaults and one ongoing survival from a sample of four UK hotels.

For the Greek hotel market, Diakomihalis (2012) applied three versions of MDA models calibrated on different sectors for a sample of 15 failed and 131 non-failed hotels. By adjusting the distress zone to lower cut-off points, the original Altman (1968) manufacturing model scored best 88%, with the private firm and the services models reaching 83 and 80% respectively. Also, the three and five-star hotels were found riskier to the four-star category.

A significant number of studies come from the Iberian Peninsula. Fernández-Gámez et al. (2016) contested probabilistic neural network and multi-layer perceptron methods for 108 Spanish hotels, with a one to three-year bankruptcy horizons. The multi-layer perceptron performed 95, 93 and 90% respectively for the three horizons and probabilistic neural networks followed with a less than 2% difference for all time windows. For the more transparent probabilistic neural networks method, the most important variables were the ratio of EBITDA to current liabilities, the net profit margin, total liabilities to total assets, liabilities to net worth and the account receivable turnover ratio as sales to account receivables. While the most important ratio of the one-year model i.e., EBITDA to current liabilities was the most influential variable in the two-year model too, return on assets was found best in the three-year model and all horizons promoted a different mix of covariates.

Gémar et al. (2016) used a Cox proportional hazards model to evaluate internal and external factors related to hotel survival in Spain. Internal factors reducing risk were found to be the legal form of being a corporation and profit margin measured as pre-tax profit to operating income. The ratio of employee cost to operating revenue representing management practices, in the case of being higher to 43% was found to increase risk. From the non-internal factors, an increasing risk relationship was found for hotels located in the region of Catalonia or Valencia and for a distance over 100 kilometers from an airport, while being launched between 2003 and 2009 reduced the exit risk. Other internal variables, as the number of employees to proxy size, the typology of hotel, belonging to a chain and various traditional financial ratios, were not found significant.

Gemar et al. (2019) replicated the previous study but focused solely on the niche of resort hotels. Again, the employee cost to operation revenues ratio being higher to 43% appeared to increase the hazard of exit, as also the location factor of operating in a tourism area and the Canary Islands. A decreased risk was related to the legal form of a corporation, located in the community of Madrid and being launched between years 2003 and 2009.

Escribano-Navas and Gemar (2021) applied a discrete-time hazard model and introduced the CEO gender dimension among other firm variables for a heavily imbalanced hotel sample. The estimations showed that performance as net income to total assets, size as the natural logarithm of net sales, hotel age and the gender of the CEO being female, all reduced risk, while an opposite effect was found unexpectedly for the liquidity ratio of working capital to total assets.

Narration continues with another scientific team from Spain that offer continuous contributions to the sub-strand of hotel failure research. Vivel-Búa et al. (2016) contested logistic regression and probit and estimated the economic structure as current assets to total assets and indebtedness as total liabilities to total assets to increase the likelihood of default. Variables reducing probability of default were found to be the financial balance as equity to current liabilities, profitability as operating income to total assets, size as the absolute number of total assets, overall activity as net turnover to total assets, delegations meaning the operation of more than one hotel and hotel age. The destination level metrics of occupancy, demand level in terms of number of visitors, seasonality and a low market concentration via a

Herfindahl-Hirschman index, reduced failure. Finally, logit proved marginally better to probit and models including variables of both types, performed slightly better.

Lado-Sestayo et al. (2016) employed a similar approach to their abovementioned study and examined hotel and external variables. From the hotel-specific variables, the financial balance as equity to current liabilities, profitability as operating income to total assets, size in terms of the logarithm of total assets, liquidity as net operating cash flow to total assets and belonging to a hotel group, all contributed significantly to reducing probability of exit. The economic structure variable as current assets to total assets and the number of stars, had the opposite effect. At a destination level, occupancy and destination profitability reduced risk, while increased risk was related to the Herfindahl-Hirschman index and for beginning operation in the year 2010.

Vivel-Búa et al. (2019) examined the likelihood of financial insolvency for a big number of micro, small and medium-sized hotels with four specifications of survival models. A positive effect on survival was related to asset turnover as net sales to total assets, to performance as net income to total assets and the ratio of cash flow to total sales. A negative effect stemmed from size as the logarithm of total assets, having though a smaller effect for micro hotels and debt as total liabilities to total assets. The external factors though, showed more diverse effects among hotel sizes, as destination occupancy reduced hazard of exit for small and medium hotels only, as also seasonality for micro hotels only. A bigger market share reduced hazard for micro and small hotels, the Herfindahl-Hirschman index increased hazard for the small category only, while the distance to an airport reduced the hazard for micro, having though an opposite effect for medium-sized hotels.

Vivel-Búa and Lado-Sestayo (2023) introduced a contagion effect, in addition to financial and destination variables. Probit analysis showed that the accounting variables of asset efficiency as income to total assets and size represented by total assets had a reducing effect to failure. From the destination variables, a protective effect to failure was related to the Herfindahl-Hirschman metric to proxy concentration, to occupancy rate, to distance to airports and train stations and seasonality, while the average number of rooms in the destination had a minor opposite effect. The spatial probit estimations retained most of the abovementioned variables qualitatively intact and added also leverage as total liabilities to total assets with a protective effect for the two and three-year delay models, the market share as total hotel revenues to total destination revenues with a positive sign too but only in the three-year delay model. Finally, the sign of asset efficiency turned positive and the authors overall concluded that a temporal contagion effect was present.

Pelaez-Verdet and Loscertales-Sanchez (2021) examined with Cox regression 2,639 lodging firms. Having set the year of 2008 to mark the financial crisis, as an anchor year and having a forward-looking approach, by discretizing the variable return on capital employed measured as earnings plus financial expenses to the sum of shareholder's equity and fixed liabilities, they found that achieving lower levels of this ratio reduced hazard for small-sized hotels. For medium-sized hotels, the legal status of being public instead of private had a similar effect.

Del Castillo García and Fernández Miguélez (2021) examined 138 hotels from a broader tourism firm sample of 406 firms. Multi-layer perceptron was applied with financial ratios from the tourism firm bankruptcy literature. The hotel model reached an accuracy over 90% and selected as the best variables return on equity as net profit to net equity, return on assets as EBIT to total assets and net profit margin as net profit to turnover. The global models, including the base and sectoral variables produced better accuracies to sector models and the authors concluded that global models increase accuracy and minimize costs of design.

Maté-Sánchez-Val (2021) investigated the probability of financial distress for non-multinational hotels with neighboring Airbnb accommodation in the city of Barcelona in Spain. Logistic regression attributed a negative effect to financial distress to exist with profitability as profits before interest and taxes to total assets, size in terms of the logarithm of total assets, as also the market position of the hotel based on customer rankings from TripAdvisor, but only for the full sample. A U-shaped relation, with an initial positive effect to distress stemmed from the average advertised price at the same website. The environment factors of income per capita as also the overall density of Airbnb listings around hotels reduced risk, the latter showing an enhancive role of Airbnb. By segmenting though the Airbnb market by room and host type, the density of full apartment listings and density of hosts with less than three listings decreased hotel risk, thus signifying a complementary character. A substitutive effect increasing risk, was found for the higher density of private rooms and for hosts with over two listings.

Correia et al. (2022) applied probit for accommodation establishments in Portugal and found sales to total assets, retained earnings to total assets and net income to total assets to reduce probability of failure, while the opposite effect was related to current assets to total assets.

Caires et al. (2023) examined the survival determinants through a discrete-time survival model among various sectors that also included the tourism and hotel sector in Portugal. The accommodation-only model showed a reduced exit influence related to operating profit to total assets, for fixed assets to total assets and the logarithm of sales. When all accommodation firms were incorporated into the wider sector model named mainly tourism, the variable of age turned slightly significant reducing likelihood of failure. The total tourism model, representing all the broader related sectors, found age and its squared and cubic terms to affect survival, as also debt with a positive association, signifying sectoral influences and possible bias.

Departing from the Iberian Peninsula, Piacentino et al. (2021) examined exit determinants for new accommodation firms in the island of Sicily in Italy. An increased risk of exit was found for localization as a competition measure and for distance from the coast farther than two kilometers. Reduced risk stemmed from size as the sales turnover of first year of operation and relatedness to complementary services. The interaction of localization and relatedness showed increased risk, thus congestion through localization nullifies the positive effects of relatedness and no difference in risk was observed between hotels and other accommodation services.

Falk and Hagsten (2018) investigated exit for urban and non-urban accommodation in Sweden. The research showed that survival increased for size measured as overnight stays, price levels as the logarithm of revenues to overnight stays and with fibre broadband infrastructure, except though for urban hotels. Seasonality affected survival negatively, as also minorly, competition for city hotels. While hostels and cottages faced higher risk, no effect was found for age, international demand, airport access, the economic crisis and for second homes ownership.

Zhang and Xie (2023) analyzed hotel bankruptcy in Norway for the years 2008-2018 with Cox regression. With the use of traditional financial variables, age and number of firms, they tested the impact of seasonality, in an overall sense and in the leisure, business and conference segments. The results showed initially that the book value of equity to total liabilities, retained earnings to total assets and age reduced risk. For the seasonality measures, while the overall estimations were not significant, when separate measures were applied for the segments of leisure, business and conference, business seasonality contributed to the exit risk by increasing it.

The final study of Situm (2023) assessed financial distress for Austrian restaurants and hotels with financial, destination and macro variables. Age, size as the logarithm of total assets, total equity to total assets, EBIT to total assets and operating in cities and suburbs reduced the distress probability. On the other hand, the legal form of a corporation and a dummy variable to represent negative equity, being one in the case where debt was bigger to total assets, increased distress. By examining the restaurant sector alone and the combined sample, some different results appeared, implying possible sectoral bias. Overall, the financial variables were able to explain the biggest part of the variation, thus been more informative to the other types of variables.

3.5 Table of studies with the isolated financial factors

The isolated information of interest that is extracted from the previously narrated studies, is now placed in Table 3.4. The table follows the logic of Lado-Sestayo et al. (2016, p.21) with the addition of the definition of default applied in the study. This addition is made mainly because the criterion of firm failure can have significant implications on the results (Balcaen & Ooghe, 2006; Pretorius, 2009) as it defines the dependent variable. The table consists of seven columns and the information is arranged in alphabetical and chronological order. The first column records author information, the second the country the study was conducted and the third the period of study. The fourth column provides sample details in terms of listed or private hotels and the proportion of failed and non-failed hotels. The fifth column documents the definition of default and column six presents the methods applied. The final column presents the financial determinants related to failure. These determinants are composed by the financial variables found significant in the source study and generally reported as important predictors. For artificial intelligence methods and MDA, only the presence and inclusion of variables having no signs attached are presented, as these approaches do not draw such inferences (Altman & Sabato, 2007; Kim, 2018), as happens in contrast with econometric methods, where a positive or negative sign to default is given and allows a direct interpretation. A positive and a negative sign represents here statistical significance of any level. As survival analysis is used in several studies and determinants of survival may have been reported, the interpretation is adjusted appropriately to mirror the relationship to hotel failure and exit.

Table 3.4 Information on study design and financial ratios of the selected studies

Authors	Country	Period	Sample	Definition of default	Method	Results
Cho (1994)	USA	1982-1993	15 failed and 15 non-failed listed hotels	3 or more consecutive years of negative net income	Logit	Cash flow per share (-)
Adams (1995)	UK	1986-1993	4 listed hotels of which 3 were suspended	Broad definition including suspension of trading	MDA	Altman (1968) variables
Gu and Gao (2000)	USA	1987-1996	4 failed and 4 non-failed hotels	Bankruptcy	MDA	Total liabilities / TA, sales / fixed assets, EBIT / current liabilities, gross profit / sales, long-term liabilities / TA
Youn and Gu (2010)	Korea	2000-2005	102 failed and 102 non-failed listed lodging companies	3 consecutive years of negative net income	Logit, NN	EBIT / interest expenses, current assets / current liabilities, quick assets / current liabilities,

						EBITDA / current liabilities
S. Y. Kim (2011)	Korea	1995-2002	33 failed and 33 non-failed hotels	Broad definition	MDA, logit, NN, SVM	ROE, current assets / current liabilities, sales / fixed assets, fixed assets / long-term capital, ordinary income / owner's equity, growth in owner's equity, growth in assets
Chen and Yeh (2012)	Taiwan	1995-2008	10 failed and 10 non-failed international tourist hotels	Bankruptcy by Taiwan Tourism Bureau database	Logit	Average operating revenue per employee (-)
Diakomihalis (2012)	Greece	2007-2008	15 failed from 146 hotels, with 4 listed hotels	Bankruptcy	3 MDA models	Altman (1968) variables
Li and Sun (2012)	China	1998-2010	7 failed and 16 non-failed listed tourism firms with hotel businesses	2 consecutive years of negative net income	MDA, logit, NN, SVM with nearest neighbor up-sampling technique	Altman (1968) variables
Li and Sun (2013)	China	N.A.	154 failed and 159 non-failed listed hotel samples	2 years of negative net income	Case-base reasoning, case-base reasoning ensemble, MDA, logit, SVM	Altman and Hotchkiss (2005) variables
Fernández-Gámez et al. (2016)	Spain	2005-2012	54 failed and 54 non-failed hotels	Bankruptcy	Multi-layer perceptron, probabilistic neural network	EBITDA / current liabilities, net profit margin, liabilities / net worth, total liabilities / TA, sales / accounts receivable
Gémar et al. (2016)	Spain	1997-2009	79 failed from 1,033 hotels opened in 1997-2009	Bankruptcy	Cox model	Pre-tax profit / operating revenue (-), employee cost / operating revenues over 43% (+)
Lado-Sestayo et al. (2016)	Spain	2005-2011	106 failed from 6,494 hotels	Bankruptcy	Cox, Weibull, Gompertz	Operating net income / TA (-), equity / current liabilities (-),

						net operating cash flow / TA (-), log TA (-), current assets / TA (+)
Vivel-Búa et al. (2016)	Spain	2008-2011	154 failed from 836 micro, small and medium hotels	Bankruptcy	Logit, probit	Total liabilities / TA (+), current assets / TA (+), operating income / TA (-), equity / current liabilities (-), net turnover / TA (-), TA (-)
Falk and Hagsten (2018)	Sweden	2002-2012	580 failed from 2,557 hotels, hostels and cottages	No longer report revenue to the official statistics agency	Cox model	Log revenues / overnight stays (-)
S. Y. Kim (2018)	USA	1988-2010	26 listed distressed hotels and motels and 132 non-distressed	Financial distress based on the Zmijewski (1984) probit model	Ensemble methods with SVM, NN and decision trees	Debt / equity, stock price trend, sales / accounts receivable
Gemar et al. (2019)	Spain	1997-2016	41 failed from 354 resort hotels	Bankruptcy	Cox model	Employee cost / operating revenues over 43% (+)
Vivel-Búa et al. (2019)	Spain	2007-2015	1,747 distressed from 11,558 small and medium-sized hotels	Financial insolvency legal status	Cox, exponential, Weibull, Gompertz	Net income / TA (-), cash flow / TA (-), net sales / TA (-), total liabilities / TA (+), TA (+, less for micro)
Lin and Kim (2020)	Texas, USA	2000-2018	3,619 exits from 45,606 hotels	Exit from public hotel tax file	Cox model	Log revenues (-)
Türkcan and Erkuş-Öztürk (2020)	Antalya, Turkey	2000-2016	470 failed from 1,487 hotels	Exit from Chamber of Commerce and Industry database	Discrete-time survival model	Size as a dummy variable taking the value of one for medium and large firms based on initial capital (-)
del Castillo García and Fernández Miguélez (2021)	Spain	2017-2019	69 failed and 69 non-failed hotels	Bankruptcy	Multi-layer perceptron	Net profit / net equity, EBIT / TA, net profit / turnover, EBITDA / current liabilities, cash flow / total liabilities,

						current assets / current liabilities, turnover / TA, total liabilities / TA
Escribano-Navas and Gemar (2021)	Spain	2005-2018	70 failed from 2,615 hotels	Bankruptcy and insolvency	Discrete-time survival model	Ln net sales (-), net income / TA (-), working capital / TA (+)
Maté-Sánchez-Val (2021)	Barcelona, Spain	2015-2018	29 distressed from 235 hotels	2 or 3 years of negative shareholder equity	Logit	Log TA (-), profit before interest and taxes / TA (-)
Pelaez-Verdet and Loscertales-Sanchez (2021)	Spain	2008-2019	2,639 lodging enterprises	Bankruptcy	Cox model	Return of capital employed (+, for small-sized hotels)
Piacentino et al. (2021)	Sicily, Italy	2010-2014	166 failed from 660 start-ups in the accommodation sector	Exit from Italian Institute of Statistics database	Cox model	Sales turnover of first year of activity (-)
Correia et al. (2022)	Portugal	2014-2018	57 solvent and 57 insolvent accommodation firms from NACE codes 5520 and 5590	Bankruptcy and insolvency	Probit	Net income / TA (-), sales / TA (-), retained earnings / TA (-), current assets / TA (+)
Caires et al. (2023)	Portugal	2006-2017	N.A.	N.A.	Discrete-time survival model	Log sales (-), operating profit / TA (-), fixed assets / TA (-)
Situm (2023)	Austria	2005-2015	162 observations in the financial distressed group and 304 for the healthy group	Financial distress: negative cash flow and/or negative earnings	Logit	Log TA (-), EBIT / TA (-), Equity / TA (-), dummy variable taking the value of one if total debt > TA (+)
Vivel-Búa and Lado-Sestayo (2023)	Spain	2012-2015	507 failed from 3,948 hotels	Financial insolvency	Spatial and nonspatial probit	TA (-), income / TA (-, in the non-spatial probit, + in the spatial probit), total liabilities / TA (-, only for the three-year delay spatial probit)

Zhang and Xie (2023)	Norway	2008-2018	104 failed hotels	Insolvency and liquidation	Cox model	Retained earnings / TA (-), book value of equity / total liabilities (-)
+/- signs mean a positive/negative relationship to failure. EBIT = earnings before interest and taxes, EBITDA = earnings before interest, taxes, depreciation and amortization, MDA = multiple discriminant analysis, N.A. = not available, NN = neural networks, ROE = return on equity, SVM = support vector machine, TA = total assets.						

3.6 Discussion of main results from previous studies

Having recorded the most important financial information of 29 studies related to hotel failure, a discussion will take place, where some common facts will be sought. Initially, the five standard set of the co-called Altman (1968) variables which are used in the studies of Adams (1995), Diakomihalis (2012) and Li and Sun (2012), as also Li and Sun (2013) in the form of the Altman and Hotchkiss (2005) set which is essentially the same, seem capable of providing very reliable accuracies as they cover fundamental dimensions from broad categories of financial ratios.

Financial metrics capturing earnings, efficiency, cash flow, profitability, sales and generally revenues exhibit a negative relationship to default, thus have an overall protective effect. Financial leverage, in the form of debt, negative equity or liabilities tend to exhibit a positive relationship to hotel failure. Cathcart, Dufour, Rossi and Varotto (2020, p.1) have stated that for unlisted and private firms, financial leverage is possibly the most important determinant that enhances default prospects. These two facts stemming from revenues and leverage can be considered ubiquitous stylized facts that are in line with economic intuition.

The asset dimension of size, usually found in the logarithmic form of total assets, is estimated in five out of six studies (Lado-Sestayo et al., 2016; Maté-Sánchez-Val, 2021; Situm, 2023; Vivel-Búa et al., 2016; Vivel-Búa & Lado-Sestayo, 2023) with the exception of Vivel-Búa et al. (2019), to be negatively related to default. An equal effect can be attributed to initial capital (Türkcan & Erkuş-Öztürk, 2020). Regarding fixed assets, a limited participation of related metrics was observed in the literature. The fixed-asset turnover ratio is found influential only in the studies of Gu and Gao (2000) and Kim (2011), but because of the methods used no certain sign can be related directly. Eventually, only in the study of Caires et al. (2023) a negative sign is attached to the ratio of fixed assets to total assets with certainty. This limited evidence in a fixed asset-intensive sector can be seen as a kind of a shortfall.

Studies with listed hotels to stock markets are performed in six occasions. For market variables, which are available only for this type of firms, besides of stock price trend in Kim (2018) and the equity market value in the studies using as inputs the Altman (1968) set, which again due to the methods followed cannot attach a certain effect, cash flow per share was only observed in Cho (1994) with a protective effect on failure. Most of the studies reviewed, have sampled private hotels, and the whole economic activity of accommodation more recently is being researched in the sense of larger samples. This practice, which is opposite to random sampling that shapes equal samples, is considered to be closer to real-world conditions. Regarding the definitions of failure used in the relevant literature, legal bankruptcy is the most applied, followed though closely by financial distress.

Regarding methodologies, survival analysis has taken over in the econometric field, being the base method of investigation in 11 occasions, with logit and probit following. Artificial intelligence methods have the biggest variety and an increased presence, and in the six studies that competed statistical models, performed in most cases marginally better.

Some business implications stemming from this review of the empirical evidence, follow the general notion of this strand of literature, that hotel management should monitor closely the evolution of the most significant ratios (Cultrera & Brédart, 2016). Since leverage in terms of liabilities was found the most ubiquitous default enhancing measure, this implies that liabilities should be continuously monitored and controlled. Min et al. (2009) also have proposed the betterment of the debt ratio as a fit survival tactic. Based on the results for size and its protective effect, suggest that firms in the hotel sector benefit from increased assets and probably harvest economies of scale.

Some brief policy implications related to the basic results for leverage and size, is the establishment of schemes that may affect these quantities. Plausible policies can be the creation of competitive employment and renovation schemes able to reduce costs and liabilities for hotels. The former can mitigate unemployment and the latter can be combined with climate change policies for energy efficient infrastructure.

An inherent limitation of this review on the financial determinants of hotel default literature, is the limited quantity of studies conducted in this sub-strand. This dictates that there is confined depth of evidence to identify other recurrent results and trends for financial ratios that may persist in broader strands, as also on study design.

Conclusions

Although firm failure research is growing and indeed focuses on separate sectors, a general gap was detected in literature reviews upon specific sectors, as also a gap for the hotel sector. With the above argument as a motivation, a systematic review was conducted to filter studies that examined the relationship of financial ratios and hotel failure. Through a review protocol, 29 studies were recognized, presented and recorded in a cumulative table. A discussion followed about study design and variable participation. The core results showed three financial metrics to be most recurrent, leverage with an enhancing effect to failure and revenues with size having the opposite effect.

CHAPTER 4: The hotel sector and bankruptcies in Greece

This chapter presents some fragmented information and data, that will assist to better comprehend in full the aim of the thesis. It begins with the contribution of tourism to the country's economy and the relative contribution of accommodation. Then, the economic activity of accommodation firms is described and more specifically the four counterpart subcodes from the perspective of NACE typology. Afterwards, bankruptcy data are displayed for Greece across sectors and specifically for the hospitality sector.

4.1 Overview of the economic activity of hotels

Greece is renowned for being a traditional Mediterranean destination, where travel and tourism contributed over 20% in 2019 to the formation of gross domestic product (Statista, 2023), just second behind Iceland with 21.8% among OECD countries (Adamopoulou, Kapopoulos & Marinopoulou, 2022). Tourism has a multiplying effect to an economy (Tribe, 2006), which for Greece is estimated between a factor of 2.2 and 2.65 (Adamopoulou et al., 2022), meaning that for a euro spent, approximately another one and a half euro is further generated.

The part of tourism activities consumed by inbound travelers i.e., the travel receipts, are considered an export and travel payments is the value spent abroad. The difference of these two items, is the balance of travel services. Table 4.1 shows the evolution of these figures for a 20-year period, where a constant surplus in the balance of travel services exist, that further reduce general deficit. In Greece, travel receipts are estimated to be 90% of total travel services value (Avramidis, Asimakopoulos & Malliaropulos, 2023), which is the sum of receipts and payments. The last column of Table 4.1 confirms that recently the ratio of travel receipts divided by the sum of travel receipts and travel payments exceeded 90%.

Table 4.1 Balance of travel services, travel receipts and travel payments (million euros)

Year	Travel receipts	Travel payments	Balance of travel services	Travel receipts to total travel services
2003	9,495	2,136	7,359	0,8164
2004	10,347	2,310	8,037	0,8175
2005	10,729	2,445	8,283	0,8144
2006	11,356	2,382	8,973	0,8266
2007	11,319	2,485	8,833	0,8200
2008	11,635	2,679	8,956	0,8128
2009	10,400	2,424	7,975	0,8110
2010	9,611	2,156	7,455	0,8168
2011	10,504	2,266	8,238	0,8226
2012	10,442	1,843	8,598	0,8500
2013	12,152	1,835	10,317	0,8688
2014	13,393	2,076	11,316	0,8658
2015	14,125	2,037	12,088	0,8740
2016	13,206	2,005	11,201	0,8682
2017	14,630	1,904	12,725	0,8848
2018	16,085	2,191	13,894	0,8801
2019	18,178	2,743	15,434	0,8689
2020	4,318	792	3,525	0,8450
2021	10,502	1,112	9,390	0,9043
2022	17,676	1,924	15,751	0,9018

Source: Bank of Greece (2023) and own calculations

Though Tourism Satellite Accounts can be a more analytic tool for the economic measurement of tourism activities, a more simplified approach is taken here regarding its impact. Travel costs generally refer to the costs made for a round-trip between a country of origin and destination country, and transportation is a considerable proportion of this cost, especially for long-haul travel (G. Li, 2008). But accommodation costs represent a significant part of this value. While 45% of expenditures remains in the origin country and are related to travel arrangements as tour operators, travel agencies and airlines, 55% is transferred to the destination country, where further 36% is distributed to accommodation expenses (Labrianidis, 2020). These figures show the rough estimated value generated by the accommodation sector, implying the importance of the sector in relation to the whole tourism product.

4.2 Description of the four codes in the accommodation sector

This section will describe some dimensions of the specific economic activity, as accommodation and hotels are a wide concept. Accommodation establishments can vary, from hotels, motels and luxury hotels to traditional inns, camping sites and student accommodation (Sherif & Littlejohn, 2006). A way to officially distinguish between these different types is through the NACE classification, which is currently in its second revised edition and is based on the United Nations International Standard Industrial Classification of all Economic Activities. Based on this classification, the accommodation sector coded as 55, is comprised by four subcodes, namely subcode 5510 which corresponds to hotels and similar accommodation, 5520 for holiday and other short-stay accommodation, 5530 for camping grounds, recreational vehicle parks and trailer parks and code for other accommodation.

Based on the guidelines of the official sources (Nacev2.com, n.d.), the first subcode 5510, involves the provision of furnished accommodation, typically on a daily or weekly basis, principally for short stays by visitors with daily cleaning and bed-making. Services as food and beverage, parking, laundry, swimming pools, recreational and convention facilities may be provided. This subcode includes hotels, resort hotels, suite/apartment hotels and motels, and excludes the provision of accommodation on a permanent monthly or annual basis. This latter type of accommodation is included in division 68 related to real estate.

Subcode 5520 includes provision of accommodation in self-contained space consisting of furnished rooms or areas for living/dining and sleeping, with cooking facilities or fully equipped kitchens. This may take the form of apartments or flats in multi-storey buildings, or single-storey bungalows, chalets, cottages and cabins. Very minimal complementary services are provided, if any, and no housekeeping services. Youth hostels and mountain refuges are positioned here, while it excludes furnished short-stay accommodation with daily cleaning, bed-making and food and beverage services which are part of 5510.

Subcode 5530 includes accommodation for short stay visitors in campgrounds, trailer parks, recreational camps and fishing and hunting camps, while it excludes mountain refuge, cabins and hostels, which are placed in 5520. Lastly, subcode 5590 includes temporary or longer-term accommodation in single or shared rooms or dormitories for students, seasonal workers and railway sleeping cars. Here, school dormitories, student residences, workers hostels and railway sleeping cars are included.

From the four subcodes description, it is well understood that there is a variety of services offered in the accommodation sector and every subcode is distinct, thus there is a high degree of heterogeneity of firms in the broader accommodation sector, an issue that is going to be revisited in section 5.4 regarding the data sample.

4.3 Cumulative data on Greek bankruptcies

This section provides data on bankruptcies that have taken place in Greece. In Table 4.2, there are aggregate numbers of bankruptcies for the years 1973 to 2022. One can observe that for this period, a total of 24,733 official bankruptcies have occurred.

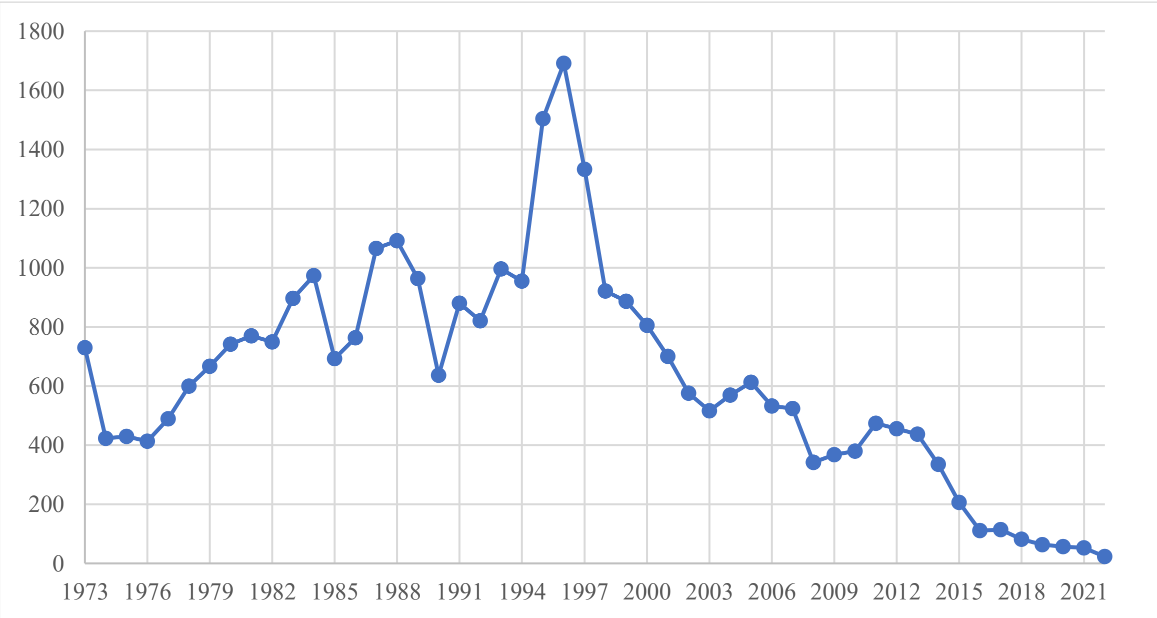
Table 4.2 Business bankruptcies in Greece

Year	N	Year	N	Year	N	Year	N
1973	729	1986	763	1999	886	2012	455
1974	423	1987	1,065	2000	805	2013	437
1975	429	1988	1,091	2001	700	2014	335
1976	413	1989	963	2002	576	2015	206
1977	489	1990	636	2003	516	2016	111
1978	600	1991	880	2004	569	2017	114
1979	667	1992	820	2005	612	2018	82
1980	741	1993	996	2006	532	2019	63
1981	770	1994	955	2007	524	2020	57
1982	749	1995	1,504	2008	342	2021	53
1983	896	1996	1,691	2009	368	2022	23
1984	973	1997	1,333	2010	380		
1985	693	1998	921	2011	474	Total	24,733

Source: Own process with combined data from Arnis (2018) and ELSTAT

A linear representation of the above data can be seen in the corresponding Graph 4.1. One can easily spot increasing bankruptcy events from 1990 to 1996, which then decreases till today.

Graph 4.1 Firm bankruptcies in Greece for 1973 - 2022



4.4 Sectoral data on Greek bankruptcies

Table 4.3 shows a sectoral perspective for the whole economy for years 2015 to 2022 (ELSTAT, 2023). For the last year of 2022, the breakdown of the available bankruptcy data by sector indicates that most of the companies declared bankruptcy, belong to section G that represent wholesale and retail trade, repair of motor vehicles and motorcycles reaching 56.5% of total bankruptcies. 13% belong to sector F in construction. Sectors C for manufacturing, H for transportation and storage and I for accommodation and food service activities accounted for 8.7% each, and 4.3% to sector N for administrative and support service activities.

Table 4.3 Bankruptcy frequency by sector for 2015-2022

NACE	2015	2016	2017	2018	2019	2020	2021	2022	Average
A	0.5	1.8	0.0	1.2	1.6	3.5	1.9	0.0	1.3
B	0.0	0.0	0.0	1.2	0.0	0.0	0.0	0.0	0.1
C	18.9	18.9	19.3	24.4	23.8	24.6	22.6	8.7	20.1
D	0.0	0.9	1.8	0.0	0.0	0.0	0.0	0.0	0.3
E	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
F	3.4	7.2	8.8	4.9	6.3	7.0	9.4	13.0	7.5
G	41.7	30.6	32.5	46.3	38.1	28.1	35.8	56.5	38.7
H	3.9	3.6	4.4	0.0	1.6	7.0	7.5	8.7	4.5
I	11.2	16.2	18.4	13.4	15.9	12.3	15.1	8.7	13.9
J	5.8	1.8	1.8	1.2	3.2	5.3	0.0	0.0	2.3
K	1.0	0.9	1.8	1.2	3.2	0.0	0.0	0.0	1.0
L	0.5	0.9	0.0	1.2	0.0	1.8	3.8	0.0	1.0
M	4.4	5.4	2.6	2.4	1.6	3.5	0.0	0.0	2.4
N	3.9	4.5	3.5	1.2	1.6	3.5	1.9	4.3	3.0
O	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
P	0.5	0.0	0.0	1.2	0.0	1.8	0.0	0.0	0.4
Q	1.9	5.4	1.8	0.0	0.0	0.0	0.0	0.0	1.1
R	0.5	1.8	0.9	0.0	1.6	1.8	0.0	0.0	0.8
S	1.9	0.0	2.6	0.0	1.6	0.0	1.9	0.0	1.0
T	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

U	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	4.7

A = Agriculture, forestry and fishing, B = Mining and quarrying, C = Manufacturing, D = Electricity, gas, steam and air conditioning supply, E = Water supply, sewerage, waste management and remediation activities, F= Construction, G = Wholesale and retail trade, repair of motor vehicles and motorcycles, H = Transportation and storage, I = Accommodation and food service activities, J = Information and communication, K = Financial and insurance activities, L = Real estate activities, M = Professional, scientific and technical activities, N = Administrative and support service activities, O = Public administration and defense, compulsory social security, P = Education, Q = Human health and social work activities, R = Arts, entertainment and recreation, S = Other services, T = Activities of households as employers, undifferentiated goods and services, producing activities of households for own use, U = Activities of extraterritorial organizations and bodies.

Source: ELSTAT (2023) and own calculations

Through the eight available years, the average bankruptcy rate, depicted in the last column, shows that code G for wholesale and retail trade, repair of motor vehicles and motorcycles has the highest average rate in total country bankruptcies configured at 38.7%. Sector C for manufacturing follows with 20.1%, sector I for accommodation and food service activities with 13.9%, sector F for construction with 7.5% and sector H for transportation and storage with 4.5%, showing a historical qualitatively identical pattern to the year 2022. Greece is not the only country where bankruptcy frequencies differ per sector. Caves (1998) has provided evidence for varying firm exits in eight countries, Khoja et al. (2019) for three and De Leonardis and Rocci (2008) for Italy. Similar varying patterns are expected to be found in many countries.

4.5 Hospitality sector data on Greek bankruptcies

Table 4.4 presents bankruptcies for sector I, which represents the hospitality sector, for the years 2010 to 2022. The I sector, includes subsector I55 which include accommodation firms and I56 that include food and beverage services firms. Column I show total bankruptcy events of the two subsectors together, but when separated into respective subsectors, sole accommodation accounts for 0.08% (29/338) of bankruptcies and food services for 91.1% (309/338).

Table 4.4 Year distribution of business bankruptcies in I55 and I56

Year	I	I55	I56
2010	39	6	33
2011	47	4	43
2012	49	0	49
2013	54	2	52
2014	49	5	44
2015	23	1	22
2016	18	2	16
2017	21	3	18
2018	11	1	10
2019	10	2	8
2020	7	2	5
2021	8	0	8
2022	2	1	1
Total	338	29	309

Source: ELSTAT

The recent two tables, depict a constant uneven distribution of bankruptcies through the years for broad sectors as also within the hospitality subsectors of the Greek economy. This implies that when broad sectors are investigated as a whole, an introduction of cross-sectoral bias cannot be overseen. This issue, i.e., that sectors differ in terms of failures, and was initially discussed in Section 2.2, seems to apply for the Greece economy too.

Conclusions

This chapter discussed initially the contribution of tourism and the hotel sector to the Greek economy, to underline the importance of the sector to the tourism product. Then the definitions of the four subcodes of the accommodation sector based on NACE was analyzed in order to show the differences in the services offered by accommodation firms, which essentially gives rise to the possible need for focus on specific subcodes to attain bigger sample and firm homogeneity. Finally, bankruptcy figures for Greece were presented, showing mainly the differences across sectors but also within the hospitality sector which includes accommodation and the food and beverage subsectors. These facts are translated as a possible cross-sectoral bias when examining broad sectors together, an issue that augments the argument that all sectors should not be seen as equal in terms of failures. The empirical treatment of this view will be processed in the next chapter, where the methodological framework and the hotel dataset are presented.

CHAPTER 5: Methodological framework

This chapter presents the base of the methodological framework followed in the thesis. It begins with the research objectives, which essentially sum up the previous chapters' main arguments and sets the research questions of the forthcoming analysis. Then, the econometric specification of the multi-period logit is presented and the available dataset on Greek hotels in terms of bankruptcies and financial ratios. The chapter continues with an initial treatment of the data and some variable exclusion techniques, that will lead to the main estimations of the next chapter.

5.1 Research objectives

Having pointed out in the previous chapters, the theoretical part and the literature's main discourses regarding firm and hotel failure, a brief recap is provided. In Chapter 2, the key concepts running the field were posited. The financial ratio approach was recognized as the most applied research path to deal with firm failures. Arguments were set regarding research performed in broad samples or with a sectoral focus, finding the sectoral approach more efficient. The definitions of firm failure used in the literature were presented, expressing the tendency that bankruptcy is a more objective measure to financial distress, as also the part of methodologies and the better interpretability that econometric methods offer. Chapter 3 was devoted to a systematic review of the prior literature, that accumulated the financial factors related to hotel failure from 29 studies. Chapter 4, discussed about the importance of the hotel sector in the tourism chain, the heterogeneity of accommodation firms according to NACE classification, as also data on bankruptcies in Greece were presented, showing the wide sectoral differences in observed failure rates, even for the hospitality sector which include accommodation and food and beverage services.

All previous arguments, delineate the forthcoming research leitmotif of this thesis towards examining the financial determinants of bankruptcy, as the most popular research approach and definition of failure. The hotel sector is chosen, as it is a separate subsector and an important economic activity that creates increased value for the Greek economy and to the best of our knowledge, besides the studies of Diakomihalis (2011, 2012) no other attempts are made to research hotel failure in Greece. The chosen methodology is the multi-period logistic regression model in Stata, a dynamic econometric specification with a finer interpretation to artificial intelligence methodologies and many applications in finance but not for the hotel sector. Despite the small number of hotel bankruptcies in Greece, showing the sector is not in an alarming state, having set a sufficient layer of empirical evidence, the further econometric evaluation will attempt to derive new results and contrast them with previous evidence.

5.2 Research questions

After setting the objectives of the thesis, the articulation of the main research questions will take place. The first research question is:

1) which are the financial determinants related to hotel bankruptcies observed in Greece in the years 2010-2020?

This basic research question will be answered through the econometric evaluation that is going to be performed in the subsequent chapters. Firstly, a competent and dynamic estimation technique will be applied to provide information about the observed hotel bankruptcies. Also**,** sensitivity checks as the model re-estimation and the extension of the bankruptcy horizon, will be performed to provide robust evidence and assess the information content for bigger periods.

The second research question is:

2) are models estimated in two previous studies for the whole economy and the hotel sector in Greece, equally efficient related to the current hotel sample estimations?

To answer this question, the variables of two Greek studies, the one for the whole economy and the second for the hotel sector with the standard Altman (1968) variable set, will be used in the main specification and the results will be evaluated within a statistical and prior literature framework. Any differences that may appear, will provide evidence that will assist to reach conclusions about the rationale of conducting updated research at the sector level, or put in other words, to develop sectoral models instead of wider sector models.

5.3 Multi-period logistic regression model

The main econometric specification, the multi-period logistic regression model is presented here. As this parameterization builds and extends the standard logit framework, its full analysis from scratch will be bypassed, but as a swift historical comment, the logit model was invented by the Belgian mathematician Pierre-François Verhulst in 1938 and used thereafter in many independent fields as chemistry and demography (Cramer, 2004).

To fix current ideas, the analysis is based on Shumway (2001) who inaugurated this computational approach to bankruptcy research and elaborated upon the fact that a multi-period logit is interwoven to a discrete-time hazard model, due to their mathematical properties of the likelihood functions (Apergis, Bhattacharya & Inekwe, 2019). Following Allison (1982), a discrete-time hazard rate is defined as

$$P_{it} = \Pr\left[T_i = t \mid T_i \geq t, \mathrm{X}_{i,t}\right] \tag{5.1}$$

where T is a discrete random variable of the observable time of an event occurrence, t is a positive integer of time and $\mathrm{X}_{i,t}$ a $k \times 1$ vector of time-varying explanatory variables. Notionally, it can be seen as the conditional probability of bankruptcy or any event of interest occurring at time t, given it has not occurred in any previous time period.

When time is measured in a discrete scale, the proportional odds model can be used (Jenkins, 2005). This model suggests the relative odds of a transition in time j, given survival or generally appearance up to the end of the previous period, can take the expression

$$\frac{h\,(j,X)}{1-h\,(j,X)} = \left[\frac{h_0\,(j)}{1-ho\,(j)}\right]\exp(\beta'\mathrm{X}) \tag{5.2}$$

where $h\,(j,X)$ is the discrete hazard rate for time j, and $h_0(j,X)$ is the baseline hazard when covariates equal zero, thus $X = 0$. The relative odds of transitioning to the state of the event of interest at any time is given by the product of two quantities, a relative odds which is common for all firms and an individual-specific factor. By taking the logs follows that

$$\operatorname{logit}\left[h\,(j,X)\right] = \log\left[\frac{h\,(j,\mathrm{X})}{1-\ h\,(j,\mathrm{X})}\right] = \ \alpha_j + \beta^{'}\mathrm{X} \tag{5.3}$$

where α_j = logit $[h_0\,(j)]$. This expression is the logistic hazard model with a proportional odds interpretation (Jenkins, 2005) and the version with a slightly different notation, with the natural logarithm instead and the vector of predictors able to accommodate time-varying variables, coincides the model used in Charalambakis (2015) and Charalambakis and Garrett (2016, 2019) as the initial estimation expression for a discrete hazard model

$$\ln\left[\frac{h_i(t)}{1-h_i(t)}\right] = \alpha(t) + \beta'\mathrm{X}_{i,t} \tag{5.4}$$

where $h_i(t)$ represents the hazard of bankruptcy at time *t* for the *i*th firm conditional that the firm survived until *t-1*, $\alpha(t)$ is the baseline hazard when covariates are set to zero, β' is the inverted vector of estimated coefficients and X_{it} a $k \times 1$ vector of observations of the *i*th covariate at time *t*. From Allison (1982) and equations 5.3 and 5.4, the probability of observing bankruptcy can be written and estimated as

$$P_{i,t}(Y_{i,t} = 1) = \frac{1}{1 + \exp\,(-\alpha_t - \beta'\mathrm{X}_{i,t})} \tag{5.5}$$

where $Y_{i,t}$ is the dependent variable that takes the value of one in the occurrence of bankruptcy and zero in case it operates and survives in the market. An alternative expression is the discrete-time counterpart of the continuous Cox (1972) model given by

$$P_{it} = 1 - \exp\,[-\exp(\alpha_t + \beta'\mathrm{X}_{i,t})] \tag{5.6}$$

which yields the complementary log-log function

$$\log[-\log(1 - P_{it})] = \alpha_t + \beta'\mathrm{X}_{i,t} \tag{5.7}$$

This model, often abbreviated cloglog, originates in the study of Prentice and Gloeckler (1978), it is named also as minimum extreme value or grouped proportional hazards model (Tutz & Schmid, 2016), it is considered the discrete-time analogue of the proportional hazards Cox (1972) model (Jenkins, 1995) and its' response curve is not mirror symmetric as logit (Box-Steffensmeier & Jones, 2004; Dendramis, Tzavalis & Adraktas, 2018). Despite measuring slightly different quantities, as the discrete logit model measures the log odds as a linear function of regression parameters and the cloglog model the log negative log of the survival probability (Kleinbaum & Klein, 2012, p.324), it has many applications in firm bankruptcy research (e.g., Chiaramonte, Liu, Poli & Zhou, 2016; Görg & Spaliara, 2014; Männasoo & Mayes, 2009; Türkcan & Erkuş-Öztürk, 2020) and tends to provide very close results to logit in the case of rare events of interest (J. Gupta, Barzoto et al., 2018), meaning the case where ones i.e., bankruptcies, are a very small proportion compared to zeros or when the occurrence of the event of interest is very high (Chiaramonte & Casu, 2017). For these reasons, it is going to be used as an alternative estimation technique to safeguard against possible misapplication of the multi-period logit model to Stata software. For this estimation, the logit link function is replaced by the cloglog function.

Both these models, the discrete-time logit and the complementary log-log, share the same likelihood function (Allison, 1982) which is

$$L = \prod_{i=1}^{n} [\Pr(T_i = t_i)]^{\delta_i} \; [\Pr(T_i > t_i)]^{1-\delta_i} \tag{5.8}$$

where the superscript δ_i denotes the familiar to survival analysis censoring indicator, taking the value of one in the case of the event happening. This holds particularly under noninformative censoring (Chava & Jarrow, 2004; Christopoulos et al., 2019). Using properties of conditional probabilities, it follows that

$$\Pr(T_i = t) = P_{it} \prod_{j=1}^{t-1} (1 - P_{i,j)} \tag{5.9}$$

and

$$\Pr(T_i > t) = \prod_{j=1}^{t} (1 - P_{i,j}) \tag{5.10}$$

Substituting equations 5.9 and 5.10 into 5.8 and taking the logarithm, results in this log-likelihood function

$$\log L = \sum_{i=1}^{n} \delta_{i,t} \log \{P_{i,t} \,/\, (1 - P_{i,t)}\} + \sum_{i=1}^{n} \sum_{j=1}^{t_i} \log (1 - P_{i,j}) \tag{5.11}$$

By further substituting the discrete hazard logit of 5.5 or the cloglog model of 5.6 and maximize log L with respect to α_t (t = 1, 2, …) and β, and by replacing $\delta_{i,t}$ to a dummy variable $\mathrm{Y}_{i,t}$ thus the current dependent variable, 5.11 can be re-expressed as

$$\log L = \sum_{i=1}^{n} \sum_{j=1}^{t_i} \mathrm{Y}_{i,t} \log \{P_{i,j} \,/\, (1 - P_{i,j})\} + \sum_{i=1}^{n} \sum_{j=1}^{t_i} \log \,(1 - P_{ij}) \tag{5.12}$$

which is the log likelihood for the regression of binary or dichotomous dependent variables (Allison, 1982, p.75), implying that discrete-time hazard models can be estimated using software for analysis of binary data (Allison, 1982; Singer & Willett, 1993; Yamaguchi, 1991) with an augmented dataset, where every available firm-year is represented with a row of data. This observation was first made by Brown (1975) (Allison, 1982; Chava & Jarrow, 2004)[5]. Besides the fact that logit and hazard models have the same likelihood function, they share also the same variance-covariance matrix (Abid et al., 2018; Amemiya, 1985; Shumway, 2001).

Based again on Shumway (2001), there is one computational proviso that needs to be accounted. The static logit model with no time-varying covariates assumes n to be the number of firms in the test statistics i.e., the Wald χ^2 which is of the form

$$\frac{1}{n}(\hat{\mu}_k - \mu_0)'^{\Sigma^{-1}}(\hat{\mu}_k - \mu_0) \sim \chi^2(k) \tag{5.13}$$

In order to calculate correctly the test statistics of the multi-period logit specification, as the static logit assumes no dependence for firm-years, to correct this effect there is the need for the appropriate sample size adjustment, meaning the scaling of the test statistics with the average number of firm-years per hotel (Abid et al., 2018; Agarwal & Taffler, 2008; Charalambakis & Garrett, 2016, 2019; Christopoulos et al., 2019; Cole, Taylor & Wu, 2021; Filipe et al., 2016; Shumway, 2001).

[5] In a similar manner, the multinomial logit can be estimated as the survival analysis analogue of competing risks (Allison, 1982; Beck, Katz & Tucker, 1998; Fahrmeir & Wagenpfeil, 1996; Rabe-Hesketh & Skrondal, 2022; Weterings & Marsili, 2015).

As this is computationally unattainable outside a software framework, a refined solution is the use of the clustered version of the Huber-White sandwich variance estimator (Cameron & Trivedi, 2009), which is based on the estimator of Liang and Zeger (1986), and is an extension of the robust variance estimators of Huber (1967) and White (1980) (Buckley & Westerland, 2004) and further populated by Froot (1989) and Williams (2000).

This is technically equivalent by taking into account the firm's clustered robust standard errors (Charalambous, Martzoukos & Taoushianis, 2020, 2023; Elsayed, Elshandidy & Ahmed, 2022; Filipe et al., 2016; Rabe-Hesketh & Skrondal, 2022; Tomas Žiković, 2018). At Stata level, this is done through adjusting standard errors on the subject's, in the case here, the hotel's unique identification number (Cameron & Trivedi, 2022) and for this command there is no direct or canned routine in the software, rather the syntax is manually parameterized.

This type of errors, which are robust to serial correlation and heteroscedasticity (Hillegeist, Keating, Cram & Lundstedt, 2004) are named also as Rogers standard errors (Petersen, 2009), the contributor of this development to Stata (Rogers, 1993). With this practical treatment, the multi-period logit model acquires the ability to use the whole time-series of a variable (Shumway, 2001), the variation of repeated financial observations of firms is computationally accounted, correlation is allowed within clusters i.e., intracluster correlation per hotel, but not across hotels, and essentially the simple logit model is augmented to receive panel data. Also, the data independence assumption of logit relaxes, as there is no conflict under this scheme with this strong and limiting assumption (Buchholst & Rangvid, 2013).

In contrast, the static logit model, so-called as single-period or cross-sectional logit, uses only one observation (Almaskati et al., 2021; Charalambakis & Garrett, 2019; J. Gupta, Gregoriou

& Healy, 2015; Hillegeist et al., 2004; Yamaguchi, 1991), treats firms as a snapshot in time (M. H.-Y. Kim, Ma & Zhou, 2016) and adheres to the assumption of observations being independent.

One negative aspect of the multi-period logit specification is that dealing with subject-period or firm-year data structures, the dataset can become large and unruly (Mills, 2011). Also, the use of a large imbalanced dataset, instead of a balanced one with a matched sampling, at least at the cross-sectional version, affects only the constant of the model and not the covariate coefficients (Maddala, 1983, 2001). Hosmer, Lemeshow and Sturdivant (2013) comment for Breslow (1996), that this effect of invariant odds ratios under different sampling methods i.e., case-control or cohort study, was first observed by Cornfield (1951) and was later proved by Farewell (1979) and Prentice and Pyke (1979) and the same might hold for matched or random sampling. In addition, Allison (2010, 2014) and Pierri, Stanghellini, and Bistoni (2016) state that no extra gain is induced by adding more observations to the majority sample over a ratio of one to five, as the minority class of events is of biggest importance. In the bankruptcy field, the study of Zmijewski (1984) provided notable evidence, where under match-paired and random sampling, despite some minor differences, the overall results were qualitatively the same (Hambrick & D'Aveni, 1988).

This modeling approach is useful also when there is a wide range of time-varying potential predictors to assess (Mills, 2011) and does not require balanced samples (Cathcart et al., 2020). The latter feature allows to perform real-world experiments using all the available firms of the sector. Regarding the issue, in the field of geosciences Oommen, Baise and Vogel (2011) argue that in study areas where the distribution is known a priori, as the case here where the distribution of bankrupt hotels is minimal but known, the sampling procedure that mimic the real population can lead to optimal use of logit. This model also finds applications in other fields where the minority class is indeed scarce, as the case of rare diseases (Kalbfleisch & Prentice, 2002) or the extinction of species (Salas-Eljatib, Fuentes-Ramirez, Gregoire, Altamirano & Yaitul, 2018).

The modeling approach of Shumway (2001) and its further developments and interpretations i.e., a logit with clustered robust standard errors, is used extensively in finance bankruptcy studies (Abid et al., 2018; Agarwal & Taffler, 2008; Almaskati et al., 2021; Bai & Tian, 2020; Beaver et al., 2019, 2023; Cathcart et al., 2020; Charalambous et al., 2020, 2022, 2023; Chava & Jarrow, 2004; Christopoulos et al., 2019; Cole et al., 2021; Darrat, Gray, Park & Wu, 2016; Ding, Tian, Yu & Guo, 2012; El Kalak & Hudson, 2016; Elsayed et al., 2022; Elsayed & Elshandidy, 2020; J. Garcia, 2022; J. Gupta et al., 2015; J. Gupta & Gregoriou, 2018; Hillegeist et al., 2004; Jia, Shi, Yan & Duygun, 2020; Mayew, Sethuraman & Venkatachalam, 2015; Tian & Yu, 2017; Tomas Žiković, 2018; Topaloğlu, 2012; Wu, Gaunt & Gray, 2010) and becoming increasingly popular (Beaver et al., 2019), but mainly appears in economy-wide studies with firms from many sectors. For the tourism and the hotel sector, besides the cloglog specification (Caires et al., 2023; Escribano-Navas & Gemar, 2021; Türkcan & Erkuş-Öztürk, 2020), the continuous-time survival model (Falk & Hagsten, 2018; Gémar et al., 2016; Gemar et al., 2019; Lado-Sestayo et al., 2016; Lin & Kim, 2020; Pelaez-Verdet & Loscertales-Sanchez, 2021; Piacentino et al., 2021; Vivel-Búa et al., 2019; D. Zhang & Xie, 2023), and the study of Crespí-Cladera et al. (2021) for forecasting though COVID-19 effects in Spanish hotels, this exact discrete-time logit approach with a justification for the adjustment of clustered robust standard errors is not used to investigate hotel failure**.**

Returning to the basic specification, in the case where the horizon of bankruptcy is extended by *n* years, the estimation of the probability of bankruptcy becomes

$$P_{i,t}(Y_{i,t} = 1) = \frac{1}{1 + \exp\left(-a - \beta' \mathrm{X}_{i,t-n}\right)} \tag{5.14}$$

Thus, for one and two years, the covariate vector becomes $\mathrm{X}_{i,t-1}$ and $\mathrm{X}_{i,t-2}$ respectively simply by lagging the covariates. The difference with the notation of Charalambakis and Garrett (2019) is that the vector $\mathrm{X}_{i,t-1}$ was used for the prediction of bankruptcy over the next year and to ensure data visibility. Here, due to data limitations to be discussed in the next section, as the bankrupt hotel datapoints are more scarce, the dataset is adjusted in such a way that in the case of the bankruptcy event, the dependent variable is set to one at the last available datapoint, as Stata drops entirely years with missing data.

5.4 Data

Detailed data for hotel-specific bankruptcies and the exact date of bankruptcy were retrieved from the Hellenic Statistical Authority (ELSTAT), with a timespan between years 2010-2020. For the definition of firm failure, the legal or judicial (*de jure*) dimension of bankruptcy is adopted. Initially, 28 unique bankruptcies are available on the subcode 5510 which corresponds to hotels and similar accommodation and is considered as more representative, populated and homogenous of the entire economic activity coded 55.

The financial data were obtained from ICAP database, a credible source of information used in many finance studies conducted in Greece (e.g., Arnis et al., 2018; Arnis, Karamanis & Kolias, 2020; Balios et al., 2016; Charalambakis & Garrett, 2019; Fotopoulos & Louri, 2000; Niklis, Doumpos & Zopounidis, 2014; Papoulias & Theodossiou, 1992; Theodossiou, 1991;

Tsiapa, 2022; Voulgaris, Doumpos & Zopounidis, 2000). The timespan of these data is for 2005-2020 and after an initial preparation in spreadsheets, the merged dataset is imported to Stata 17 software. The imported dataset contains an initial number of 5,946 hotels and 13 bankrupt hotels with available financial data. This reduction and mismatch of bankrupt hotels with the available financial data, is believed to persist due to General Data Protection Regulation (GDPR) issues, as such information may be kept anonymized and confidential for some types of business entities and under specific circumstances. Practical examples of this missing data attrition are the studies of Zmijewski (1984) where the initial sample had 129 failed firms but ended with 89 will full data and Christidis and Gregory (2010) where 589 failed firms were reduced to 558.

Other treatments for the dataset, is the deletion of firms with one year of appearance (Mousavi & Ouenniche, 2018), especially in the case where the date of foundation and the observed year of participation is wider to one. Also, common hotel names were changed by adding a numerical factor. Following Shumway (2001) who eliminated firm-years after the designated firm failure, this procedure was done here for one hotel that appeared to still exist in the financial database after its official bankruptcy. The final sample contains 5,766 unique hotels with a total of 55,816 firm-years, with the 13 bankrupt hotels contributing 87 firm-years.

Essentially, the type of the specific dataset at hand, shares many basic common features with data that are met in the literature named as duration, failure time, sojourn (Tutz & Schmid, 2016), interval-censored (Kleinbaum & Klein, 2012; Mills, 2011), time-series and cross-section data with a binary dependent variable (Beck et al., 1998) or lifetime data (Stogiannis & Caroni, 2013).

It should be noted that only in one bankruptcy occasion out of the 13, financial data is available exactly one-year prior bankruptcy, with the average frame being 3.6 years. For this reason, as mentioned in the previous section, the dataset is adjusted to reflect this fact and to exploit all available datapoints. This gap of information can exist due to missing data or because firms may disrupt providing such information as they tend towards a failure state and market exit. For example, Balcaen, Manigart, Buyze and Ooghe (2012, p.963) in their study for Belgium, noted that 81.5% of the firms stopped declaring their annual accounts as they approached exit. A discussion of this topic with some references can be found in Christidis and Gregory (2010, p.7-8). This issue is mainly confronted in studies of private and small sized firms (Keasey & Watson, 1987; L. Li & Faff, 2019; Z. Li et al., 2021; Luypaert, Van Caneghem & Van Uytbergen, 2016; Pierri et al., 2016; Qiu, Rudkin & Dłotkoet, 2020; Sensini, 2016), showcasing also the fact that financial information is more opaque for smaller firms (Ciampi et al., 2021) in contrast to large and listed firms, where besides stock market information, financial statements can be published quarterly.

Regarding the limited number of bankruptcy events, it can be noted that various studies have used a similar or analogous number of events. For example, H. Li and Sun (2012) augment the sample of seven failed hotels with simulation methods, Chen and Yeh (2012) use logit and 10 failed Taiwanese hotels, Sandin and Porporato (2008) use MDA with 11 events for Argentina, Pereira (2014) use Cox regression with 11 events too, Ho et al. (2013) apply logit with 12 bankruptcies from the pulp and paper industry in the US, S. Li and Wang (2014) use logit with 17 Chinese distressed firms, Charalambakis (2015) utilize a discrete hazard approach with 37 bankruptcies and suspensions of Greek listed firms, Gemar et al. (2019) use a Cox model with 41 failed resort hotels, J. Garcia (2022) apply advanced artificial intelligence techniques with 47 bankruptcies and Escribano-Navas and Gemar (2021) use a complementary log-log model with 70 failed hotels.

Despite the absolute numbers of events related to firm failure, the percentage of firms observed to be in the default state, tends not to be a problem too, as for example J. Garcia (2022) conducted his research with 47 bankruptcies from a total sample of 1,824 US public firms, thus a 2.5% bankrupt firm rate. Another comment is that to our notice, relevant bankruptcy studies do not perform a sample adequacy test, rather use the whole available sample at hand. An exception in the hotel failure literature is Vivel-Búa et al. (2016) who checked if overall sample size was representative of the population. Next, Table 5.1 shows the year distribution of the 13 available hotel bankruptcies that define the dependent variable.

Table 5.1 Year distribution of available hotel bankruptcies

Year	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

For the years 2012, 2014 and 2015 there are no bankruptcy events recorded in the final dataset i.e., there are empty intervals for the event under study. For this issue, Allison (2010) has stated that when the dependent variable corresponds to empty intervals the maximization of likelihood will not converge in SAS software. For Stata, the estimations were performed normally, but rather the software dropped lines of data when there was missing or incomplete variable information. Having years with no events of interest, is not uncommon in bankruptcy studies (e.g., Beaver, McNichols & Rhie, 2005; Campbell et al., 2008; Carmona, Climent & Momparler, 2019; Chava & Jarrow, 2004; Gupta et al., 2018; Ho et al., 2013; D. Zhang & Tveterås, 2022).

5.5 Independent variables

The initial basket of predictors consists of 14 financial ratios and belong to the broader categories of profitability, performance, liquidity, leverage and size. These 14 ratios are selected based on database availability and the previous related literature. Next, the presentation and the exact construction of the ratios follows: 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). This information is presented again in Table 5.2 alongside with an indicative source of prior use in the literature.

Table 5.2 Variable names, construction and source

Variable	Construction	Source
ROA	Net profit / TA × 100	Altman et al. (2020)
ROE	Equity / TA × 100	Kim (2011)
ROCE	Capital employed / TA × 100	Pelaez-Verdet and Loscertales-Sanchez (2021)

SATA	Sales / TA	Correia et al. (2022)
SAEQ	Sales / equity	Beaver (1966), Edmister (1972) *
SAFA	Sales / fixed assets	Gu and Gao (2000), Kim (2011)
EQTA	Equity / TA	Altman et al. (2020)
EQTL	Equity / total liabilities	Altman (1968), Diakomihalis (2012)
WCTA	Working capital / TA	Altman (1968)
RETA	Retained earnings / TA	Correia et al. (2022)
EBTA	EBITDA / TA	Charalambakis and Garrett (2019)
EBTL	EBITDA / total liabilities	Beaver et al. (2005), Charitou et al. (2004), Fernández-Gámez et al. (2016)
TLTA	Total liabilities / TA	Charalambakis and Garrett (2019), Vivel-Búa et al. (2019)
LnTA	Natural logarithm of TA	Back (2005), Belda and Cabrer-Borrás (2020), Charalambakis and Garrett (2019), Mselmi et al. (2017), Vivel-Búa et al. (2019)

* In both these studies this ratio appears inverted. TA = total assets.

5.6 Winsorization

This section proceeds to a preliminary analysis of the merged dataset and more specifically with the initial treatment of winsorizing the variables. In order to limit the effect of extreme outliers, a fact that may be inherent to databases due to mistaken values, all variables are winsorized at the 1 and 99% levels (e.g., Altman et al., 2020; Charalambakis & Garrett, 2019). Two main techniques exist to deal with this issue, truncation and winsorization (Balcaen & Ooghe, 2006). Truncation or trimming deletes the observations at a specified level (e.g., Chava & Jarrow, 2004), while winsorization simply replaces the outliers to the value of the specified percentage of the distribution (Barnes, 1987). Various two-sided values have been used in the literature, as 0.1% (X. Zhang et al., 2022), 0.5% (Tsoukas, 2011), 2% (Beaver et al., 2019), 3% (Amendola et al., 2015), 5% (Christidis & Gregory, 2010), but the 1% level is possibly the most applied. Another less applied treatment is the logarithmic transformation (Altman & Sabato, 2007). Due to winsorization, all variables are replicated, and the new version inherit the extension of letter *w* which is produced automatically by the software. This winsorization notation will be skipped but will be implied on further analysis.

5.7 Descriptive statistics

This section provides the variable descriptive statistics for the whole sample of hotels, in terms of observations, mean, standard deviation, minimum and maximum values. This information is placed in Table 5.3. From an initial inspection, most of the outliers seem to be eliminated, except for the variable EQTL where a maximum value of 1890.29 persists.

Table 5.3 Descriptive statistics for the whole sample

Variable	Obs	Mean	Std. Dev.	Min	Max
De_jure	55819	.0002329	.0152593	0	1
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 5.4 presents the same statistical information, this time for the two classes of hotels, the non-bankrupt and the bankrupt. After the inspection of the values, four variables, ROE,

ROCE, SAEQ and SAFA will be excluded from further consideration. The rationale for this decision is based on the missing information in the minority sample of the bankrupt hotels, which in this setting is the most sparse and can prohibit the software to estimate effectively.

Table 5.4 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

5.8 T-tests

Table 5.5 presents the t-tests for the mean difference between the two subsamples. A significant difference is found for ROA, EQTA, WCTA, TLTA, EBTA and LnTA. It should be acknowledged though, that t-tests in a time-varying setting with a panel data structure, may exhibit discriminatory bias (J. Gupta et al., 2015), though are not forbidden. Also, no tests for normality are undertaken, as logit does not require such an assumption (Apergis et al., 2019; J. Gupta & Gregoriou, 2018) as for example MDA (Barboza, Basso & Kimura, 2023; García & Herrero, 2021).

Table 5.5 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

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

5.9 Univariate analysis

Since no unified protocol is followed by researchers for variable selection (Bauweraerts, 2016; Veganzones & Severin, 2021), the technique of univariate analysis will be employed as a further variable selection treatment. For this reason, a univariate regression with the main multi-period logit specification will take place in Table 5.6, with a p-value threshold set to be less than 0.25 (J. Gupta, Gregoriou & Ebrahimi, 2018; Hosmer et al., 2013). From this procedure, SATA will be excluded with a p-value of 0.867.

Table 5.6 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

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

5.10 Correlation analysis

The next and final procedure in this chapter, is correlation analysis which is placed in Table 5.7. An increased correlation implies redundant information and the existence of multicollinearity which can drive to inflated standard errors. The correlation matrix for the nine remaining variables shows a high correlation of 0.807 for ROA and EBTA and a perfect negative relationship for EQTA and TLTA. Despite these facts, both pairs will remain in the sample with the rationale that these pairs represent some fundamental accounting relations and the decision to remove a variable at this stage might bias results. This issue is going to be treated in the next chapter with the assistance of stepwise regression.

Table 5.7 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

Conclusions

This chapter entered the methodological framework of the thesis. The first two sections articulated the research objectives and research questions. The third section presented the derivation of the econometric specification, discussed its main features and its adaptation to Stata. Then the dataset was described, the independent variables were introduced and some data curation and initial variable assessments were performed, namely winsorization, t-tests, univariate and correlation analysis, in order to prepare the setting for the main econometric estimations of the next chapter.

CHAPTER 6: Econometric analysis

In this chapter the main econometric estimations are deployed. After having introduced in the previous chapter the research objectives and questions, the method, the data and processed the variables in a preliminary manner, the final set of variables are estimated initially in a stepwise setup. After the basic results are obtained, the logit specification is cross-checked for its reliability with four additional models derived from the literature, as there is no direct command for its execution but rather is parameterized manually. The estimations continue with the horizon extension, with comparisons to two previous Greek studies in terms of model efficiency and variable relevancy and conclude with robustness checks for the variable of size.

6.1 Stepwise multi-period logistic regression

At this stage, a stepwise regression will be performed to reach the final set of independent variables. The stepwise procedure is a heuristic method which automates variable selection. When having to choose among a wide set of potential covariates, as in the case of financial ratios derived from balance sheets, techniques as stepwise regression facilitate variable selection, as from a k number of available covariates, 2^k models can be extracted (Acosta-González et al., 2019; Tian et al., 2015).

As there are three main stepwise procedures, the forward, the backward and its combination (Dastile et al., 2020), as also many minor variations based on software-specific commands, here the combination process is followed and more specifically the forward stepwise selection with backward elimination.

For this reason, the forward stepwise procedure is going to take place with the main multi-period logit specification (Charalambous, Martzoukos & Taoushianis, 2022) with an entry p-value of 0.15, and the backward elimination with an exit p-value of 0.20, following the suggestions of Hosmer et al. (2013). The model is loaded with the nine variables that qualified the univariate regressions in the previous chapter, namely, ROA (return on assets), EQTA (equity to total assets), EQTL (equity to total liabilities), WCTA (working capital to total assets), RETA (retained earnings), EBTA (EBITDA to total assets), EBTL (EBITDA to total liabilities), TLTA (total liabilities to total assets) and LnTA (natural logarithm of total assets). This reiterative process begins with a null model and based on the specified p-values, at every step it assesses the statistical significance of the variables and the Wald statistic of the whole model. The aim is to exclude redundant variables and reach the jointly most influential set of variables.

The results from this procedure are presented in Table 6.1. As the setting of this table is the basis of all further estimations, it will be briefly explained. On the horizontal axis, the names of the models are placed, and the vertical axis hosts initially the variable names. Within the table, the first quantity is the estimated coefficient, with the asterisks presenting statistical significance at the 10, 5 and 1% levels. Beneath coefficients, standard errors are placed in parentheses.

Under the variable names, follows the constant of the model (cons), the Akaike information criterion (AIC), the Bayesian or Schwartz criterion (BIC), the area under the curve (AUC), sensitivity, specificity, overall classification, log likelihood, pseudo R^2 and lastly the number of observations (N). For AIC and BIC, lower values show a better model fit, while for AUC higher values are preferred. Sensitivity measures the correct classifications of the failed hotels as failed, thus the true positive rate (Barboza et al., 2017). Following Cathcart et al. (2020) and Q. Zhang, Vallascas, Keasey and Cai (2015), the cutoff level for this metric is set to the number of bankruptcies divided by the total number of observations i.e., 13/55,819=0.0002328, which is the mean value of the dependent variable. Specificity or the true negative rate captures the cases of non-failed observations estimated as non-bankrupt and overall classification is the predictive accuracy rate for both categories. Higher values for sensitivity (specificity) correspond to a smaller type I (II) error. As type I error, i.e., classifying a bankrupt firm as non-bankrupt, is likely to be more expensive to its counterpart (Back, 2005; S. Y. Kim, 2011) and can be translated into actual losses, in the corporate failure setting sensitivity is more cherished, as it involves the classification of the group of bigger interest (Barboza et al., 2017, p.412). Also, in a context of unbalanced samples as the case here, it is best to evaluate performance based on measures that weigh this specific data characteristic, as overall classification can be misleading (Barboza et al., 2023; Palepu, 1986, p.27) as it averages both. So, more attention will be given to sensitivity among all efficiency measures.

Table 6.1 Results for 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%	
Specificity	77.75%		77.75%		77.69%	
Overall classification	77.75%		77.75%		77.70%	
Log-likelihood	-105.9901		-105.9929		-106.0740	
Pseudo R^2	0.1269		0.1268		0.1262	
N	54327		54328		54328	

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

The stepwise procedure selected the three covariates of EBTL, TLTA and LnTA which are embodied in the model MStepwise on the second column of Table 6.1. More specifically, the model resulted to EBTL with a coefficient of -0.076 and statistical significance at the 1% level, to TLTA with a coefficient of 3.517 at 1% and LnTA with a coefficient of 0.372 at 5%. AIC for this model is configured at 219.980, BIC at 255.591, AUC is 0.896, sensitivity reaches 92.31% classifying correctly 12 from the 13 bankruptcies, specificity with overall classification reach 77.75%, log-likelihood is -105,990 and pseudo R^2 0.126.

The same three variables are re-estimated in model M1, as it is not certain that a stepwise and a non-stepwise regression estimation provide identical results. The basic results in this case remain intact, with only minor differences in AIC, BIC, log likelihood and pseudo R^2 values.

In model M2, TLTA is replaced with EQTA, as a safeguard exercise against their perfect negative correlation and as a stability check, as these two variables share the same accounting relations, rooted in the accounting equation, where assets is the sum of equity and liabilities. EBTL and LnTA remain as previously and EQTA enters with a coefficient of -3.501 at 1%, opposite to TLTA, validating their substitutive relationship.

All three models share the same sensitivity, but since M1 is slightly improved to M2 in terms of AIC, BIC, AUC, specificity, overall classification, log likelihood and pseudo R^2, the M1 model, thus the model incorporating leverage, will be considered the best model and will become the base model for further estimations.

As coefficients in logit estimations, come with a log odds interpretation which is not so straightforward, and despite the fact that many firm default studies in quality journals that have used the multi-period logit method tend not to report this measure and limit the analysis to coefficients (e.g., Campbell et al., 2008; Charalambakis & Garrett, 2019; Elsayed et al., 2022; Filipe et al., 2016; Mayew et al., 2015; Tomas Žiković, 2018), here, the comment of an anonymous reviewer is followed, and the odds ratios are estimated and presented. By exponentiating the coefficients of a logit model, the odds ratios are obtained. For the first variable of EBTL, the odds ratio becomes 0.926, having the interpretation that for a unit increase in EBTL the odds of bankruptcy are reduced by 0.074 or by 7.4%, holding at the same time all other predictors constant i.e., *ceteris paribus*. For TLTA the odds ratio is 33.673, meaning that a unit increase of this covariate increases the odds by a factor of 33.6 *ceteris paribus*. For LnTA the odds ratio is 1.45, suggesting an increase of 45% or almost by half, for a unit increase in size *ceteris paribus.*

At this point, a comment for the odds ratio of 33.6 obtained for leverage will take place, as at a first glance seemed extremely high, especially in comparison to the rest. This fact provoked a mini-research for similar magnitudes and since firm failure studies do not report this measure, the research expanded to the broader literature. Finally, this magnitude seems not so surprising, as Box-Steffensmeier and Jones (2004, p.109) present an odds ratio of 13 in the political context for congressional career paths involved in a scandal, Rabe-Hesketh and Skrondal (2022, p.854), after analyzing the data of the Long, Allison and McGinnis (1993) study for biochemists provide a ratio of 98, Pyke and Sheridan (1993, p.54) estimate odds ratios of 30, 46 and 108 in their study regarding factors related to the retention of Master's students and just recently Dioko and Guo (2024) estimated an odds ratio of 33 for the variable parking and accessibility related to hotel failure.

6.2 Horizon extension

As mentioned in the methodology part, applying lagged versions of independent variables is equivalent with increasing the horizon of bankruptcy prediction. This exercise has the purpose to check the efficiency, stability and information content over bigger time frames and is widely met in the literature (e.g., Charitou et al., 2004). For this reason, two additional models based on M1 are estimated, where each model uses one and two-year lags of the covariates. The models are named as M1_lag and M1_2lag with the results appearing in Table 6.2. For comparison reasons, the base M1 model is placed on the first column. For compactness reasons, and although each model uses different lagged versions of the three covariates as inputs, the covariate names and coefficient estimations are still placed at the same level. With this technique of extending the horizon with lags, the number of available observations per year are reduced and postestimation measures as sensitivity, specificity and overall classification are recalculated accordingly. It should be noted that the only difference with the previous regression estimation table is the addition of the last row with the number of bankruptcies.

Table 6.2 Results for models M1, M1_lag and M1_2lag

	M1		M1_lag		M1_2lag	
EBTL	-.07621	***	-.07036	**	-.05763	
	(.02225)		(.03285)		(.042642)	
TLTA	3.51671	***	3.29178	***	3.57382	***
	(.49470)		(.45911)		(.65437)	
LnTA	.37269	**	.26143		.36292	**
	(.15054)		(.16806)		(.16273)	
_cons	-15.9277	***	-13.89964	***	-15.86062	***
	(2.40616)		(2.65313)		(2.63914)	
AIC	219.9859		222.6047		157.7839	
BIC	255.597		257.7818		192.4837	
AUC	0.8962		0.8765		0.8905	
Sensitivity	92.31%		84.62%		77.78%	
Specificity	77.75%		74.03%		79.63%	
Overall classification	77.75%		74.03%		79.63%	
Log-likelihood	-105.9929		-107.3023		-74.8919	
Pseudo R^2	0.1268		0.1057		0.1220	
N	54328		48742		43259	
Bankruptcies	13		13		9	

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

The estimated coefficients for EBTL become in the M1_lag model -0.070 being significant at 5% and loses significance in the two-year model. TLTA remains equally significant over all periods, preserving also its relative magnitude. LnTA loses significance in the one lag model but re-enters in the two-lag model with a coefficient of 0.362 at 5%, same as the base model. Sensitivity gradually reduces, overall classification reduces and increases, but both measures still retain high accuracy.

6.3 Specification robustness checks

As classification algorithms may not perform well when the dataset is heavily imbalanced (J. Garcia, 2022) as the case here, and since the model is not a canned routine and requires manual intervention, a robustness check regarding the applied specification will follow. For this reason, four additional econometric specifications will be estimated to safeguard against any possible misspecification.

The first method is the complementary log-log (*cloglog*) and was described in the methodology chapter. For this estimation, the logit link function is replaced by the *cloglog* function. The next two methods are the logistic panel regression, named *xtlogit* and the population-averaged generalized linear model, named *xtgee*, which according to Cameron and Trivedi (2022) are considered as equivalent calculations to the multi-period logit in Stata and can possibly provide better estimates. For *xtlogit* and *xtgee* models, the textbook of Cameron and Trivedi (2022) is used as a guidance.

The fourth model is the user-written command *relogit* for rare events (Tomz et al., 1999, 2003). This command is based on the theoretical and practical work of King and Zeng (2001a, 2001b) and adapted to the field of international conflicts, where the rarity of such events between country pairs or dyads, is the norm. Following the command's manual and the exact parameterizations of the application of Helmke (2017) in a political context with repeated observations for countries, the data are clustered by hotel, sampling correction is suppressed, and a prior correction is set to 13/55,806 based on the proportion of bankruptcy events to bankruptcy-free years.

At Table 6.3, the alternative method estimations are placed in a parsimonious way, presenting only coefficients, standards errors in parentheses, statistical significance, constant and number of observations for the base period only, meaning with no lags, and all four specifications give almost identical results.

Table 6.3 Results for models cloglog, xtlogit, xtgee and relogit

	cloglog		xtlogit		xtgee		relogit	
EBTL	-.076134	***	-.076192	***	-.076192	***	-.076214	***
	(.022174)		(.022252)		(.022252)		(.022253)	
TLTA	3.5128	***	3.5166	***	3.5166	***	3.5167	***
	(.49303)		(.49466)		(.49466)		(.49468)	
LnTA	.37222	**	.37273	**	.37273	**	.37268	**
	(.15016)		(.15054)		(.15054)		(.15053)	
_cons	-15.918	***	-15.928	***	-15.928	***	-15.955	***
	(2.3988)		(2.4062)		(2.4062)		(2.406)	
N	54328		54328		54328		54328	

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

More intuitively, the three first models suggest that the main specification is correctly parameterized. The fourth estimation demonstrates that all models can handle and accommodate effectively imbalanced data, since the rare events model accounts explicitly for heavily imbalanced samples and their proportions. Unreported estimations of the above specifications with the one and the two-lagged versions of the variables, replicated the lagged model results of Table 6.2, demonstrating a high degree of specification robustness and subsequently, the reliability of the results. The above facts, provide the empirical evidence to cover the first research question.

6.4 Comparisons of efficiency

This section deals with the second research question and will compare the base M1 model, loaded with the financial variables of two close related studies, to check model efficiency and variable relevancy.

It should be noted, that since the econometric model is parameterized in such way with clustered robust standard errors, the likelihood-ratio test is not appropriate to be performed (Stata.com, 2024), as also the Vuong (1989) test used in prior literature to compare multi-period logit models (e.g., Charalambakis, 2015; Charalambakis & Garrett, 2016), to the best of our current knowledge, is no longer supported by Stata (Cameron & Trivedi, 2022, p.1076) and more research needs to be done for this issue. So, the main quantities to assess the comparisons are the variable significance and sign, thus relevancy and model sensitivity.

This approach mimics mainly the exercise of Shumway (2001) who uses the variables of Altman (1968) and Zmijewski (1984) into a discrete-time hazard model setting. Relevant to the comparison approach here, one main finding of the Shumway (2001) study is that many financial variables of the comparison studies become insignificant, as for example from the Altman (1968) set of five ratios, only two appear relevant (Beaver, Correia & McNichols, 2010, p.120). Charitou et al. (2004) tested too the Altman (1968) set within a logit model, to find that only two variables being significant. The studies of Grice and Dugan (2001) and Grice and Dugan (2003) tested the models of Ohlson (1980) and Zmijewski (1984) to conclude that model re-estimations are time and industry sensitive (Allen et al., 2015, p.306) and raised a model's construct validity issue. All these comparison studies, generally agree that when such models are applied to other areas, sectors and time periods different from the ones calibrated, their performance generally erode (Beaver et al., 2010). The estimations of the exercise are placed in Table 6.4 where again, the first column replicates M1 model results to facilitate readability.

Table 6.4 Results for 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%	
Specificity	77.75%		80.54%		73.52%	
Overall classification	77.75%		80.54%		73.53%	
Log-likelihood	-105.9929		-103.6901		-103.7994	
Pseudo R^2	0.1268		0.1483		0.1449	
N	54328		55812		54327	

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

The first study to compare, is the study of Charalambakis and Garrett (2019), named CG19, where the same econometric specification is applied for Greek private firms, excluding financial firms and state-owned enterprises for the years 2003-2011. It must be noted that the comparison study uses a broader definition of default that covers not only bankruptcy, but also liquidation, dissolution and inactivity due to insolvency. This broader definition does not make directly comparable the two studies in terms of the definition of firm failure, as it incorporates also a much larger number of default events i.e., 1,770, but nevertheless, this study uses the same financial data source, for a previous time period and is performed for the biggest part of the economy. Besides the fact that the study uses additional variables as export capacity, dividend payout, a crisis dummy and the macroeconomic dimension of real gross domestic product growth, here, only the accounting model variables will be employed, which are total liabilities to total assets (TLTA), the natural logarithm of total assets (LnTA), working capital to total assets (WCTA), EBITDA to total assets (EBTA) and retained earnings to total assets (RETA).

For this purpose, the logit model is loaded with the above five inputs, with the results placed in the CG19 column of Table 6.4. and show that TLTA has a positive effect to bankruptcy with a coefficient of 2.165 statistically significant at 5% and LnTA with a positive coefficient of 0.468 significant at 1%. The result for size can be considered a notable result, as the original study estimates this exact variable consistently across all five models with a negative sign. The rest three covariates are not significant but bear a negative sign in line with literature and economic intuition. Sensitivity reduces to 76.92% capturing 10 from the 13 events of bankruptcy, while specificity and overall classification improve to 80.54%.

The second comparison study is of Diakomihalis (2012), named D12, and the respective results are presented in the fourth column of Table 6.4. The reason to select this study, as mentioned in Section 5.1 with the research objectives, is that with its companion conference version (Diakomihalis, 2011) is the only study that has assessed hotel bankruptcies in Greece. Here, a MDA approach was used in conjunction with the Altman (1968) set of financial ratios of working capital to total assets (WCTA), EBIT to total assets (EBTA)[6], retained earnings to total assets (RETA), equity to total liabilities (EQTL) and sales to total assets (SATA) to

[6] As EBIT is used in the study of Diakomihalis (2012) but was not available, EBITDA is used instead to construct EBTA.

investigate bankruptcy for years 2007-2008, with a sample of 146 hotels where 15 failed. Three versions of the Z-score model were applied, each model been calibrated for different sectors, with the best model being finally the original 1968 version for manufacturing firms.

The estimations of the multi-period logit model with this new set of variables, identified EQTL with a coefficient of -1.231 significant at the 1% level and WCTA with a coefficient of -1.333 significant at 10%. The rest regressors are rendered not significant, with RETA and SATA having an expected negative sign and EBTA an unexpected positive sign. Regarding EQTL**,** which in the descriptive statistics of Section 5.7 in Table 5.4, had an extreme outlier in the non-bankrupt sample, different winsorization levels of 2, 5 and 10% were applied, as also the deletion of that outlier, and the results remained unaltered**.** For this model, sensitivity becomes 84.62% capturing 11 of the 13 bankruptcies, one less event from the base model, and specificity and overall classification are almost identical and configured at 73.5%.

6.5 Sensitivity for size

In order to investigate the positive sign for size across the previous estimations, this section will employ alternative metrics of size in line with firm assets. This emphasis is given to this variable, as the size sign contradicts the original study of Charalambakis and Garrett (2019), as also five out of six hotel failure studies (Lado-Sestayo et al., 2016; Maté-Sánchez-Val, 2021; Situm, 2023; Vivel-Búa et al., 2016; Vivel-Búa & Lado-Sestayo, 2023) except Vivel-Búa et al. (2019).

The first measure used is the logarithm of total assets (Lado-Sestayo et al., 2016; Situm, 2023) and named LogTA. The second measure is the natural logarithm of fixed assets proxied by the accounting item of property, plant and equipment, named LnFA. As mentioned in the literature review part, the involvement of fixed assets is scarce in the hotel default sub-strand, where only three studies have identified this measure as a default predictor (Caires et al., 2023; Gu & Gao, 2000; S. Y. Kim, 2011) in the sense though of fixed asset turnover and the fixed asset to total assets ratio, so an effort should be made to reach better results, as the hotel industry is a fixed asset-intensive industry. M. C. Gupta and Huefner (1972) have found the fixed asset turnover to be the most discriminating ratio in their study and Sayari and Mugan (2017) discuss that fixed assets are dependent on industry, so in an industry as accommodation, it could be researched more. The third size variable is sole the measure of total assets (Vivel-Búa et al., 2016), named TA. The three variables are winsorized respectively at 1% both sides and are estimated in the M1 and CG19 variable settings, replacing only LnTA, with the coefficient and standard errors appearing parsimoniously in Table 6.5.

Table 6.5 Results for models M1 and CG19 with alternative size measures

	M1		CG19	
LogTA	.37269	**	.46862	***
	(.15054)		(.17973)	
LnFA	.48295	***	.61754	***
	(.12679)		(.17624)	
TA	1.93e-08	**	2.37e-08	**
	(9.36e-09)		(1.12e-08)	

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

All estimations show a stable positive sign, being at least significant at the 5% level for all measures, and in the cases of the natural logarithm of fixed assets and for the logarithm of total assets in the CG19 model, statistical significance is even improved to 1%. Sole the measure of total assets, display very small coefficients due to non-normalization of the variable but still are positively signed. In all these size estimations, the rest of the variables retained their signs and statistical significance, except for leverage where significance was lost in the CG19 setting with LnFA. These results show that the positive effect to bankruptcy for all different proxies of assets is uniform for the hotel dataset. With the estimations of Section 6.4 and 6.5, the empirical facts for the second research question are covered.

Conclusions

In this chapter the main econometric estimations were performed. A stepwise process assisted the selection of the most influential variables, which were found to be leverage, size and liabilities coverage. Leverage has a positive effect on hotel bankruptcy which is stably significant at 1% across all three horizons and in terms of odds ratio has the biggest magnitude. Size as the natural logarithm of total assets has an intermittent positive and statistically significant effect at 5% in the base and two-year models. Liabilities coverage has a negative effect for the base and the one-year models with a diminishing significance from 1 to 5%. Sensitivity checks for the basic multi-period model with four related methods gave identical results, proving that the specification followed in Stata is robust. Comparisons with two relevant Greek studies gave slightly diminished results regarding statistical relevance of the variables and lower model sensitivity in all cases. Parallel estimations with three alternative size measures, confirmed the positive effect on bankruptcy in the base and CG19 models, where in some cases as with the use of the natural logarithm of fixed assets, statistical significance was even improved to the 1% level, thus providing uniform evidence of the stable positive sign. This outcome contrasts though the findings of the origin Charalambakis and Garrett (2019) study for the Greek economy. With this evidence the two research questions are addressed and will be discussed extensively in the next chapter.

CHAPTER 7: Discussion of results

This chapter will initially provide a more detailed discussion and economic inferences stemming from the econometric results of the two research questions. Then, it continues with implications for management, policymakers and research, and will conclude with the limitations of the thesis and few insights for future research.

7.1 Discussion of the first research question

The first research question of the thesis is "which are the financial determinants related to hotel bankruptcies observed in Greece in the years 2010-2020". For this reason, a stepwise variable selection from nine variables with a multi-period logit model identified three accounting variables to jointly relate. The leverage variable, named TLTA and constructed as total liabilities to total assets, appeared to be the most robust predictor of hotel bankruptcy across all three horizons, with a positive effect at the 1% level and an odds ratio of 33.6 for the base estimation with the last available data, and 26.8 and 35.5 for the one and two-year lag models respectively. This result is in full accordance with the broader private firm bankruptcy literature (Cathcart et al., 2020), as also with the Greek economy (Axioglou & Christodoulakis, 2021; Charalambakis & Garrett, 2019) and the hotel literature (Vivel-Búa et al., 2016, 2019) confirming that leverage is the most hazardous empirical regularity in failure studies. The big magnitude of this odds ratio was cross-checked with the wider literature and appeared computationally not unusual.

The second most influential variable is the natural logarithm of total assets, named LnTA proxying size, which was found with a positive coefficient at the 5% level in the base and the two-year lagged models, and odds ratios of 1.45 and 1.38 respectively. For the one-year lagged model no significance was reached, thus size exhibits here an intermittent statistical significance. This positive effect on firm failure is in line with Vivel-Búa et al. (2019) for Spanish hotels, though in a non-logarithmic form, and contradicts the rest five hotel bankruptcy studies that identified this metric as negatively significant (Lado-Sestayo et al., 2016; Maté-Sánchez-Val, 2021; Situm, 2023; Vivel-Búa et al., 2016; Vivel-Búa & Lado-Sestayo, 2023). In the broader literature, this expression of total assets, is usually found with a negative sign, thus having a protective effect to firm default, in a variety of studies that examined failure of private firms in broader sectors, as for Belgium (Bauweraerts, 2016; Cultrera & Brédart, 2016; Dewaelheyns, Van Hulle, Van Landuyt & Verreydt, 2021), in the study of Mselmi et al. (2017) for France but in the two-lag model only, in Holland (Rikkers & Thibeault, 2011), Finland (Back, 2005), as also for the Spanish hospitality sector (Belda & Cabrer-Borrás, 2020).

The third selected variable, the liabilities coverage ratio, named as EBTL and composed by EBITDA to total liabilities, appears a jointly significant covariate in the base and the one-lag model with a protective effect and odds ratios of 0.92 and 0.93 significant at the 1% and 5% levels respectively. In the two-lag model though it loses statistical significance. The liabilities coverage result agrees with the broader literature (Beaver et al., 2005), but isn't so frequently used in hotel default studies. One exception is Fernández-Gámez et al. (2016) for the Spanish hotel sector in the two-year horizon model and the 8th place of relative importance. Instead, the closely related variable of EBITDA to current liabilities, is found in Fernández-Gámez et al. (2016) as the most important default predictor in the one and two-year models. This latter version is found within the most influential variables in the studies of Youn and Gu (2010) and Del Castillo García and Fernández Miguélez (2021) as in Laguillo et al. (2019) for the hospitality sector in Spain. The close version of EBIT to total liabilities, aside the tourism sector, was estimated with a negative sign in Charitou et al. (2004) for public UK companies.

A further comment on the horizon extension exercise is that the explanatory power of variables reduces, as mirrored well in the liabilities coverage result. Sensitivity also gradually diminished from 92.3% to 84% and 77%. Overall classification shows a U-shaped trajectory, as it falls and increases again. The general reduction of explanatory power and statistical properties as the event horizon distance increase is generally met in the literature (e.g., Campbell et al., 2008) and expected.

As mentioned in Section 5.4 of the dataset presentation, since the data had gaps of missing values averaging 3.6 years prior to the observed available bankruptcies**,** an issue frequently encountered in the relevant literature (e.g., Balcaen et al., 2012), in addition to the two-year lags that were applied, the estimated results, especially for leverage and size, can convey prognostic ability that can reach an average period of five years prior to bankruptcy.

In sum, it can be stated for the first research question that the bankruptcy probability in the available hotel sample in Greece for years 2010 to 2020, is an increasing function of leverage and size in terms of total assets and a decreasing function of liabilities coverage with EBITDA. Regarding size, the positive sign implies that the "too big to fail" principle does not hold for the Greek hotel sample.

Specification robustness can be claimed also from the estimated alternative models which provided identical results. The complementary log-log model, which was presented in Section 5.3 and is used due to its skewness and when the minority sample is very small, provided identical coefficients, similarly to the two commands proposed by Cameron and Trivedi (2022). The same results obtained from the rare events logit specification of Helmke (2017) safeguards also for the severe imbalance in the available data sample and renders the previous specifications competent to handle imbalanced datasets, as this model explicitly allows calibration for this dimension. The use of these multi-period logit specifications is an econometric originality for the hotel failure literature, as can be compared also with the literature review part. These specification exercises strengthen the validity of the results regarding the three most influential variables and comprise the answering facts for the first research question of the thesis.

7.2 Discussion of the second research question

The second research question of this thesis is "if models estimated in two previous studies for the whole economy and the hotel sector in Greece are equally efficient related to the current hotel sample estimations" and pertains to the comparison of the first research question estimations with the two selected Greek studies of Charalambakis and Garrett (2019) and Diakomihalis (2012).

In the current absence of a statistical test in Stata to compare non-nested models i.e., not being a subset in terms of variables, as the case here, as in the past the Vuong (1989) test was used but is not supported in the software at use (Cameron & Trivedi, 2022), and in the same time the inappropriateness of the likelihood-ratio test to be performed in this setting with clustered robust standard errors (Stata.com, 2024), the analysis relied on an efficiency comparison in terms of their relevance, thus statistical significance and sign of the variables, and model accuracy mainly sensitivity, which is the true positive rate and weighs the minority sample of bigger interest. For this exercise, the variables of the comparison studies were loaded in the multi-period logit, the estimations were performed for the base model with no lags and the results were contrasted.

The estimation of the five Charalambakis and Garrett (2019) variables, calculated leverage with a positive effect on bankruptcy being significant at 5% and an odds ratio of 8.7. Size was estimated with a positive effect too with an odds ratio of 1.5 significant at 1%, while the rest regressors were rendered insignificant. This estimation led also to lower efficiency in terms of sensitivity, as it captured 10 out of the 13 bankruptcies, two less than the base model. Overall classification increased compared to the base model, but as mentioned this metric was not given so importance as it may be misleading (Palepu, 1986).

The contradiction of the size sign with this comparison study for the Greek economy and most of the findings presented for the hotel sector, suggests the economic interpretation that size in terms of total assets may not necessarily lead hotels to reach economies of scale, but on the contrary, it was a jointly significant financial clause for the existing cases of bankruptcies.

The positive effect of size, despite its intermittent statistical significance, as it was insignificant in the one-lag model, was reassured for the base estimation through additional sensitivity checks with alternative versions of asset size, namely the logarithm of total assets, the natural logarithm of fixed assets and the absolute measure, and showed a satisfying degree of robustness as it maintained its positive effect, and in the cases of the use of the natural logarithm of fixed assets, its significance even improved to the maximum level. This further reinforces the result and the economic interpretation from the first research question that the "too big to fail" principle does not hold in this sample and that possibly fixed assets could be researched more. It should be reminded though, that Charalambakis and Garrett (2019) use a slightly broader definition for firm default, more sectors, it is conducted for an earlier time period, but had the same financial database information, while here the sample was focused only on the code 5510 of hotels, thus was more limited and with a judicial definition of failure.

Regarding the second comparison with the Diakomihalis (2012) study that essentially uses the Altman (1968) variables, the estimations provided significant results only for two variables. The strongest effect stemmed from equity to total liabilities, named EQTL, with a negative coefficient being significant at 1% and an odds ratio of 0.29. These results remained stable after treating this variable for an extreme outlier. The second variable of working capital to total assets, named WCTA, provided too a negative coefficient significant at 10% and an odds ratio of 0.26. Sensitivity was by one bankruptcy event lower than the base model, capturing 11 out of 13 bankruptcies, as also overall classification diminished.

For the prespecified set of the Altman (1968) variables, Levratto (2013) has pointed out that they own their popularity due to the increased efficiency of the origin study and indeed these variables are of fundamental nature, as recently Serrano-Cinca, Gutiérrez-Nieto and Bernate-Valbuena (2019) commented on the study of Altman, Iwanicz-Drozdowska, Laitinen and Suvas (2017) that this original set remains still resilient. H. Li and Sun (2013) also has validated in the tourism sector its increased efficiency. But this set does not include size or fixed assets in a distinct manner, an issue to be discussed in the theoretical implications section.

Overall, both comparisons showed reduced efficiency in variable relevancy and sensitivity, the two measures selected to assess the results. This fact, i.e., the reduction in efficiency when sets of variables produced elsewhere are re-estimated, is generally met in the literature (Charitou et al., 2004; Grice & Dugan, 2003; Shumway, 2001). For overall classification the results are mixed, but more focus was placed on sensitivity. It can be argued though, that the results of both the research questions provide roundly affirmative indications that accounting ratios provide effective and satisfying information content even for longer horizons, financial ratios may exhibit an opposite behavior in different samples, and taking into account variables that may differentiate firm balance sheets to other sectors can possibly increase efficiency further.

As an extension of thought, normally, it would be expected that what holds for the whole economy, as the constant negative sign for size in Charalambakis and Garrett (2019) and in the broader literature, would hold for the specific hotels sample here. But since in the estimations the sign was constantly positive under different size proxies scenarios, it can be said that for the current sample, an inverse fallacy of composition holds.

As one cannot exclude cross-sectoral bias (Barreda et al., 2017; Caires et al., 2023; Cho, 1994; S. Y. Kim, 2018; H. Li & Huang, 2012; Topaloğlu, 2012), one cannot exclude also a possible inverse fallacy of composition bias to exist in other economic activity-specific models, since sectors differ and firms even in the accommodation sector are not entirely homogenous as discussed in the description of the NACE codes.

Under the light that sectors have different nature of operations mirrored too on their balance sheets and face different levels of risk and failure rates, in conjunction with the results and implications from the second research question, one can assume that one model does not fit all, as models are predictive tools and their efficiency does not necessarily transcend across time and industries (Grice & Dugan, 2003). So, developing bankruptcy research models per sector or economic activity in a regular base, with an *ad hoc* variable selection, can be an appropriate treatment that can offer focused results, reach more suitable inferences and may be the best of two worlds in terms of details.

7.3 Implications for management and policy makers

As firms should monitor constantly the accounting items found important in bankruptcy studies (Cultrera & Brédart, 2016), one first implication stemming from this empirical analysis is that hotel management ought to be cautious about the level of liabilities related to total assets, as it is the most influential metric increasing the probability of a bankruptcy event. Also, management should have in mind that the "too big to fail" principle is not so uncommon and should plan meticulously asset growth and avoid ballooning assets (Altman & La Fleur, 1981), as an increase may not lead to economies of scale but was estimated here as a financial clause of bankruptcy. As a reminder Carmona et al. (2019) found size of personnel the most important bank failure factor and Vivel-Búa et al. (2019) identified size of assets to increase hotel failure probability. Regarding the third significant variable of liabilities coverage, hotels should be aiming for an increased profitability in terms of EBITDA and opting at the same time for a balance with total liabilities.

7.4 Implications for policymakers

Policies regarding the hotel sector's financial sustainability and resilience can be the establishment of credit channels that can complementarily assist hotels limit certain types of liabilities, as for example the partial coverage of employment costs through employment schemes. Size, asset attainment and sustained asset growth could be influenced by incentivizing hotel renovations and energy-efficient buildings in the context of climate change mitigation.

Other policies can include quantitative intervention tools, can be the creation of bankruptcy assessment and credit ratings tools for sectors that offer increased value in an economy. The similar tool of CAMELS (Christopoulos, Mylonakis & Diktapanidis, 2011; Cole & Gunther, 1998) is used for banking. Regulators can possibly get access more easily to such information, by combining financial information that firms are obliged to share, with the national statistics databases. These tools, that tend to be created across Europe for SMEs (Altman et al., 2022, 2023; Cultrera, 2020) can become a quantitative canary in a coalmine in terms of early warning systems and can be linked to rescue plans and second chance programs to enhance the viability of some firms and avoid loss of social welfare. Furthermore, the creation of firm bankruptcy registries can be set up in order to enhance research and be augmented towards a specific dimension of interest. One such example is the UCLA-LoPucki Bankruptcy Research Database (LoPucki & Doherty, 2015) that contains records of large firm bankruptcies in the US involving financial ratios and the law dimension. These registries can be enriched with sectoral variables that can lead to a more detailed view on the differential impact some factors exert on different sectors.

7.5 Theoretical implications

A theoretical implication for research is the future inclusion of size. Size as a distinct measure in terms of the logarithm of assets entered recently in hotel bankruptcy modeling in the studies of Lado-Sestayo et al. (2016) and Vivel-Búa et al. (2016), but it appears to be a crucial variable in this study and in broader finance studies (Back, 2005; Belda & Cabrer-Borrás, 2020; Charalambakis & Garrett, 2019; Mselmi et al., 2017; Vivel-Búa et al., 2019). Similarly, additional analysis can be undertaken with fixed assets, especially in the hotel sector which is fixed asset-intensive and there are scarce results except in three studies (Caires et al., 2023; Gu & Gao, 2000; S. Y. Kim, 2011). Size also conveys the capital intensity of the sector in a very interpretable manner, which in turn can lead to useful inferences regarding economies or diseconomies of scale.

Based on this size implication, equal matched sampling by size and industry can be partially questioned, though it has its merits (Charitou et al., 2004, p.494), as size is omitted in these studies (Jones, 2023; e.g., Altman et al., 1994; Charitou et al., 2004; Elsayed & Elshandidy, 2020; Khoja et al., 2019), thus excluding an important factor, and as contemporary methodologies can accommodate even severely imbalanced samples. Also, working with prespecified set of ratios as the Altman (1968) set that do not include size, limits possible efficiency gains implying that bigger attention should be given to *ad hoc* variable selection.

Size could contribute also to qualitative studies, as in three studies where questionnaires were posed to academics to evaluate ratios of tourism firms regarding business failure (Korol & Spyridou, 2020) and to hotel executives to assess financial health (Singh & Schmidgall, 2001, 2002), size was not considered and thus not investigated as a factor. By being included, it can increase awareness of hotel executives and academia.

7.6 Limitations

One limitation of the thesis is the small available sample of bankrupt hotels which prohibits generalization. Unfortunately, due to data issues a bigger sample could not be collected, as the true number of official bankruptcies was bigger for the study period. This may have introduced a selection bias, where research is performed only with firms with complete data (Jayasekera, 2018). The small number of bankruptcy events also, firstly hindered research per firm size as bankrupt hotels were equally distributed across size bands based on the European Union definition of SMEs, and secondly out-of-sample predictions. Also, the required clustering for the estimations of the multi-period logit model and the comparison studies that did not involve nested models, did not allow statistical tests to be performed and more research is needed for this. In a technical manner, to have reached a better *lege artis* technical level, marginal effects, as also the recently embedded variable selection method of LASSO to Stata could have been applied.

7.7 Future research

Future paths can explore further hotel-specific variables beyond accounting measures, as quality of hotels, size in terms of employment, bed capacity, the corporate governance and the social media linguistic content dimensions, as also a systematic recording of the external variables related to failure can be conducted. A hotel bankruptcy study with samples from different countries is believed to provide fresher and robust insights, as at the moment such study is missing. Artificial intelligence models can be used in order to take advantage of their increased efficiency in settings with large samples representing the whole economic activity, as from the literature review part, the current samples used are relatively small. Also, there is space for methods accommodating more than one event of interest.

Finally, in the similar manner of Zhang and Xie (2023), who examined the nexus of financial ratios and seasonality to hotel default, and studies that included macroeconomic variables (e.g. Baum & Mezias, 1992; Charalambakis & Garrett, 2019; Gémar et al., 2016; Türkcan & Erkuş-Öztürk, 2020), the tourist destination lifecycle theory of Butler (1980) and its relation to tourism firms failure can be investigated. Since there are limited data on hotel bankruptcies, an augmented tourism related firm dataset can be used that will merge restaurants, travel agencies, museums and similar activities (e.g., Caires et al., 2023; Piacentino et al., 2021; Türkcan & Erkuş-Öztürk, 2020). The ranking of areas to stages of the theory can follow for example the study of Polyzos and Saratsis (2013) and this approach could combine naturally a traditional tourism theory with the applied field of firm bankruptcy.

CHAPTER 8: Conclusions

As firm failures can be a potential threat to social welfare and given the huge volume of studies, this thesis aimed to investigate the financial determinants of hotel default in Greece with an advanced econometric methodology. To provide a complete as possible framework for such an empirical work, the theoretical frame was paved in the first half of the thesis. This included thorough discussions on the basic positions that exist in the firm failure literature, that all contribute to the better understanding of the failure phenomenon. Though a general theory of firm failure is missing, and no clear consensus exists, the approaches of the internal and external variables were initially presented. The financial ratio approach was selected as the empirical setting to address the issue and the basic concepts that run this sub-strand of the literature were presented. The definitions of firm failure were discussed, as it immediately relates to the exact firm status under study and the dependent variable.

Then, the interest moved to the issue of segregated and aggregated research. This is another interesting part, as much empirical evidence was posed regarding research conducted at the economy or at the sector level. A basic argument here, is that firms across sectors tend to be differentiated and this is mirrored also in their financial statement and accounting items, which in turn is the primary source of independent variables in this sub-strand. Different default risk is related to sectors and evidence is provided that the hospitality sector has high failure rates. Also, the literature has identified a differential impact of factors on firm failure risk, suggesting a cross-sectoral bias when different sectors are examined together.

Also, the variety of methodologies were briefly classified, placing a bigger weight on interpretability, as econometric models tend to be intrinsically capable of being more explanative in relation to artificial intelligence methodologies. Econometric methods can attach an effect with certainty, minimizing errors, as artificial intelligence models tend to create a list based on the importance of the variables, but may miss a logical explanation. This first theoretical part of the thesis closes with the unique technical tool met in the financial ratio approach, the extension of the failure horizon, that offers the ability to assess the information content over longer time periods.

The next stage of the theoretical part is related to the prior literature of the subject. For this reason, a systematic literature review was conducted to identify the relevant hotel failure studies that included financial items. 29 studies were collected through a review protocol, and the studies were narrated and analyzed with the aim to isolate these financial ratios. The basic features of the studies were recorded in a cumulative table and besides an overall discussion of this tranche of the literature, the main results showed that the most common observed factors affecting hotel failure were financial leverage in terms of debt and liabilities having a hazardous effect, while profitability, generally revenues and size proxied through total assets having a protective effect.

The theoretical part of this study closes with the chapter that adapts the issue to the Greek economy and the hotel market. The contribution of tourism and an approximation of the accommodation sector's contribution to the Greek economy is given. Based on the typologies of accommodation firms, a description of the four NACE subcodes is given, as it assists to better understand the differences of accommodation establishments and the possible implications that this issue might have on researching heterogenous firm samples, as noticeable differences exist between firms designated to the four accommodation subsectors. Finally, firm bankruptcy figures are presented for Greece, showing mainly that some sectors are more susceptible to bankruptcy, as also that the hospitality industry that is constituted by accommodation and food and beverage sectors, exhibit large differences in observed bankruptcy events. The general notion of this representation of the Greek data is, that since firms in one subsector as accommodation are heterogenous, examining wider economic activities in terms of broader samples may logically involve cross-sectoral bias.

The second half of the thesis shifts towards the econometric evaluation of hotel bankruptcies in Greece. The objectives of the thesis are composed based on the previous theoretical analysis, i.e., the financial ratio approach is the most popular approach, sectoral focus can be a more appropriate angle, the importance of tourism and accommodation in Greece, the gap in the literature for Greek hotel bankruptcy studies and the sufficient interpretation of econometric models, all shape the empirical research leitmotif. The main research questions which are posited are "which are the financial determinants of bankruptcy for the Greek sample" and "if models and their variables, from two relevant Greek studies are equally efficient" to the modeling strategy that was applied here with the base specification.

The multi-period logistic regression method was selected be processed in Stata, as it is considered an appropriate technique based on its firm failure applications in quality journals, its robust statistical foundations and its ability to account for repeated financial observations of firms. After the model articulation, the available dataset of the hotel sample is presented, that includes eventually 13 bankruptcies and over 5,500 non-bankrupt hotels and an extensive discussion is made about its features. Preliminary analysis in terms of data curation, as also some procedures that facilitate an initial variable selection screening, as t-tests, correlation and univariate analysis are performed.

The first econometric estimation part, which is related to the first research question, begun with a stepwise procedure with the basic specification, that led to three statistically significant variables: total liabilities to total assets that proxy financial leverage, the natural logarithm of total assets to proxy size and EBITDA to total liabilities that proxy liabilities coverage. While leverage and size increase the probability of bankruptcy, liabilities coverage had a decreasing effect. More precisely, leverage yields an odds ratio of 33, size of 1.45 and liabilities coverage of 0.9. By stretching the bankruptcy horizon by two periods though lagging the independent variables, the results appeared fairly robust. Leverage retained its effect for all periods, liabilities coverage remained significant only for one additional period, and sizes' significance appeared intermittent, being insignificant for one additional period but re-entering in the two-period estimation, thus all three variables exhibited a satisfying information content over longer periods and the odds ratios retained their average magnitude too. The information content is considered further satisfying, as the 3.6 years of missing data on average prior to bankruptcy, did not hinder the results to be effective for an average period of over 5 years prior failure. For the generic results, the leverage and liabilities coverage effects are in line with the literature, but the positive sign for size generally contrasts the majority of hotel failure literature except one study.

Regarding the second research question, the financial variable inputs that were used in two relevant studies, the one for the whole Greek economy and the second for the Greek hotel sector, were loaded to the main specification of the multi-period logit and the results were evaluated on the basis of relevance in terms of statistical significance, the accompanying sign and the sensitivity measure which was calibrated upon the sample proportions. These measures were selected as a *grosso modo* comparison strategy, in the absence of a statistical test to compare non-nested models with the specific standard errors structure. For the first study of Charalambakis and Garrett (2019), that investigated the issue of bankruptcy and financial distress for the whole economy with the same method, but for an earlier time period and a broader default definition, the results from running the regression with the five variables of the study, showed only leverage and size to be significant predictors, both increasing the likelihood of bankruptcy, with the rest of the regressors not being significant. Two important artifacts here are the opposite sign for size, as in original study there is a constantly negative sign for size across all the augmented models estimated and the small reduction in sensitivity.

The comparison with the second study of Diakomihalis (2012), that examined hotel bankruptcies with MDA and the standard set of Altman (1968) ratios, selected equity to total liabilities and working capital to total assets with negative, thus protective effect to bankruptcy. The results are in accordance with economic logic, but most of the variables are rendered with no statistically significant content and the model exhibited a lower sensitivity to the base model.

Sensitivity analysis for size took place also with closely related measures involving assets and showed that statistical significance and the positive sign remained, and in some cases, as with the use of the natural logarithm of fixed assets, significance even increased. Conjointly, the stable positive sign of size and the improved significance of fixed assets, may suggest that one type of model does not fit all circumstances and that ratios involving fixed assets deserve possibly to have an increased participation in a fixed asset-intensive sector, as their participation in the hotel bankruptcy literature is limited except in three studies and in another form.

Robustness checks for the statistical method took place, with the complementary log-log link and three more models suggested in the broader literature and the results coincided. This additional check safeguarded, firstly against a possible misapplication of the base multi-period logit model, as this procedure is not offered as a canned routine and its syntax requires a manual parameterization, and secondly against the heavy imbalanced dataset, via the rare events logit specification extracted from the political sciences context. This use of these multi-period logit models can be considered an originality of this thesis, as it aspires to link a contemporary finance methodology appearing mainly in the G33 code related to bankruptcy under the umbrella of financial economics, with the Z33 code regarding marketing and finance of tourism economics.

After the derivation of the main results, a discussion followed. Initially, the results were contrasted to the hotel as also the broader default literature. The effects of leverage and liabilities coverage are in accordance with the literature. More weight is placed on the positive sign for size, as this contrasts the literature and implies that the "too big to fail" principle does not hold in the available Greek hotel sample. It can be derived also, that studying specific economic sectors and economic activities, may provide indeed important differentiations in the determinants of failure. The comparisons showed reduced variable relevance and sensitivity and suggest that one model does not fit all cases and that an estimation efficiency achieved under a specific modeling strategy may not necessarily replicate to other areas.

Some implications were provided at the management level, especially focusing on the significant variables, and specifically for the "too big to fail" principle that does not hold in the sample due to the positive sign of size. This conveys the message that ballooning assets should be avoided and an increased size of assets may not always lead to economies of scale.

It should be noted though, that these results cannot replace professional judgement, but rather be comprehended as having some incremental information from a statistical examination of the specific sample through a specific angle.

Some policy recommendations were provided, regarding the creation of channels to subsidize the reduction of costs and liabilities through employment or renovation schemes. Another viable policy is developing early warning systems, even at a sectoral level, as such processes are already in use in Europe for SMEs and in the banking sector, to link firms with second chance rescue plans and increase firm financial sustainability.

The theoretical implications for research are the inclusion of size in terms of total assets and fixed assets as potential covariates and a discussion is provided for the matched-sampling technique and the Altman (1968) set that omit size.

As the firm failure literature acknowledges cross-sectoral bias, one cannot exclude with certainty that a possible inverse fallacy of composition bias may hold too. This bias stems from the positive sign of size which contrasts the literature, as what holds for the general part does not hold for the specific economic activity of hotels.

Developing further sectoral models, does not mean necessarily that results will deviate substantially, as for example leverage is a ubiquitous contributing failure factor, but one cannot exclude that further sector-adjusted research may reveal interesting facts that reflect closer the nature of the business and can translate to useful inferences.

Towards the closure of the thesis, the limitations of the study are re-stated, as the small number of bankruptcy events and missing data of actual bankruptcies that may have introduced a sample-selection bias and some interesting potential avenues of research are suggested.

References

Abid, I., Mkaouar, F., & Kaabia, O. (2018). Dynamic analysis of the forecasting bankruptcy under presence of unobserved heterogeneity. *Annals of Operations Research*, *262*(2), 241–256. https://doi.org/10.1007/s10479-016-2143-2

Abidali, A. F., & Harris, F. (1995). A methodology for predicting company failure in the construction industry. *Construction Management and Economics*, *13*(3), 189–196. https://doi.org/10.1080/01446199500000023

Abidin, J. Z., Abdullah, N. A. H., & Khaw, K. L.-H. (2020). Predicting SMEs failure: Logistic regression vs artificial neural network models. *Capital Markets Review*, *28*(2), 29–41. https://www.mfa.com.my/cmr/v28_i2_a3/

Abidin, J. Z., Abdullah, N. A. H., & Khaw, K. L.-H. (2021). Bankruptcy prediction: SMEs in the hospitality industry. *International Journal of Banking and Finance*, *16*(2), 51–80. https://doi.org/10.32890/ijbf2021.16.2.3

Acosta-González, E., & Fernández-Rodríguez, F. (2014). Forecasting financial failure of firms via genetic algorithms. *Computational Economics*, *43*(2), 133–157. https://doi.org/10.1007/s10614-013-9392-9

Acosta-González, E., Fernández-Rodríguez, F., & Ganga, H. (2019). Predicting corporate financial failure using macroeconomic variables and accounting data. *Computational Economics*, *53*(1), 227–257. https://doi.org/10.1007/s10614-017-9737-x

Adamopoulou, E., Kapopoulos, P., & Marinopoulou, E. (2022). *Greek tourism industry reloaded: Post-pandemic rebound and travel megatrends*. https://www.alpha.gr/-/media/alphagr/files/group/agores/insights/2022/insights_tourism_052022.pdf

Adams, D. J. (1991). Do corporate failure prediction models work? *International Journal of Contemporary Hospitality Management*, *3*(4), 25–29. https://doi.org/https://doi.org/10.1108/EUM0000000001681

Adams, D. J. (1995). Methods for predicting financial failure in the hotel industry. In P. Harris (Ed.), *Accounting and Finance for the International Hospitality Industry* (pp. 19–38). Butteworth-Heinemann. https://doi.org/https://doi.org/10.4324/9780080938684

Agarwal, V., & Taffler, R. (2008). Comparing the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking and Finance*, *32*(8), 1541–1551. https://doi.org/10.1016/J.JBANKFIN.2007.07.014

Akron, S., Demir, E., Díez-Esteban, J. M., & García-Gómez, C. D. (2020). Economic policy uncertainty and corporate investment: Evidence from the U.S. hospitality industry. *Tourism Management*, *77*, 104019. https://doi.org/10.1016/j.tourman.2019.104019

Alaka, H. A., Oyedele, L. O., Owolabi, H. A., Kumar, V., Ajayi, S. O., Akinade, O. O., & Bilal, M. (2018). Systematic review of bankruptcy prediction models: Towards a framework for tool selection. *Expert Systems with Applications*, *94*, 164–184. https://doi.org/10.1016/j.eswa.2017.10.040

Alaka, H. A., Oyedele, L. O., Owolabi, H. A., Oyedele, A. A., Akinade, O. O., Bilal, M., & Ajayi, S. O. (2017). Critical factors for insolvency prediction: Towards a theoretical model for the construction industry. *International Journal of Construction Management*, *17*(1), 25–49. https://doi.org/10.1080/15623599.2016.1166546

Alaminos, D., Del Castillo, A., & Fernández, M. Á. (2016). A global model for bankruptcy prediction. *PLOS ONE*, *11*(11), e0166693. https://doi.org/10.1371/journal.pone.0166693

Alaminos, D., & Fernández, M. Á. (2019). Why do football clubs fail financially? A financial distress prediction model for European professional football industry. *PLOS ONE*, *14*(12), e0225989. https://doi.org/10.1371/journal.pone.0225989

Allen, D. E., Powell, R. J., & Singh, A. K. (2015). A critique of credit risk models with evidence from mid-cap firms. In C. Zopounidis & E. Galariotis (Eds.), *Quantitative Financial Risk Management: Theory and Practice* (pp. 296–311). Wiley. https://doi.org/10.1002/9781119080305.ch11

Allison, P. D. (1982). Discrete-time methods for the analysis of event histories. In S. Leinhardt (Ed.), *Sociological Methodology* (Vol. 13, pp. 61–97). Jossey-Bass Publishers. https://doi.org/10.2307/270718

Allison, P. D. (2010). *Survival analysis using SAS: A practical guide* (2nd ed.). SAS Institute.

Allison, P. D. (2014). *Event history and survival analysis* (2nd ed.). SAGE. https://doi.org/10.4135/9781452270029

Almaskati, N., Bird, R., Yeung, D., & Lu, Y. (2021). A horse race of models and estimation methods for predicting bankruptcy. *Advances in Accounting*, *52*, 100513. https://doi.org/10.1016/j.adiac.2021.100513

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589–609. https://doi.org/https://doi.org/10.1111/j.1540-6261.1968.tb00843.x

Altman, E. I. (1971). Railroad bankruptcy propensity. *The Journal of Finance*, *26*(2), 333–345. https://doi.org/10.2307/2326049

Altman, E. I., Balzano, M., Giannozzi, A., & Srhoj, S. (2022). Revisiting SME default predictors: The Omega Score. *Journal of Small Business Management*, *61*(6), 1–35. https://doi.org/10.1080/00472778.2022.2135718

Altman, E. I., Balzano, M., Giannozzi, A., & Srhoj, S. (2023). The Omega Score: An improved tool for SME default predictions. *Journal of the International Council for Small Business*, *4*(4), 362–373. https://doi.org/10.1080/26437015.2023.2186284

Altman, E. I., Haldeman, R. G., & Narayanan, P. (1977). ZETATM analysis: A new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance*, *1*(1), 29–54. https://doi.org/10.1016/0378-4266(77)90017-6

Altman, E. I., & Hotchkiss, E. (2005). *Corporate financial distress and bankruptcy*. Wiley. https://doi.org/10.1002/9781118267806

Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2017). Financial distress prediction in an international context: A review and empirical analysis of Altman's Z-score model. *Journal of International Financial Management and Accounting*, *28*(2), 131–171. https://doi.org/10.1111/jifm.12053

Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2020). A race for long horizon bankruptcy prediction. *Applied Economics*, *52*(37), 4092–4111. https://doi.org/10.1080/00036846.2020.1730762

Altman, E. I., & La Fleur, J. K. (1981). Managing a return to financial health. *Journal of Business Strategy*, *2*(1), 31–38. https://doi.org/10.1108/eb038922

Altman, E. I., Marco, G., & Varetto, F. (1994). Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience). *Journal of Banking and Finance*, *18*(3), 505–529. https://doi.org/10.1016/0378-4266(94)90007-8

Altman, E. I., & Sabato, G. (2007). Modelling credit risk for SMEs: Evidence from the U.S. market. *Abacus*, *43*(3), 332–357. https://doi.org/10.1111/j.1467-6281.2007.00234.x

Altman, E. I., Sabato, G., & Wilson, N. (2010). The value of non-financial information in SME risk management. *The Journal of Credit Risk*, *6*(2), 95–127. https://doi.org/10.21314/JCR.2010.110

Álvarez-Ferrer, A., & Campa-Planas, F. (2020). Predicting business failure in the hotel sector. *Cuadernos de Turismo*, *45*, 33–59. https://doi.org/10.6018/turismo.426031

Amankwah-Amoah, J., Khan, Z., & Wood, G. (2021). COVID-19 and business failures: The paradoxes of experience, scale, and scope for theory and practice. *European Management Journal*, *39*(2), 179–184. https://doi.org/10.1016/j.emj.2020.09.002

Amemiya, T. (1985). *Advanced econometrics*. Havard University Press.

Amendola, A., Restaino, M., & Sensini, L. (2015). An analysis of the determinants of financial distress in Italy: A competing risks approach. *International Review of Economics and Finance*, *37*, 33–41. https://doi.org/10.1016/j.iref.2014.10.012

Apergis, N., Bhattacharya, M., & Inekwe, J. (2019). Prediction of financial distress for multinational corporations: Panel estimations across countries. *Applied Economics*, *51*(39), 4255–4269. https://doi.org/10.1080/00036846.2019.1589646

Appiah, K. O., Chizema, A., & Arthur, J. (2015). Predicting corporate failure: A systematic literature review of methodological issues. *International Journal of Law and Management*, *57*(5), 461–485. https://doi.org/10.1108/IJLMA-04-2014-0032

Argenti, J. (1976). Corporate planning and corporate collapse. *Long Range Planning*, *9*(6), 12–17. https://doi.org/10.1016/0024-6301(76)90006-6

Arnis, N. (2018). *Bankruptcy of small or large size corporations: A comparative application of prediction methods* [Doctoral dissertation, University of Patras, Greece]. https://doi.org/10.12681/eadd/45018

Arnis, N. I., Chytis, E. T., & Kolias, G. D. (2018). Bankruptcy prediction and homogeneity of firm samples: The case of Greece. *Journal of Accounting and Taxation*, *10*(9), 110–125. https://doi.org/10.5897/jat2018.0321

Arnis, N. I., Karamanis, K., & Kolias, G. (2020). Factors affecting business failure of small and very small Greek family enterprises. *Accounting and Finance Research*, *9*(2), 35–45. https://doi.org/10.5430/afr.v9n2p35

Asimakopoulos, I., Lalountas, D., & Siriopoulos, C. (2008). The determinants for the survival of firms in the Athens Exchange. *Economic Bulletin Bank of Greece*, *31*, 7–30. https://www.bankofgreece.gr/Publications/econbull200810.pdf

Avramidis, P., Asimakopoulos, I., & Malliaropulos, D. (2023). Disrupted lending relationship and borrower's strategic default. *Journal of Financial Services Research*, *63*(1), 91–116. https://doi.org/10.1007/s10693-021-00368-7

Axioglou, C., & Christodoulakis, N. (2021). Which firms survive in a crisis? Investigating Gibrat's Law in Greece 2001–2014. *Journal of Industrial and Business Economics*, *48*(2), 159–217. https://doi.org/10.1007/s40812-020-00176-5

Aziz, A. M., & Dar, H. A. (2006). Predicting corporate bankruptcy: Where we stand? *Corporate Governance*, *6*(1), 18–33. https://doi.org/10.1108/14720700610649436

Back, P. (2005). Explaining financial difficulties based on previous payment behavior, management background variables and financial ratios. *European Accounting Review*, *14*(4), 839–868. https://doi.org/10.1080/09638180500141339

Bai, Q., & Tian, S. (2020). Innovate or die: Corporate innovation and bankruptcy forecasts. *Journal of Empirical Finance*, *59*, 88–108. https://doi.org/10.1016/j.jempfin.2020.09.002

Balcaen, S., Manigart, S., Buyze, J., & Ooghe, H. (2012). Firm exit after distress: Differentiating between bankruptcy, voluntary liquidation and M&A. *Small Business Economics*, *39*(4), 949–975. https://doi.org/10.1007/s11187-011-9342-7

Balcaen, S., & Ooghe, H. (2006). 35 years of studies on business failure: An overview of the classic statistical methodologies and their related problems. *British Accounting Review*, *38*(1), 63–93. https://doi.org/10.1016/j.bar.2005.09.001

Balios, D., Daskalakis, N., Eriotis, N., & Vasiliou, D. (2016). SMEs capital structure determinants during severe economic crisis: The case of Greece. *Cogent Economics and Finance*, *4*(1), 1145535. https://doi.org/10.1080/23322039.2016.1145535

Bank of Greece. (2023). *Travel services*. https://www.bankofgreece.gr/en/statistics/external-sector/balance-of-payments/travel-services

Barboza, F., Basso, L. F. C., & Kimura, H. (2023). New metrics and approaches for predicting bankruptcy. *Communications in Statistics - Simulation and Computation*, *52*(6), 2615–2632. https://doi.org/10.1080/03610918.2021.1910837

Barboza, F., Kimura, H., & Altman, E. I. (2017). Machine learning models and bankruptcy prediction. *Expert Systems with Applications*, *83*, 405–417. https://doi.org/10.1016/j.eswa.2017.04.006

Barnes, P. (1987). The analysis and use of financial ratios: A review article. *Journal of Business Finance and Accounting*, *14*(4), 449–461. https://doi.org/10.1111/j.1468-5957.1987.tb00106.x

Barreda, A. A., Kageyama, Y., Singh, D., & Zubieta, S. (2017). Hospitality bankruptcy in United States of America: A multiple discriminant analysis-logit model comparison. *Journal of Quality Assurance in Hospitality and Tourism*, *18*(1), 86–106. https://doi.org/10.1080/1528008X.2016.1169471

Baum, J. A. C. (1995). The changing basis of competition in organizational populations: The Manhattan hotel industry, 1898-1990. *Social Forces*, *74*(1), 177–204. https://doi.org/10.1093/sf/74.1.177

Baum, J. A. C., & Haveman, H. A. (1997). Love thy neighbor? Differentiation and agglomeration in the Manhattan hotel industry, 1898-1990. *Administrative Science Quarterly*, *42*(2), 304–338. https://doi.org/10.2307/2393922

Baum, J. A. C., & Ingram, P. (1998). Survival-enhancing learning in the Manhattan hotel industry, 1898–1980. *Management Science*, *44*(7), 996–1016. https://doi.org/10.1287/mnsc.44.7.996

Baum, J. A. C., & Lant, T. K. (2003). Hits and misses: Managers' (mis)categorization of competitotrs in the Manhattan hotel industry. In J. A. C. Baum & O. Sorenson (Eds.), *Geography and Strategy (Advances in Strategic Management)* (Vol. 20, pp. 119–156). Emerald Group Publishing Limited. https://doi.org/10.1016/S0742-3322(03)20004-8

Baum, J. A. C., & Mezias, S. J. (1992). Localized competition and organizational failure in the Manhattan hotel industry. *Administrative Science Quarterly*, *37*(4), 580–604. https://doi.org/https://doi.org/10.2307/2393473

Bauweraerts, J. (2016). Predicting bankruptcy in private firms: Towards a stepwise regression procedure. *International Journal of Financial Research*, *7*(2), 147–153. https://doi.org/10.5430/ijfr.v7n2p147

Beade, Á., Rodríguez, M., & Santos, J. (2023). Multiperiod bankruptcy prediction models with interpretable single models. *Computational Economics*. https://doi.org/10.1007/s10614-023-10479-z

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, *4*, 71–111. https://doi.org/https://doi.org/10.2307/2490171

Beaver, W. H. (1968). Market prices, financial ratios, and the prediction of failure. *Journal of Accounting Research*, *6*(2), 179–192. https://doi.org/https://doi.org/10.2307/2490233

Beaver, W. H., Cascino, S., Correia, M., & McNichols, M. F. (2019). Group affiliation and default prediction. *Management Science*, *65*(8), 3559–3584. https://doi.org/10.1287/mnsc.2018.3128

Beaver, W. H., Cascino, S., Correia, M., & McNichols, M. F. (2023). Bankruptcy in groups. *Review of Accounting Studies*, 1–48. https://doi.org/10.1007/s11142-023-09779-4

Beaver, W. H., Correia, M., & McNichols, M. F. (2010). Financial statement analysis and the prediction of financial distress. *Foundations and Trends in Accounting*, *5*(2), 99–173. https://doi.org/10.1561/1400000018

Beaver, W. H., McNichols, M. F., & Rhie, J.-W. (2005). Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy. *Review of Accounting Studies*, *10*(1), 93–122. https://doi.org/https://doi.org/10.1007/s11142-004-6341-9

Beck, N., Katz, J. N., & Tucker, R. (1998). Taking time seriously: Time-series-cross-section analysis with a binary dependent variable. *American Journal of Political Science*, *42*(4), 1260–1288. https://doi.org/10.2307/2991857

Belda, P. R., & Cabrer-Borrás, B. (2020). Size and survival of the hospitality industry: The case of Spain. *Tourism Economics*, *27*(5), 933–951. https://doi.org/10.1177/1354816620909997

Bellovary, J. L., Giacomino, D. E., & Akers, M. D. (2007). A review of bankruptcy prediction studies: 1930 to present. *Journal of Financial Education*, *33*, 1–42. http://www.jstor.org/stable/41948574

Berryman, J. (1983). Small business failure and survey of the literature. *European Small Business Journal*, *1*(4), 47–59. https://doi.org/10.1177/026465608300100404

Boer, A. (1992). The banking sector and small firm failure in the UK hotel and catering industry. *International Journal of Contemporary Hospitality Management*, *4*(2), 13–16. https://doi.org/https://doi.org/10.1108/09596119210010411

Box-Steffensmeier, J. M., & Jones, B. S. (2004). *Event history modeling: A guide for social scientists*. Cambridge University Press. https://doi.org/10.1017/CBO9780511790874

Breslow, N. E. (1996). Statistics in epidemiology: The case-control study. *Journal of the American Statistical Association*, *91*(433), 14–28. https://doi.org/10.1080/01621459.1996.10476660

Brouder, P., & Eriksson, R. H. (2013). Staying power: What influences micro-firm survival in tourism? *Tourism Geographies*, *15*(1), 125–144. https://doi.org/10.1080/14616688.2011.647326

Brown, C. C. (1975). On the use of indicator variables for studying the time-dependence of parameters in a response-time model. *Biometrics*, *31*(4), 863–872. https://doi.org/10.2307/2529811

Buchholst, B. V., & Rangvid, J. (2013). *Leading indicators of distress in Danish banks in the period 2008-12* (85; Danmarks Nationalbank Working Papers). https://www.nationalbanken.dk/en/news-and-knowledge/publications-andspeeches/archive-publications/2013/leading-indicators-of-distress-in-danish-banks-in-the-period-2008-12

Buckley, J., & Westerland, C. (2004). Duration dependence, functional form, and corrected standard errors: Improving EHA models of state policy diffusion. *State Politics and Policy Quarterly*, *4*(1), 94–113. https://doi.org/10.1177/153244000400400105

Butler, R. W. (1980). The concept of a tourist area cycle of evolution: Implications for management and resources. *Canadian Geographer*, *24*(1), 5–12. https://doi.org/https://doi.org/10.1111/j.1541-0064.1980.tb00970.x

Caires, F. B., Reis, H., & Rodrigues, P. M. M. (2023). Survival of the fittest: Tourism exposure and firm survival. *Applied Economics*, *55*(60), 7150–7177. https://doi.org/10.1080/00036846.2023.2208858

Calabrese, R. (2023). Contagion effects of UK small business failures: A spatial hierarchical autoregressive model for binary data. *European Journal of Operational Research*, *305*(2), 989–997. https://doi.org/10.1016/j.ejor.2022.06.027

Cameron, C. A., & Trivedi, P. K. (2009). *Microeconometrics using Stata*. Stata Press.

Cameron, C. A., & Trivedi, P. K. (2022). *Microeconometrics using Stata Volume II: Nonlinear models and causal inference methods* (2nd ed.). Stata Press.

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. *Journal of Finance*, *63*(6), 2899–2939. https://doi.org/10.1111/j.1540-6261.2008.01416.x

Carmona, P., Climent, F., & Momparler, A. (2019). Predicting failure in the U.S. banking sector: An extreme gradient boosting approach. *International Review of Economics and Finance*, *61*, 304–323. https://doi.org/10.1016/j.iref.2018.03.008

Carmona, P., Dwekat, A., & Mardawi, Z. (2022). No more black boxes! Explaining the predictions of a machine learning XGBoost classifier algorithm in business failure.

Research in International Business and Finance, *61*, 101649. https://doi.org/10.1016/j.ribaf.2022.101649

Carter, R., & Van Auken, H. (2006). Small firm bankruptcy. *Journal of Small Business Management*, *44*(4), 493–512. https://doi.org/10.1111/j.1540-627X.2006.00187.x

Cathcart, L., Dufour, A., Rossi, L., & Varotto, S. (2020). The differential impact of leverage on the default risk of small and large firms. *Journal of Corporate Finance*, *60*, 101541. https://doi.org/10.1016/J.JCORPFIN.2019.101541

Caves, R. E. (1998). Industrial organization and new findings on the turnover and mobility of firms. *Journal of Economic Literature*, *36*(4), 1947–1982. https://doi.org/https://www.jstor.org/stable/2565044

Charalambakis, E. C. (2015). On the prediction of corporate financial distress in the light of the financial crisis: Empirical evidence from Greek listed firms. *International Journal of the Economics of Business*, *22*(3), 407–428. https://doi.org/10.1080/13571516.2015.1020131

Charalambakis, E. C., & Garrett, I. (2016). On the prediction of financial distress in developed and emerging markets: Does the choice of accounting and market information matter? A comparison of UK and Indian Firms. *Review of Quantitative Finance and Accounting*, *47*(1), 1–28. https://doi.org/10.1007/s11156-014-0492-y

Charalambakis, E. C., & Garrett, I. (2019). On corporate financial distress prediction: What can we learn from private firms in a developing economy? Evidence from Greece. *Review of Quantitative Finance and Accounting*, *52*(2), 467–491. https://doi.org/10.1007/s11156-018-0716-7

Charalambous, C., Martzoukos, S. H., & Taoushianis, Z. (2020). Predicting corporate bankruptcy using the framework of Leland-Toft: Evidence from U.S. *Quantitative Finance*, *20*(2), 329–346. https://doi.org/10.1080/14697688.2019.1667519

Charalambous, C., Martzoukos, S. H., & Taoushianis, Z. (2022). Estimating corporate bankruptcy forecasting models by maximizing discriminatory power. *Review of Quantitative Finance and Accounting*, *58*(1), 297–328. https://doi.org/10.1007/s11156-021-00995-0

Charalambous, C., Martzoukos, S. H., & Taoushianis, Z. (2023). A neuro-structural framework for bankruptcy prediction. *Quantitative Finance*, *23*(10), 1445–1464. https://doi.org/10.1080/14697688.2023.2230241

Charitou, A., Neophytou, E., & Charalambous, C. (2004). Predicting corporate failure: Empirical evidence for the UK. *European Accounting Review*, *13*(3), 465–497. https://doi.org/10.1080/0963818042000216811

Chathoth, P. K., Tse, E. C. Y., & Olsen, M. D. (2006). Turnaround strategy: A study of restaurant firms. *International Journal of Hospitality Management*, *25*(4), 602–622. https://doi.org/10.1016/j.ijhm.2005.04.010

Chava, S., & Jarrow, R. A. (2004). Bankruptcy prediction with industry effects. *Review of Finance*, *8*, 537–569. https://doi.org/https://doi.org/10.1093/rof/8.4.537

Chen, C. M., & Yeh, C. Y. (2012). The causality examination between demand uncertainty and hotel failure: A case study of international tourist hotels in Taiwan. *International Journal of Hospitality Management*, *31*(4), 1045–1049. https://doi.org/10.1016/j.ijhm.2011.12.011

Chiaramonte, L., & Casu, B. (2017). Capital and liquidity ratios and financial distress. Evidence from the European banking industry. *British Accounting Review*, *49*(2), 138–161. https://doi.org/10.1016/j.bar.2016.04.001

Chiaramonte, L., Liu, F. H., Poli, F., & Zhou, M. (2016). How accurately can Z-score predict bank failure? *Financial Markets, Institutions & Instruments*, *25*(5), 333–360. https://doi.org/10.1111/fmii.12077

Cho, M. H. (1994). *Predicting business failure in the hospitality industry: An application of logit model*. [Doctoral dissertation, Virginia Polytechnic Institute and State University, United States]. https://vtechworks.lib.vt.edu/handle/10919/40201

Choi, H., Son, H., & Kim, C. (2018). Predicting financial distress of contractors in the construction industry using ensemble learning. *Expert Systems with Applications*, *110*, 1–10. https://doi.org/10.1016/J.ESWA.2018.05.026

Choi, S.-J., & Lee, S.-W. (2014). A development of hotel bankruptcy prediction model on artificial neural network. *Journal of the Korea Society of Computer and Information*, *19*(10), 125–133. https://doi.org/10.9708/jksci.2014.19.10.125

Christidis, A. C.-Y., & Gregory, A. (2010). Some new models for financial distress prediction in the UK. *Xfi - Centre for Finance and Investment Discussion Paper No. 10*, 1–46. https://doi.org/https://dx.doi.org/10.2139/ssrn.1687166

Christopoulos, A. G., Dokas, I. G., Kalantonis, P., & Koukkou, T. (2019). Investigation of financial distress with a dynamic logit based on the linkage between liquidity and profitability status of listed firms. *Journal of the Operational Research Society*, *70*(10), 1817–1829. https://doi.org/10.1080/01605682.2018.1460017

Christopoulos, A. G., Mylonakis, J., & Diktapanidis, P. (2011). Could Lehman Brothers' collapse be anticipated? An examination using CAMELS rating system. *International Business Research*, *4*(2), 11–19. https://doi.org/10.5539/ibr.v4n2p11

Chudson, W. A. (1945). A survey of corporate financial structure. In *The Pattern of Corporate Financial Structure: A Cross-Section View of Manufacturing, Mining, Trade, and Construction, 1937* (pp. 1–16). National Bureau of Economic Research. https://www.nber.org/system/files/chapters/c9209/c9209.pdf

Ciampi, F. (2015). Corporate governance characteristics and default prediction modeling for small enterprises. An empirical analysis of Italian firms. *Journal of Business Research*, *68*(5), 1012–1025. https://doi.org/10.1016/j.jbusres.2014.10.003

Ciampi, F., Cillo, V., & Fiano, F. (2020). Combining Kohonen maps and prior payment behavior for small enterprise default prediction. *Small Business Economics*, *54*(4), 1007–1039. https://doi.org/10.1007/s11187-018-0117-2

Ciampi, F., Giannozzi, A., Marzi, G., & Altman, E. I. (2021). Rethinking SME default prediction: a systematic literature review and future perspectives. *Scientometrics*, *126*(3), 2141–2188. https://doi.org/10.1007/s11192-020-03856-0

Cohen, S., Doumpos, M., Neofytou, E., & Zopounidis, C. (2012). Assessing financial distress where bankruptcy is not an option: An alternative approach for local municipalities. *European Journal of Operational Research*, *218*(1), 270–279. https://doi.org/10.1016/j.ejor.2011.10.021

Cole, R. A., & Gunther, J. W. (1995). Separating the likelihood and timing of bank failure. *Journal of Banking and Finance*, *19*, 1073–1089.

Cole, R. A., & Gunther, J. W. (1998). Predicting bank failures: A comparison of on-and off-site monitoring systems. *Journal of Financial Services Research*, *13*, 2–103.

Cole, R. A., Taylor, J., & Wu, Q. (2021). Predicting bank failures using simple static and time-varying models. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1460526

Cole, R. A., & White, L. J. (2012). Déjà vu all over again: The causes of U.S. commercial bank failures this time around. *Journal of Financial Services Research*, *42*(1–2), 5–29. https://doi.org/10.1007/s10693-011-0116-9

Cook, G. A. S., Pandit, N. R., & Milman, D. (2012). A resource-based analysis of bankruptcy law, SMEs and corporate recovery. *International Small Business Journal*, *30*(3), 275–293. https://doi.org/10.1177/0266242611407409

Cornfield, J. (1951). A method of estimating comparative rates from clinical data. Applications to cancer of the lung, breast, and cervix. *JNCI: Journal of the National Cancer Institute*, *11*(6), 1269–1275. https://doi.org/10.1093/jnci/11.6.1269

Correia, C., Costa, R. A., Mota, J., & Breda, Z. (2022). How can insolvency in tourism be predicted? The case of local accommodation. *International Journal of Tourism Cities*, *8*(4), 1127–1140. https://doi.org/10.1108/IJTC-08-2021-0166

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society. Series B (Methodological)*, *34*(2), 187–220. https://doi.org/https://doi.org/10.1111/j.2517-6161.1972.tb00899.x

Cramer, J. S. (1999). Predictive performance of the binary logit model in unbalanced samples. *Journal of the Royal Statistical Society: Series D (The Statistician)*, *48*(1), 85–94. https://doi.org/10.1111/1467-9884.00173

Cramer, J. S. (2004). The early origins of the logit model. *Studies in History and Philosophy of Science Part C: Studies in History and Philosophy of Biological and Biomedical Sciences*, *35*(4), 613–626. https://doi.org/10.1016/j.shpsc.2004.09.003

Crespí-Cladera, R., Martín-Oliver, A., & Pascual-Fuster, B. (2021). Financial distress in the hospitality industry during the Covid-19 disaster. *Tourism Management*, *85*, 104301. https://doi.org/10.1016/j.tourman.2021.104301

Crosato, L., Domenech, J., & Liberati, C. (2023). Websites' data: A new asset for enhancing credit risk modeling. *Annals of Operations Research*, 1–16. https://doi.org/10.1007/s10479-023-05306-5

Crutzen, N., & Van Caillie, D. (2008). The business failure process. An integrative model of the literature. *Review of Business and Economics*, *53*(3), 287–316. https://doi.org/https://hdl.handle.net/2268/6551

Cultrera, L. (2020). Evaluation of bankruptcy prevention tools: Evidences from COSME programme. *Economics Bulletin*, *40*(2), 978–988. http://www.accessecon.com/Pubs/EB/2020/Volume40/EB-20-V40-I2-P83.pdf

Cultrera, L., & Brédart, X. (2016). Bankruptcy prediction: The case of Belgian SMEs. *Review of Accounting and Finance*, *15*(1), 101–119. https://doi.org/10.1108/RAF-06-2014-0059

Cybinski, P. (2001). Description, explanation, prediction – the evolution of bankruptcy studies? *Managerial Finance*, *27*(4), 29–44. https://doi.org/10.1108/03074350110767123

Dalbor, M. C., & Upneja, A. (2004). The investment opportunity set and the long-term debt decision of U.S. lodging firms. *Journal of Hospitality and Tourism Research*, *28*(3), 346–355. https://doi.org/10.1177/1096348004265024

Darrat, A. F., Gray, S., Park, J. C., & Wu, Y. (2016). Corporate governance and bankruptcy risk. *Journal of Accounting, Auditing and Finance*, *31*(2), 163–202. https://doi.org/10.1177/0148558X14560898

Dastile, X., Celik, T., & Potsane, M. (2020). Statistical and machine learning models in credit scoring: A systematic literature survey. *Applied Soft Computing*, *91*, 106263. https://doi.org/10.1016/j.asoc.2020.106263

Davalos, S., Gritta, R. D., & Chow, G. (1999). The application of a neural network approach to predicting bankruptcy risks facing the major US air carriers: 1979-1996. *Journal of Air Transport Management*, *5*, 81–86. https://doi.org/10.1016/S0969-6997(98)00042-8

De Leonardis, D., & Rocci, R. (2008). Assessing the default risk by means of a discrete-time survival analysis approach. *Applied Stochastic Models in Business and Industry*, *24*(4), 291–306. https://doi.org/10.1002/asmb.705

Del Castillo García, A., & Fernández Miguélez, S. M. (2021). Predictive potential of the bankruptcy global models in the tourism industry. *Tourism and Management Studies*, *17*(4), 23–31. https://doi.org/10.18089/tms.2021.170402

Dendramis, Y., Tzavalis, E., & Adraktas, G. (2018). Credit risk modelling under recessionary and financially distressed conditions. *Journal of Banking and Finance*, *91*, 160–175. https://doi.org/10.1016/j.jbankfin.2017.03.020

Devesa, M. J. S., & Esteban, L. P. (2011). Spanish hotel industry: Indebtedness determinants. *Applied Economics*, *43*(28), 4227–4238. https://doi.org/10.1080/00036846.2010.491446

Dewaelheyns, N., Van Hulle, C., Van Landuyt, Y., & Verreydt, M. (2021). Labor contracts, wages and SME failure. *Sustainability*, *13*(14), 7864. https://doi.org/10.3390/su13147864

Diakomihalis, M. (2011, 11-12 July). *Insolvency prediction: Evidence from Greek hotels*. [Conference paper]. 8th ICESAL International Conference on Enterprise Systems, Systems, Accounting and Logistics, Thassos Island, Greece, 377–387. https://www.researchgate.net/profile/Mihail-Diakomihalis/publication/225091140_Insolvency_prediction_Evidence_from_Greek_Hotels/links/0912f4fedb216780d9000000/Insolvency-prediction-Evidence-from-Greek-Hotels.pdf

Diakomihalis, M. (2012). The accuracy of Altman's models in predicting hotel bankruptcy. *International Journal of Accounting and Financial Reporting*, *2*(2), 1–18. https://doi.org/10.2367/xxx.vxix.xxx

Dimitras, A. I., Zanakis, S. H., & Zopounidis, C. (1996). A survey of business failures with an emphasis on prediction methods and industrial applications. *European Journal of Operational Research*, *90*(3), 487–513. https://doi.org/10.1016/0377-2217(95)00070-4

Dimitrić, M., Tomas Žiković, I., & Arbula Bleich, A. (2019). Profitability determinants of hotel companies in selected Mediterranean countries. *Economic Research-Ekonomska Istrazivanja* , *32*(1), 1977–1993. https://doi.org/10.1080/1331677X.2019.1642785

Ding, A. A., Tian, S., Yu, Y., & Guo, H. (2012). A class of discrete transformation survival models with application to default probability prediction. *Journal of the American Statistical Association*, *107*(499), 990–1003. https://doi.org/10.1080/01621459.2012.682806

Dioko, L. (Don) A. N., & Guo, J. (Frank). (2024). Signs of imminent collapse: Can hotel bankruptcy or failure be predicted from guest reviews? *International Journal of Hospitality Management*, *119*, 103711. https://doi.org/10.1016/j.ijhm.2024.103711

Dolnicar, S., & Chapple, A. (2015). The readability of articles in tourism journals. *Annals of Tourism Research*, *52*, 161–166. https://doi.org/10.1016/j.annals.2015.03.003

Dörr, J. O., Licht, G., & Murmann, S. (2022). Small firms and the COVID-19 insolvency gap. *Small Business Economics*, *58*(2), 887–917. https://doi.org/10.1007/s11187-021-00514-4

Du Jardin, P. (2015). Bankruptcy prediction using terminal failure processes. *European Journal of Operational Research*, *242*(1), 286–303. https://doi.org/10.1016/j.ejor.2014.09.059

Dumitrescu, E., Hué, S., Hurlin, C., & Tokpavi, S. (2022). Machine learning for credit scoring: Improving logistic regression with non-linear decision-tree effects. *European Journal of Operational Research*, *297*(3), 1178–1192. https://doi.org/10.1016/j.ejor.2021.06.053

Edmister, R. O. (1972). An empirical test of financial ratio analysis for small business failure prediction. *The Journal of Financial and Quantitative Analysis*, *7*(2), 1477–1493. https://doi.org/10.2307/2329929

El Kalak, I., & Hudson, R. (2016). The effect of size on the failure probabilities of SMEs: An empirical study on the US market using discrete hazard model. *International Review of Financial Analysis*, *43*, 135–145. https://doi.org/10.1016/J.IRFA.2015.11.009

Elsayed, M., & Elshandidy, T. (2020). Do narrative-related disclosures predict corporate failure? Evidence from UK non-financial publicly quoted firms. *International Review of Financial Analysis*, *71*, 101555. https://doi.org/10.1016/j.irfa.2020.101555

Elsayed, M., Elshandidy, T., & Ahmed, Y. (2022). Corporate failure in the UK: An examination of corporate governance reforms. *International Review of Financial Analysis*, *82*, 102165. https://doi.org/10.1016/j.irfa.2022.102165

ELSTAT. (2023, November 3). *Declared business bankruptcies: Year 2022*. ELSTAT. https://www.statistics.gr/en/statistics?p_p_id=documents_WAR_publicationsportlet_INSTANCE_qDQ8fBKKo4lN&p_p_lifecycle=2&p_p_state=normal&p_p_mode=view&p_p

_cacheability=cacheLevelPage&p_p_col_id=column-2&p_p_col_count=4&p_p_col_pos=1&_documents_WAR_publicationsportlet_INSTANCE_qDQ8fBKKo4lN_javax.faces.resource=document&_documents_WAR_publicationsportlet_INSTANCE_qDQ8fBKKo4lN_ln=downloadResources&_documents_WAR_publicationsportlet_INSTANCE_qDQ8fBKKo4lN_documentID=509588&_documents_WAR_publicationsportlet_INSTANCE_qDQ8fBKKo4lN_locale=en

Enumah, S. J., & Chang, D. C. (2021). Predictors of financial distress among private U.S. hospitals. *Journal of Surgical Research*, *267*, 251–259. https://doi.org/10.1016/j.jss.2021.05.025

Escribano-Navas, M., & Gemar, G. (2021). Gender and bankruptcy: A hotel survival econometric analysis. *Sustainability*, *13*(12), 6782. https://doi.org/10.3390/su13126782

Espahbodi, H., & Espahbodi, R. (1984). Predicting failure in the airline industry with financial models. *Transportation Research Part A: General*, *5–6*, 455–4475. https://doi.org/https://doi.org/10.1016/0191-2607(84)90020-7

Everett, J., & Watson, J. (1998). Small business failure and external risk factors. *Small Business Economics*, *11*(4), 371–390. https://doi.org/10.1023/A:1008065527282

Fahrmeir, L., & Wagenpfeil, S. (1996). Smoothing hazard functions and time-varying effects in discrete duration and competing risks models. *Journal of the American Statistical Association*, *91*(436), 1584–1594. https://doi.org/10.1080/01621459.1996.10476726

Falk, M., & Hagsten, E. (2018). Influence of local environment on exit of accommodation establishments. *Tourism Management*, *68*, 401–411. https://doi.org/10.1016/j.tourman.2018.04.002

Farewell, V. T. (1979). Some results on the estimation of logistic models based on retrospective data. *Biometrika*, *66*(1), 27–32. https://doi.org/10.1093/biomet/66.1.27

Fernández, M. Á., Sánchez, J. R. S., Alaminos, D., & Casado, G. (2018). Predicting going concern opinion for hotels industry using classifiers combination. *International Journal of Scientific Management and Tourism*, *4*(1), 91–106.

Fernández-Gámez, M. Á., Cisneros-Ruiz, A. J., & Callejón-Gil, Á. (2016). Applying a probabilistic neural network to hotel bankruptcy prediction. *Tourism and Management Studies*, *12*(1), 40–52. https://doi.org/10.18089/tms.2016.12104

Filipe, S. F., Grammatikos, T., & Michala, D. (2016). Forecasting distress in European SME portfolios. *Journal of Banking and Finance*, *64*, 112–135. https://doi.org/10.1016/j.jbankfin.2015.12.007

Flannery, M. J., & Giacomini, E. (2015). Maintaining adequate bank capital: An empirical analysis of the supervision of European banks. *Journal of Banking and Finance*, *59*, 236–249. https://doi.org/10.1016/j.jbankfin.2015.06.008

Fotopoulos, G., & Louri, H. (2000). Determinants of hazard confronting new entry: Does financial structure matter? *Review of Industrial Organization*, *17*, 285–300.

Froot, K. A. (1989). Consistent covariance matrix estimation with cross-sectional dependence and heteroskedasticity in financial data. *Journal of Financial and Quantitative Analysis*, *24*(3), 333–355. https://doi.org/10.2307/2330815

Gaganis, C., Pasiouras, F., Spathis, C., & Zopounidis, C. (2007). A comparison of nearest neighbours, discriminant and logit models for auditing decisions. *Intelligent Systems in Accounting, Finance and Management*, *15*(1–2), 23–40. https://doi.org/10.1002/ISAF.283

Galil, K., & Gilat, N. (2019). Predicting default more accurately: To proxy or not to proxy for default? *International Review of Finance*, *19*(4), 731–758. https://doi.org/10.1111/irfi.12197

Gallo, P., Timková, V., Šenková, A., & Karahuta, M. (2018). Use of dashboards in predicting the development of the company using neural networks in hotel management. *GeoJournal of Tourism and Geosites*, *22*(2), 307. https://doi.org/10.30892/gtg.22202-289

García, C. J., & Herrero, B. (2021). Female directors, capital structure, and financial distress. *Journal of Business Research*, *136*, 592–601. https://doi.org/10.1016/J.JBUSRES.2021.07.061

Garcia, F. T., Ten Caten, C. S., De Campos, E. A. R., Callegaro, A. M., & De Jesus Pacheco, D. A. (2022). Mortality risk factors in micro and small businesses: Systematic literature review and research agenda. *Sustainability*, *14*(5), 2725. https://doi.org/10.3390/su14052725

Garcia, J. (2022). Bankruptcy prediction using synthetic sampling. *Machine Learning with Applications*, *9*, 100343. https://doi.org/10.1016/j.mlwa.2022.100343

Gémar, G., Moniche, L., & Morales, A. J. (2016). Survival analysis of the Spanish hotel industry. *Tourism Management*, *54*, 428–438. https://doi.org/10.1016/j.tourman.2015.12.012

Gemar, G., Soler, I. P., & Guzman-Parra, V. F. (2019). Predicting bankruptcy in resort hotels: A survival analysis. *International Journal of Contemporary Hospitality Management*, *31*(4), 1546–1566. https://doi.org/10.1108/IJCHM-10-2017-0640

Giannopoulos, G., & Sigbjørnsen, S. (2019). Prediction of bankruptcy using financial ratios in the Greek market. *Theoretical Economics Letters*, *9*(4), 1114–1128. https://doi.org/10.4236/tel.2019.94072

Giannopoulos, V., & Aggelopoulos, E. (2019). Predicting SME loan delinquencies during recession using accounting data and SME characteristics: The case of Greece. *Intelligent Systems in Accounting, Finance and Management*, *26*(2), 71–82. https://doi.org/10.1002/isaf.1456

Görg, H., & Spaliara, M. E. (2014). Financial health, exports and firm survival: Evidence from UK and French firms. *Economica*, *81*(323), 419–444. https://doi.org/10.1111/ecca.12080

Grice, J. S., & Dugan, M. T. (2001). The limitations of bankruptcy prediction models: Some cautions for the researcher. *Review of Quantitative Finance and Accounting*, *17*(2), 151–166. https://doi.org/10.1023/A:1017973604789

Grice, J. S., & Dugan, M. T. (2003). Re-estimations of the Zmijewski and Ohlson bankruptcy prediction models. *Advances in Accounting*, *20*, 77–93. https://doi.org/10.1016/S0882-6110(03)20004-3

Gu, Z., & Gao, L. (2000). A multivariate model for predicting business failures of hospitality firms. *Tourism and Hospitality Research*, *2*(1), 37–49. https://doi.org/10.1177/146735840000200108

Gudmundsson, S. V. (1999). Airline failure and distress prediction: A comparison of quantitative and qualitative models. *Transportation Research Part E: Logistics and Transportation Review*, *35*, 155–182. https://doi.org/10.1016/S1366-5545(99)00004-6

Gupta, J., Barzotto, M., & Khorasgani, A. (2018). Does size matter in predicting SMEs failure? *International Journal of Finance and Economics*, *23*(4), 571–605. https://doi.org/10.1002/ijfe.1638

Gupta, J., & Gregoriou, A. (2018). Impact of market-based finance on SMEs failure. *Economic Modelling*, *69*, 13–25. https://doi.org/10.1016/j.econmod.2017.09.004

Gupta, J., Gregoriou, A., & Ebrahimi, T. (2018). Empirical comparison of hazard models in predicting SMEs failure. *Quantitative Finance*, *18*(3), 437–466. https://doi.org/10.1080/14697688.2017.1307514

Gupta, J., Gregoriou, A., & Healy, J. (2015). Forecasting bankruptcy for SMEs using hazard function: To what extent does size matter? *Review of Quantitative Finance and Accounting*, *45*(4), 845–869. https://doi.org/10.1007/s11156-014-0458-0

Gupta, M. C., & Huefner, R. J. (1972). A cluster analysis study of financial ratios and industry characteristics. *Journal of Accounting Research*, *10*(1), 77. https://doi.org/10.2307/2490219

Habib, A., Costa, M. D', Huang, H. J., Bhuiyan, Md. B. U., & Sun, L. (2020). Determinants and consequences of financial distress: Review of the empirical literature. *Accounting and Finance*, *60*(S1), 1023–1075. https://doi.org/10.1111/acfi.12400

Hambrick, D. C., & D'Aveni, R. A. (1988). Large corporate failures as downward spirals. *Administrative Science Quarterly*, *33*(1), 1–23. https://doi.org/10.2307/2392853

Helmke, G. (2017). Institutions on the edge: The origins and consequences of inter-branch crises in Latin America. Cambridge University Press. https://doi.org/10.1017/9781139031738

Heracleous, L., & Werres, K. (2016). On the road to disaster: Strategic misalignments and corporate failure. *Long Range Planning*, *49*(4), 491–506. https://doi.org/10.1016/j.lrp.2015.08.006

Hernández, Y. G., Galvis, J. F. R., & Capacho, J. W. V. (2021). Business survival, a literary review of internal and external determinants. *Criterio Libre*, *18*(32), 261–279. https://doi.org/10.18041/1900-0642/criteriolibre.2020v18n32.7122

Hillegeist, S. A., Keating, E. K., Cram, D. P., & Lundstedt, K. G. (2004). Assessing the probability of bankruptcy. *Review of Accounting Studies*, *9*, 5–34. https://doi.org/10.1023/B:RAST.0000013627.90884.b7

Ho, C. Y., McCarthy, P., Yang, Y., & Ye, X. (2013). Bankruptcy in the pulp and paper industry: Market's reaction and prediction. *Empirical Economics*, *45*(3), 1205–1232. https://doi.org/10.1007/s00181-012-0661-6

Horrigan, J. O. (1968). A short history of financial ratio analysis. *The Accounting Review*, *43*(2), 284–294. https://doi.org/http://www.jstor.org/stable/243765

Horváthová, J., & Mokrišová, M. (2018). Risk of bankruptcy, its determinants and models. *Risks*, *6*(4), 117. https://doi.org/10.3390/risks6040117

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied Logistic Regression* (3rd ed.). Wiley. https://doi.org/10.1002/9781118548387

Huber, P. J. (1967). The behavior of maximum likelihood estimates under nonstandard conditions. *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*, *5*(1), 221–234. https://projecteuclid.org/ebooks/berkeley-symposium-on-mathematical-statistics-and-probability/Proceedings-of-the-Fifth-Berkeley-Symposium-on-Mathematical-Statistics-and/chapter/The-behavior-of-maximum-likelihood-estimates-under-nonstandard-conditions/bsmsp/1200512988

Ingram, P., & Baum, J. A. C. (1997a). Chain affiliation and the failure of Manhattan hotels, 1898-1980. *Administrative Science Quarterly*, *42*(1), 68–102. https://doi.org/10.2307/2393809

Ingram, P., & Baum, J. A. C. (1997b). Opportunity and constraint: Organizations' learning from the operating and competitive experience of industries. *Strategic Management Journal*, *18*, 75–98. https://doi.org/10.1002/(SICI)1097-0266(199707)18:1

Ingram, P., & Inman, C. (1996). Institutions, intergroup competition, and the evolution of hotel populations around Niagara Falls. *Administrative Science Quarterly*, *41*(4), 629–658. https://doi.org/10.2307/2393870

Izan, H. Y. (1984). Corporate distress in Australia. *Journal of Banking and Finance*, *8*(2), 303–320. https://doi.org/10.1016/0378-4266(84)90010-4

Jackson, R. H. G., & Wood, A. (2013). The performance of insolvency prediction and credit risk models in the UK: A comparative study. *The British Accounting Review*, *45*(3), 183–202. https://doi.org/10.1016/j.bar.2013.06.009

Jaggia, S., & Thosar, S. (2005). Survival analysis with artificially constructed events. *Review of Accounting and Finance*, *4*(4), 34–49. https://doi.org/10.1108/eb043436

Jang, S. C., & Park, K. (2011). Hospitality finance research during recent two decades: Subjects, methodologies, and citations. *International Journal of Contemporary Hospitality Management*, *23*(4), 479–497. https://doi.org/10.1108/09596111111129995

Jayasekera, R. (2018). Prediction of company failure: Past, present and promising directions for the future. *International Review of Financial Analysis*, *55*, 196–208. https://doi.org/10.1016/j.irfa.2017.08.009

Jenkins, S. P. (1995). Easy estimation methods for discrete-time duration models. *Oxford Bulletin of Economics and Statistics*, *57*(1), 129–136. https://doi.org/10.1111/j.1468-0084.1995.tb00031.x

Jenkins, S. P. (2005). *Survival Analysis*. Institute for Social and Economic Research, University of Essex. https://www.iser.essex.ac.uk/wp-content/uploads/files/teaching/stephenj/ec968/pdfs/ec968lnotesv6.pdf

Jia, Z., Shi, Y., Yan, C., & Duygun, M. (2020). Bankruptcy prediction with financial systemic risk. *The European Journal of Finance*, *26*(7–8), 666–690. https://doi.org/10.1080/1351847X.2019.1656095

Jones, S. (2023). A literature survey of corporate failure prediction models. *Journal of Accounting Literature*, *45*(2), 364–405. https://doi.org/10.1108/JAL-08-2022-0086

Jones, S., & Walker, R. G. (2008). Local government distress in Australia: A latent class regression analysis. In *Advances in Credit Risk Modelling and Corporate Bankruptcy Prediction* (pp. 242–268). Cambridge University Press. https://doi.org/10.1017/CBO9780511754197.010

Jones, S., & Wang, T. (2019). Predicting private company failure: A multi-class analysis. *Journal of International Financial Markets, Institutions and Money*, *61*, 161–188. https://doi.org/10.1016/j.intfin.2019.03.004

Kalbfleisch, J. D., & Prentice, R. L. (2002). *The Statistical Analysis of Failure Time Data*. John Wiley & Sons.

Kalnins, A. (2016). Beyond Manhattan: Localized competition and organizational failure in urban hotel markets throughout the United States, 2000–2014. *Strategic Management Journal*, *37*(11), 2235–2253. https://doi.org/10.1002/smj.2578

Kalnins, A., & Chung, W. (2006). Social capital, geography, and survival: Gujarati immigrant entrepreneurs in the U.S. lodging industry. *Management Science*, *52*(2), 233–237. https://doi.org/10.1287/mnsc.1050.0481

Kaniovski, S., Peneder, M., & Smeral, E. (2008). Determinants of firm survival in the Austrian accommodation sector. *Tourism Economics*, *14*(3), 527–543. https://doi.org/https://doi.org/10.5367%2F000000008785633587

Keasey, K., Pindado, J., & Rodrigues, L. (2015). The determinants of the costs of financial distress in SMEs. *International Small Business Journal*, *33*(8), 862–881. https://doi.org/10.1177/0266242614529317

Keasey, K., & Watson, R. (1987). Non-financial symptoms of and the small company failure: A test of the Argenti's hypothesis. *Journal of Business Finance and Accounting*, *14*(3), 335–354. https://doi.org/https://doi.org/10.1111/j.1468-5957.1987.tb00099.x

Keasey, K., & Watson, R. (1991). The state of the art of small firm failure prediction: Achievements and prognosis. *International Small Business Journal*, *9*(4), 11–29. https://doi.org/https://doi.org/10.1177/026624269100900401

Khoja, L., Chipulu, M., & Jayasekera, R. (2019). Analysis of financial distress cross countries: Using macroeconomic, industrial indicators and accounting data. *International Review of Financial Analysis*, *66*, 101379. https://doi.org/10.1016/j.irfa.2019.101379

Kim, H., Cho, H., & Ryu, D. (2020). Corporate default predictions using machine learning: Literature review. *Sustainability*, *12*(16), 6325. https://doi.org/10.3390/su12166325

Kim, H., & Gu, Z. (2006). A logistic regression analysis for predicting bankruptcy in the hospitality industry. *Journal of Hospitality Financial Management*, *14*(1), 17–34. https://doi.org/10.1080/10913211.2006.10653812

Kim, M. H.-Y., Ma, S., & Zhou, Y. A. (2016). Survival prediction of distressed firms: Evidence from the Chinese special treatment firms. *Journal of the Asia Pacific Economy*, *21*(3), 418–443. https://doi.org/10.1080/13547860.2016.1176645

Kim, S. Y. (2011). Prediction of hotel bankruptcy using support vector machine, artificial neural network, logistic regression, and multivariate discriminant analysis. *The Service Industries Journal*, *31*(3), 441–468. https://doi.org/10.1080/02642060802712848

Kim, S. Y. (2018). Predicting hospitality financial distress with ensemble models: The case of US hotels, restaurants, and amusement and recreation. *Service Business*, *12*(3), 483–503. https://doi.org/10.1007/s11628-018-0365-x

King, G., & Zeng, L. (2001a). Explaining rare events in international relations. *International Organization*, *55*(3), 693–715. https://doi.org/10.1162/00208180152507597

King, G., & Zeng, L. (2001b). Logistic regression in rare events data. *Political Analysis*, *9*(2), 137–163. https://doi.org/10.1093/oxfordjournals.pan.a004868

Kirkos, E. (2015). Assessing methodologies for intelligent bankruptcy prediction. *Artificial Intelligence Review*, *43*(1), 83–123. https://doi.org/10.1007/s10462-012-9367-6

Kleinbaum, D. G., & Klein, M. (2012). *Survival analysis* (3rd ed.). Springer. https://doi.org/10.1007/978-1-4419-6646-9

Korol, T. (2020). Long-term risk class migrations of non-bankrupt and bankrupt enterprises. *Journal of Business Economics and Management*, *21*(3), 738–804. https://doi.org/10.3846/jbem.2020.12224

Korol, T., & Spyridou, A. (2020). Examining ownership equity as a psychological factor on tourism business failure forecasting. *Frontiers in Psychology*, *10*(3048). https://doi.org/10.3389/fpsyg.2019.03048

Kristóf, T., & Virág, M. (2020). A comprehensive review of corporate bankruptcy prediction in Hungary. *Journal of Risk and Financial Management*, *13*(2), 35. https://doi.org/10.3390/jrfm13020035

Kücher, A., Mayr, S., Mitter, C., Duller, C., & Feldbauer-Durstmüller, B. (2020). Firm age dynamics and causes of corporate bankruptcy: Age dependent explanations for business failure. *Review of Managerial Science*, *14*(3), 633–661. https://doi.org/10.1007/s11846-018-0303-2

Labrianidis, Z. (2020). *The contribution of tourism to the Greek economy and the need to revisit its strategy. (in Greek)*. https://www.enainstitute.org/wp-content/uploads/2020/07/Tourismos_Updated_08072020.pdf

Lado-Sestayo, R., Vivel-Búa, M., & Otero-González, L. (2016). Survival in the lodging sector: An analysis at the firm and location levels. *International Journal of Hospitality Management*, *59*, 19–30. https://doi.org/10.1016/j.ijhm.2016.08.005

Laguillo, G., Del Castillo, A., Fernández, M. Á., & Becerra, R. (2019). Focused vs unfocused models for bankruptcy prediction: Empirical evidence for Spain. *Contaduría y Administración*, *64*(2), 1–22. https://doi.org/10.22201/fca.24488410e.2018.1488

Laitinen, E. K., & Gin Chong, H. (1999). Early-warning system for crisis in SMEs: Preliminary evidence from Finland and the UK. *Journal of Small Business and Enterprise Development*, *6*(1), 89–102. https://doi.org/10.1108/EUM0000000006665

Lane, W. R., Looney, S. W., & Wansley, J. W. (1986). An application of the Cox proportional hazards model to bank failure. *Journal of Banking and Finance*, *10*(4), 511–531. https://doi.org/10.1016/S0378-4266(86)80003-6

Lau, A. H.-L. (1987). A five-state financial distress prediction model. *Journal of Accounting Research*, *25*(1), 127–138. https://doi.org/10.2307/2491262

LeClere, M. J. (2006). Bankruptcy studies and ad hoc variable selection: A canonical correlation analysis. *Review of Accounting and Finance*, *5*(4), 410–422. https://doi.org/10.1108/14757700610712462

Lee, K. W., & Thong, T. Y. (2023). Board gender diversity, firm performance and corporate financial distress risk: International evidence from tourism industry. *Equality, Diversity and Inclusion*, *42*(4), 530–550. https://doi.org/10.1108/EDI-11-2021-0283

Lensberg, T., Eilifsen, A., & McKee, T. E. (2006). Bankruptcy theory development and classification via genetic programming. *European Journal of Operational Research*, *169*(2), 677–697. https://doi.org/10.1016/j.ejor.2004.06.013

Levratto, N. (2013). From failure to corporate bankruptcy: A review. *Journal of Innovation and Entrepreneurship*, *2*(20), 1–15. https://doi.org/10.1186/2192-5372-2-20

Li, G. (2008). The nature of leisure travel demand. In A. Graham, A. Papatheodorou, & P. Forsyth (Eds.), *Aviation and Tourism: Implications for Leisure Travel* (1st ed., pp. 7–20). Ashgate Publishing Limited.

Li, H., & Huang, H.-B. (2012). Identifying Chinese hospitality firm failures and differences from results on developed countries: Significant variables and predictive models. *2012 Fifth International Conference on Business Intelligence and Financial Engineering*, 297–302. https://doi.org/10.1109/BIFE.2012.69

Li, H., Li, J., Chang, P. C., & Sun, J. (2013). Parametric prediction on default risk of Chinese listed tourism companies by using random oversampling, isomap, and locally linear embeddings on imbalanced samples. *International Journal of Hospitality Management*, *35*, 141–151. https://doi.org/10.1016/j.ijhm.2013.06.006

Li, H., & Sun, J. (2012). Forecasting business failure: The use of nearest-neighbour support vectors and correcting imbalanced samples – Evidence from the Chinese hotel industry. *Tourism Management*, *33*(3), 622–634. https://doi.org/10.1016/j.tourman.2011.07.004

Li, H., & Sun, J. (2013). Predicting business failure using an RSF-based case-based reasoning ensemble forecasting method. *Journal of Forecasting*, *32*(2), 180–192. https://doi.org/10.1002/for.1265

Li, H., Xu, Y. H., Li, X. (Robert), & Xu, H. (2019). Failure analysis of corporations with multiple hospitality businesses. *Tourism Management*, *73*, 21–34. https://doi.org/10.1016/j.tourman.2019.01.018

Li, H., Xu, Y. H., & Yu, L. (2017). Predicting hospitality firm failure: Mixed sample modelling. *International Journal of Contemporary Hospitality Management*, *29*(7), 1770–1792. https://doi.org/10.1108/IJCHM-03-2015-0092

Li, L., & Faff, R. (2019). Predicting corporate bankruptcy: What matters? *International Review of Economics and Finance*, *62*, 1–19. https://doi.org/10.1016/j.iref.2019.02.016

Li, S., & Wang, S. (2014). A financial early warning logit model and its efficiency verification approach. *Knowledge-Based Systems*, *70*, 78–87. https://doi.org/10.1016/j.knosys.2014.03.017

Li, Z., Crook, J., Andreeva, G., & Tang, Y. (2021). Predicting the risk of financial distress using corporate governance measures. *Pacific Basin Finance Journal*, *68*, 1–12. https://doi.org/10.1016/j.pacfin.2020.101334

Liang, K. Y., & Zeger, S. L. (1986). Longitudinal data analysis using generalized linear models. *Biometrika*, *73*(1), 13–22. https://doi.org/10.1093/BIOMET/73.1.13

Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gøtzsche, P. C., Ioannidis, J. P. A., Clarke, M., Devereaux, P. J., Kleijnen, J., & Moher, D. (2009). The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration. *Journal of Clinical Epidemiology*, *62*(10), e1–e34. https://doi.org/10.1016/j.jclinepi.2009.06.006

Lin, S. C., & Kim, Y. R. (2020). Diversification strategies and failure rates in the Texas lodging industry: Franchised versus company-operated hotels. *International Journal of Hospitality Management*, *88*, 102525. https://doi.org/10.1016/j.ijhm.2020.102525

Löffler, G., & Maurer, A. (2011). Incorporating the dynamics of leverage into default prediction. *Journal of Banking and Finance*, *35*(12), 3351–3361. https://doi.org/10.1016/j.jbankfin.2011.05.015

Long, J. S., Allison, P. D., & McGinnis, R. (1993). Rank advancement in academic careers: Sex differences and the effects of productivity. *American Sociological Review*, *58*(5), 703–722. https://doi.org/10.2307/2096282

LoPucki, L. M., & Doherty, J. W. (2015). Bankruptcy survival. *UCLA Law Review*, *62*(4), 970–1015. https://escholarship.org/uc/item/7841v7jw

Lowe, A. (1988). Small hotel survival—an inductive approach. *International Journal of Hospitality Management*, *7*(3), 197–223. https://doi.org/10.1016/0278-4319(88)90021-7

Lukason, O., & Andresson, A. (2019). Tax arrears versus financial ratios in bankruptcy prediction. *Journal of Risk and Financial Management*, *12*(4), 187. https://doi.org/10.3390/jrfm12040187

Luoma, M., & Laitinen, E. K. (1991). Survival analysis as a tool for company failure prediction. *Omega*, *19*(6), 673–678. https://doi.org/10.1016/0305-0483(91)90015-L

Luypaert, M., Van Caneghem, T., & Van Uytbergen, S. (2016). Financial statement filing lags: An empirical analysis among small firms. *International Small Business Journal*, *34*(4), 506–531. https://doi.org/10.1177/0266242615569324

Maddala, G. S. (1983). *Limited-dependent and qualitative variables in econometrics*. Cambridge University Press. https://doi.org/10.1017/CBO9780511810176

Maddala, G. S. (2001). *Introduction to econometrics* (3rd ed.). Wiley.

Madrid-Guijarro, A., García-Pérez-de-Lema, D., & Van Auken, H. (2011). An analysis of non-financial factors associated with financial distress. *Entrepreneurship & Regional Development*, *23*(3–4), 159–186. https://doi.org/10.1080/08985620903233911

Männasoo, K., & Mayes, D. G. (2009). Explaining bank distress in Eastern European transition economies. *Journal of Banking and Finance*, *33*(2), 244–253. https://doi.org/10.1016/j.jbankfin.2008.07.016

Martin, D. (1977). Early warning of bank failure. *Journal of Banking and Finance*, *1*(3), 249–276. https://doi.org/10.1016/0378-4266(77)90022-X

Mason, R. J., & Harris, F. C. (1979). Predicting company failure in the construction industry. *Proceedings of the Institution of Civil Engineers Part 1*, *66*, 301–307.

Matejić, T., Knežević, S., Arsić, V. B., Obradović, T., Milojević, S., Adamović, M., Mitrović, A., Milašinović, M., Simonović, D., Milošević, G., & Špiler, M. (2022). Assessing the impact of the COVID-19 crisis on hotel industry bankruptcy risk through novel forecasting models. *Sustainability*, *14*(8), 4680. https://doi.org/10.3390/su14084680

Matenda, F. R., Sibanda, M., Chikodza, E., & Gumbo, V. (2021). Bankruptcy prediction for private firms in developing economies: A scoping review and guidance for future research. *Management Review Quarterly*, 1–40. https://doi.org/10.1007/s11301-021-00216-x

Maté-Sánchez-Val, M. (2021). The complementary and substitutive impact of Airbnb on the bankruptcy of traditional hotels in the city of Barcelona. *Journal of Hospitality and Tourism Research*, *45*(4), 610–628. https://doi.org/10.1177/1096348020950810

Maté-Sánchez-Val, M., López-Hernandez, F., & Rodriguez Fuentes, C. C. (2018). Geographical factors and business failure: An empirical study from the Madrid metropolitan area. *Economic Modelling*, *74*, 275–283. https://doi.org/10.1016/j.econmod.2018.05.022

Mayew, W. J., Sethuraman, M., & Venkatachalam, M. (2015). MD&A disclosure and the firm's ability to continue as a going concern. *The Accounting Review*, *90*(4), 1621–1651. https://doi.org/10.2308/accr-50983

McGurr, P. T., & DeVaney, S. A. (1998). Predicting business failure of retail firms: An analysis using mixed industry models. *Journal of Business Research*, *43*, 169–176. https://doi.org/https://doi.org/10.1016/S0148-2963(97)00222-1

Mellahi, K., & Wilkinson, A. (2004). Organizational failure: a critique of recent research and a proposed integrative framework. *International Journal of Management Reviews*, *5–6*(1), 21–41. https://doi.org/10.1111/j.1460-8545.2004.00095.x

Metaxas, T., & Romanopoulos, A. (2023). A literature review on the financial determinants of hotel default. *Journal of Risk and Financial Management*, *16*(7), 323. https://doi.org/10.3390/jrfm16070323

Milašinović, M., Knežević, S., & Mitrović, A. (2019). Bankruptcy forecasting of hotel companies in the Republic of Serbia using Altman's Z-score model. *Hotel and Tourism Management*, *7*(2), 87–95. https://doi.org/10.5937/menhottur1902087M

Mills, M. (2011). *Introducing survival and event history analysis*. SAGE. https://doi.org/10.4135/9781446268360

Min, H., Min, H., Joo, S. J., & Kim, J. (2009). Evaluating the financial performances of Korean luxury hotels using data envelopment analysis. *The Service Industries Journal*, *29*(6), 835–845. https://doi.org/10.1080/02642060902749393

Misund, B. (2017). Financial ratios and prediction on corporate bankruptcy in the Atlantic salmon industry. *Aquaculture Economics and Management*, *21*(2), 241–260. https://doi.org/10.1080/13657305.2016.1180646

Moncarz, E. S., & Kron, R. N. (1993). Operational analysis: A case study of two hotels in financial distress. *International Journal of Hospitality Management*, *12*(2), 175–196. https://doi.org/10.1016/0278-4319(93)90009-X

Mousavi, M. M., & Ouenniche, J. (2018). Multi-criteria ranking of corporate distress prediction models: empirical evaluation and methodological contributions. *Annals of Operations Research*, *271*(2), 853–886. https://doi.org/10.1007/s10479-018-2814-2

Mselmi, N., Lahiani, A., & Hamza, T. (2017). Financial distress prediction: The case of French small and medium-sized firms. *International Review of Financial Analysis*, *50*, 67–80. https://doi.org/10.1016/J.IRFA.2017.02.004

Nacev2.com. (n.d.). *Complete list of all NACE Code*. Retrieved November 20, 2023, from https://nacev2.com/en

Nagendrakumar, N., Madhavika, W., Weerawardhana, K., Vishwadeepa, D., Anushani, D., & Alahakoon, A. (2020). Sustainability of hotels: Evidence from tourism industry in Sri Lanka. *TEST Engineering and Management*, *83*, 15559–15561. http://www.testmagzine.biz/index.php/testmagzine/article/view/9921

Nguyen, H., & Zhou, X. (2023). Reduced-form models of correlated default timing: A systematic literature review. *Journal of Accounting Literature*, *45*(1), 190–205. https://doi.org/10.1108/JAL-08-2022-0091

Niklis, D., Doumpos, M., & Zopounidis, C. (2014). Combining market and accounting-based models for credit scoring using a classification scheme based on support vector machines. *Applied Mathematics and Computation*, *234*, 69–81. https://doi.org/10.1016/j.amc.2014.02.028

Oberhofer, H., Philippovich, T., & Winner, H. (2015). Firm survival in professional sports: Evidence from the German Football League. *Journal of Sports Economics*, *16*(1), 59–85. https://doi.org/10.1177/1527002512462582

Odom, M. D., & Sharda, R. (1990, 17-21 June). *A neural network model for bankruptcy prediction.* [Conference paper]. 1990 IJCNN International Joint Conference on Neural Networks, *2*, 163–168. https://doi.org/10.1109/IJCNN.1990.137710

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, *18*(1), 109. https://doi.org/10.2307/2490395

Olson, D. L., Delen, D., & Meng, Y. (2012). Comparative analysis of data mining methods for bankruptcy prediction. *Decision Support Systems*, *52*(2), 464–473. https://doi.org/10.1016/j.dss.2011.10.007

Oommen, T., Baise, L. G., & Vogel, R. M. (2011). Sampling bias and class imbalance in maximum-likelihood logistic regression. *Mathematical Geosciences*, *43*(1), 99–120. https://doi.org/10.1007/s11004-010-9311-8

Pacheco, L. (2015). SMEs probability of default: The case of the hospitality sector. *Tourism and Management Studies*, *11*(1), 153–159. https://www.tmstudies.net/index.php/ectms/article/view/770/1300

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *International Journal of Surgery*, *88*, 105906. https://doi.org/10.1016/j.ijsu.2021.105906

Palepu, K. G. (1986). Predicting takeover targets. *Journal of Accounting and Economics*, *8*(1), 3–35. https://doi.org/10.1016/0165-4101(86)90008-X

Papana, A., & Spyridou, A. (2020). Bankruptcy prediction: The case of the Greek market. *Forecasting*, *2*(4), 505–525. https://doi.org/10.3390/forecast2040027

Papoulias, C., & Theodossiou, P. (1992). Analysis and modeling of recent business failures in Greece. *Managerial and Decision Economics*, *13*(2), 163–169. https://doi.org/10.1002/mde.4090130208

Park, S. S., & Hancer, M. (2012). A comparative study of logit and artificial neural networks in predicting bankruptcy in the hospitality industry. *Tourism Economics*, *18*(2), 311–338. https://doi.org/10.5367/te.2012.0113

Pelaez-Verdet, A., & Loscertales-Sanchez, P. (2021). Key ratios for long-term prediction of hotel financial distress and corporate default: Survival analysis for an economic stagnation. *Sustainability*, *13*(3), 1473. https://doi.org/10.3390/su13031473

Pereira, J. (2014). Survival analysis employed in predicting corporate failure: A forecasting model proposal. *International Business Research*, *7*(5), 9–20. https://doi.org/10.5539/ibr.v7n5p9

Pereira, J. M., Basto, M., & Da Silva, A. C. F. (2016). The logistic lasso and ridge regression in predicting corporate failure. *Procedia Economics and Finance*, *39*, 634–641. https://doi.org/10.1016/S2212-5671(16)30310-0

Pereira, J. M., Basto, M., & Da Silva, A. C. F. (2017). Comparing logit model with discriminant analysis for predicting bankruptcy in Portuguese hospitality sector. *European Journal of Tourism Research*, *16*, 276–280. https://doi.org/10.54055/ejtr.v16i.289

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, *22*(1), 435–480. https://doi.org/10.1093/rfs/hhn053

Piacentino, D., Aronica, M., Giuliani, D., Mazzitelli, A., & Cracolici, M. F. (2021). The effect of agglomeration economies and geography on the survival of accommodation businesses in Sicily. *Spatial Economic Analysis*, *16*(2), 176–193. https://doi.org/10.1080/17421772.2020.1836389

Pierri, F., & Caroni, C. (2017). Bankruptcy prediction by survival models based on current and lagged values of time-varying financial data. *Communications in Statistics Case Studies, Data Analysis and Applications*, *3*(3–4), 62–70. https://doi.org/10.1080/23737484.2018.1431816

Pierri, F., Stanghellini, E., & Bistoni, N. (2016). Risk analysis and retrospective unbalanced data. *REVSTAT-Statistical Journal*, *14*(2), 157–169. https://doi.org/https://doi.org/10.57805/revstat.v14i2.184

Pindado, J., Rodrigues, L., & De La Torre, C. (2008). Estimating financial distress likelihood. *Journal of Business Research*, *61*(9), 995–1003. https://doi.org/10.1016/j.jbusres.2007.10.006

Pisula, T. (2020). An ensemble classifier-based scoring model for predicting bankruptcy of Polish companies in the Podkarpackie Voivodeship. *Journal of Risk and Financial Management*, *13*(2), 37. https://doi.org/10.3390/jrfm13020037

Platt, H. D., & Platt, M. B. (1990). Development of a class of stable predictive variables: The case of bankruptcy prediction. *Journal of Business Finance and Accounting*, *17*(1), 31–51. https://doi.org/10.1111/j.1468-5957.1990.tb00548.x

Platt, H. D., & Platt, M. B. (2002). Predicting corporate financial distress: Reflections on choice-based sample bias. *Journal of Economics and Finance*, *26*(2), 184–199. https://doi.org/10.1007/BF02755985

Platt, H. D., & Platt, M. B. (2008). Financial distress comparison across three global regions. *Journal of Risk and Financial Management*, *1*(1), 129–162. https://doi.org/10.3390/jrfm1010129

Polyzos, S., & Saratsis, Y. (2013). Analyzing the evolution of tourism in Magnesia under the prism of the Tourism Area Life Cycle Theory. *Tourism Today*, 94–113. https://www.cothm.ac.cy/_files/ugd/79301e_6c84d22de9744bd08c8d917de358d8f1.pdf

Prentice, R. L., & Gloeckler, L. A. (1978). Regression analysis of grouped survival data with application to breast cancer data. *Biometrics*, *34*(1), 57–67. https://doi.org/10.2307/2529588

Prentice, R. L., & Pyke, R. (1979). Logistic disease incidence models and case-control studies. *Biometrika*, *66*(3), 403–411. https://doi.org/https://doi.org/10.2307/2335158

Pretorius, M. (2008). Critical variables of business failure: A review and classification framework. *South African Journal of Economic and Management Sciences*, *11*(4), 408–430. https://hdl.handle.net/10520/EJC31265

Pretorius, M. (2009). Defining business decline, failure and turnaround: A content analysis. *The Southern African Journal of Entrepreneurship and Small Business Management*, *2*(1), 1–16. https://doi.org/10.4102/sajesbm.v2i1.15

Prusak, B. (2018). Review of research into enterprise bankruptcy prediction in selected Central and Eastern European countries. *International Journal of Financial Studies*, *6(3)*(60), 1–28. https://doi.org/10.3390/IJFS6030060

Pyke, S. W., & Sheridan, P. M. (1993). Logistic regression analysis of graduate student retention. *Canadian Journal of Higher Education*, *23*(2), 44–64. https://doi.org/10.47678/cjhe.v23i2.183161

Qiu, W., Rudkin, S., & Dłotko, P. (2020). Refining understanding of corporate failure through a topological data analysis mapping of Altman's Z-score model. *Expert Systems with Applications*, *156*. https://doi.org/10.1016/j.eswa.2020.113475

Rabe-Hesketh, S., & Skrondal, A. (2022). *Multilevel and longitudinal modeling using Stata Volume II: Categorical responses, counts, and survival* (4th ed.). Stata Press.

Ravi Kumar, P., & Ravi, V. (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques – A review. *European Journal of Operational Research*, *180*(1), 1–28. https://doi.org/10.1016/j.ejor.2006.08.043

Rikkers, F., & Thibeault, A. E. (2011). Default prediction of small and medium-sized enterprises with industry effects. *International Journal of Banking, Accounting and Finance*, *3*(2/3), 207–231. https://doi.org/10.1504/IJBAAF.2011.041455

Rogers, W. (1993). Regression standard errors in clustered samples. *Stata Technical Bulletin*, *3*(13), 19–23. https://www.stata.com/products/stb/journals/stb13.html

Romanopoulos, A., & Metaxas, T. (2023, 28 August - 1 September). *Financial determinants of hotel bankruptcy in Greece.* [Conference paper]. 62nd ERSA European Regional Science Association Congress: Urban Challenges and Sustainable Technological Revolution, Alicante, Spain. https://ersa.eventsair.com/QuickEventWebsitePortal/ersa2023/ersa23/Agenda/AgendaItemDetail?id=6288dc28-6d3d-0264-dbc9-3a06d85ab792

Ropega, J. (2011). The reasons and symptoms of failure in SME. *International Advances in Economic Research*, *17*, 476–483. https://doi.org/10.1007/s11294-011-9316-1

Salas-Eljatib, C., Fuentes-Ramirez, A., Gregoire, T. G., Altamirano, A., & Yaitul, V. (2018). A study on the effects of unbalanced data when fitting logistic regression models in ecology. *Ecological Indicators*, *85*, 502–508. https://doi.org/10.1016/j.ecolind.2017.10.030

Sandin, A. R., & Porporato, M. (2008). Corporate bankruptcy prediction models applied to emerging economies. *International Journal of Commerce and Management*, *17*(4), 295–311. https://doi.org/10.1108/10569210710844372

Santarelli, E. (1998). Start-up size and post-entry performance: The case of tourism services in Italy. *Applied Economics*, *30*(2), 157–163. https://doi.org/10.1080/000368498325967

Saridakis, G., Mole, K., & Storey, D. J. (2008). New small firm survival in England. *Empirica*, *35*(1), 25–39. https://doi.org/10.1007/s10663-007-9049-9

Sayari, N., & Mugan, C. S. (2017). Industry specific financial distress modeling. *BRQ Business Research Quarterly*, *20*(1), 45–62. https://doi.org/10.1016/j.brq.2016.03.003

Sensini, L. (2016). An empirical analysis of financially distressed Italian companies. *International Business Research*, *9*(10), 75–85. https://doi.org/10.5539/ibr.v9n10p75

Serrano-Cinca, C., Gutiérrez-Nieto, B., & Bernate-Valbuena, M. (2019). The use of accounting anomalies indicators to predict business failure. *European Management Journal*, *37*(3), 353–375. https://doi.org/10.1016/j.emj.2018.10.006

Sherif, R., & Littlejohn, D. (2006). The accommodation subsector. In J. Beech & S. Chadwick (Eds.), *The Business of Tourism Management* (1st ed., pp. 377–398). Pearson Education Limited.

Shi, Y., & Li, X. (2019). An overview of bankruptcy prediction models for corporate firms: A systematic literature review. *Intangible Capital*, *15*(2), 114–127. https://doi.org/10.3926/ic.1354

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business*, *74*(1), 101–124. https://doi.org/10.1086/209665

Sigrist, F., & Hirnschall, C. (2019). Grabit: Gradient tree-boosted Tobit models for default prediction. *Journal of Banking and Finance*, *102*, 177–192. https://doi.org/10.1016/j.jbankfin.2019.03.004

Singal, M. (2015). How is the hospitality and tourism industry different? An empirical test of some structural characteristics. *International Journal of Hospitality Management*, *47*, 116–119. https://doi.org/10.1016/j.ijhm.2015.03.006

Singer, J. D., & Willett, J. B. (1993). It's about time: Using discrete-time survival analysis to study duration and the timing of events. *Journal of Educational Statistics*, *18*(2), 155–195. https://doi.org/10.3102/10769986018002155

Singh, A. J., & Schmidgall, R. S. (2001). Use of ratios by financial executives in the U.S. lodging industry. *The Journal of Hospitality Financial Management*, *9*(1), 27–44. https://doi.org/10.1080/10913211.2001.10653745

Singh, A. J., & Schmidgall, R. S. (2002). Analysis of financial ratios commonly used by US lodging financial executives. *Journal of Retail and Leisure Property*, *2*(3), 201–213. https://doi.org/10.1057/palgrave.rlp.5090210

Situm, M. (2015). Analysis of correlational behavior of solvent and insolvent firms based on accounting ratios. *Journal of Modern Accounting and Auditing*, *11*(5), 233–259. https://doi.org/10.17265/1548-6583/2015.05.001

Situm, M. (2023). Financial distress in the Austrian tourism industry: Hotels and restaurants analysis. *European Journal of Tourism Research*, *34*, 3411. https://doi.org/10.54055/ejtr.v34i.2992

Smith, M., & Liou, D. (2007). Industrial sector and financial distress. *Managerial Auditing Journal*, *22*(4), 376–391. https://doi.org/10.1108/02686900710741937

Solnet, D. J., Paulsen, N., & Cooper, C. (2010). Decline and turnaround: A literature review and proposed research agenda for the hotel sector. *Current Issues in Tourism*, *13*(2), 139–159. https://doi.org/10.1080/13683500802638219

Song, H., Qiu, R. T. R., & Park, J. (2019). A review of research on tourism demand forecasting: Launching the Annals of Tourism Research Curated Collection on tourism demand forecasting. *Annals of Tourism Research*, *75*, 338–362. https://doi.org/10.1016/j.annals.2018.12.001

Špiler, M., Matejić, T., Knežević, S., Milašinović, M., Mitrović, A., Arsić, V. B., Obradović, T., Simonović, D., Despotović, V., Milojević, S., Adamović, M., Resimić, M., & Milošević, P. (2022). Assessment of the bankruptcy risk in the hotel industry as a condition of the COVID-19 crisis using time-delay neural networks. *Sustainability*, *15*(1), 272. https://doi.org/10.3390/su15010272

Spyridou, A. (2019). Evaluating factors of small and medium hospitality enterprises business failure: a conceptual approach. *Tourismos: An International Multidisciplinary Journal of Tourism*, *14*(1), 25–36.

Srhoj, S., Vitezić, V., Giannozzi, A., & Mikulić, J. (2024). Tourism SME default: A note on predictors. *Tourism Management*, *103*, 104910. https://doi.org/10.1016/j.tourman.2024.104910

Stata.com. (2024). *vce option — Variance estimators*. Stata.Com. https://www.stata.com/manuals13/rvce_option.pdf

Statista. (2023). *Travel and tourism GDP share by country EU 2022*. https://www.statista.com/statistics/1228395/travel-and-tourism-share-of-gdp-in-the-eu-by-country/

Stogiannis, D., & Caroni, C. (2013). Issues in fitting inverse Gaussian first hitting time regression models for lifetime data. *Communications in Statistics: Simulation and Computation*, *42*(9), 1948–1960. https://doi.org/10.1080/03610918.2012.687061

Stokes, D., & Blackburn, R. (2002). Learning the hard way: The lessons of owner-managers who have closed their businesses. *Journal of Small Business and Enterprise Development*, *9*(1), 17–27. https://doi.org/10.1108/14626000210419455

Sun, J., Li, H., Huang, Q.-H., & He, K.-Y. (2014). Predicting financial distress and corporate failure: A review from the state-of-the-art definitions, modeling, sampling, and featuring approaches. *Knowledge-Based Systems*, *57*, 41–56. https://doi.org/10.1016/j.knosys.2013.12.006

Suresh, K., Severn, C., & Ghosh, D. (2022). Survival prediction models: an introduction to discrete-time modeling. *BMC Medical Research Methodology*, *22*(207). https://doi.org/10.1186/s12874-022-01679-6

Süsi, V., & Lukason, O. (2019). Corporate governance and failure risk: Evidence from Estonian SME population. *Management Research Review*, *42*(6), 703–720. https://doi.org/10.1108/MRR-03-2018-0105

Tavlin, E. M., Moncarz, E. S., & Dumont, D. (1989). Financial failure in the hospitality industry. *Hospitality Review*, *7*(1), 55–77. https://digitalcommons.fiu.edu/hospitalityreviewAvailableat:https://digitalcommons.fiu.edu/hospitalityreview/vol7/iss1/7

Thammasiri, D., Delen, D., Meesad, P., & Kasap, N. (2014). A critical assessment of imbalanced class distribution problem: The case of predicting freshmen student attrition. *Expert Systems with Applications*, *41*(2), 321–330. https://doi.org/10.1016/j.eswa.2013.07.046

Theodossiou, P. (1991). Alternative models for assessing the financial condition of business in Greece. *Journal of Business Finance and Accounting*, *18*(5), 697–720. https://doi.org/10.1111/j.1468-5957.1991.tb00233.x

Thomas, R., Shaw, G., & Page, S. J. (2011). Understanding small firms in tourism: A perspective on research trends and challenges. *Tourism Management*, *32*(5), 963–976. https://doi.org/10.1016/j.tourman.2011.02.003

Tian, S., & Yu, Y. (2017). Financial ratios and bankruptcy predictions: An international evidence. *International Review of Economics and Finance*, *51*, 510–526. https://doi.org/10.1016/j.iref.2017.07.025

Tian, S., Yu, Y., & Guo, H. (2015). Variable selection and corporate bankruptcy forecasts. *Journal of Banking and Finance*, *52*, 89–100. https://doi.org/10.1016/j.jbankfin.2014.12.003

Tinoco, H. M., Holmes, P., & Wilson, N. (2018). Polytomous response financial distress models: The role of accounting, market and macroeconomic variables. *International Review of Financial Analysis*, *59*, 276–289. https://doi.org/10.1016/j.irfa.2018.03.017

Tinoco, H. M., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. *International Review of Financial Analysis*, *30*, 394–419. https://doi.org/10.1016/J.IRFA.2013.02.013

Tomas Žiković, I. (2018). Challenges in predicting financial distress in emerging economies: The case of Croatia. *Eastern European Economics*, *56*(1), 1–27. https://doi.org/10.1080/00128775.2017.1387059

Tomz, M., King, G., & Zeng, L. (1999). *RELOGIT: Rare events logistic regression, Version 1.1* (1.1). MA: Harvard University. https://gking.harvard.edu/relogit

Tomz, M., King, G., & Zeng, L. (2003). ReLogit: Rare events logistic regression. *Journal of Statistical Software*, *8*(2), 1–27. https://doi.org/10.18637/jss.v008.i02

Topaloğlu, Z. (2012). A multi-period logistic model of bankruptcies in the manufacturing industry. *International Journal of Finance and Accounting*, *1*(3), 28–37. https://doi.org/10.5923/j.ijfa.20120103.02

Torraco, R. J. (2005). Writing integrative literature reviews: Guidelines and examples. *Human Resource Development Review*, *4*(3), 356–367. https://doi.org/10.1177/1534484305278283

Toudas, K., Archontakis, S., & Boufounou, P. (2024). Corporate bankruptcy prediction models: A comparative study for the construction sector in Greece. *Computation*, *12*(1), 9. https://doi.org/10.3390/computation12010009

Tran, T., Nguyen, N. H., Le, B. T., Thanh Vu, N., & Vo, D. H. (2023). Examining financial distress of the Vietnamese listed firms using accounting-based models. *PLOS ONE*, *18*(5), e0284451. https://doi.org/10.1371/journal.pone.0284451

Tribe, J. (2006). The economic impact of tourism. In J. Beech & S. Chadwick (Eds.), *The Business of Tourism Management* (1st ed., pp. 323–338). Pearson Education Limited.

Tsai, H., Pan, S., & Lee, J. (2011). Recent research in hospitality financial management. *International Journal of Contemporary Hospitality Management*, *23*(7), 941–971. https://doi.org/10.1108/09596111111167542

Tseng, F. M., & Hu, Y. C. (2010). Comparing four bankruptcy prediction models: Logit, quadratic interval logit, neural and fuzzy neural networks. *Expert Systems with Applications*, *37*(3), 1846–1853. https://doi.org/10.1016/j.eswa.2009.07.081

Tsiapa, M. (2022). Performance of large firms in Greece during the unstable period of 2011–2016: Lessons from the weak parts of Europe. *European Journal of Management and Business Economics*, *31*(1), 94–114. https://doi.org/10.1108/EJMBE-06-2019-0109

Tsoukas, S. (2011). Firm survival and financial development: Evidence from a panel of emerging Asian economies. *Journal of Banking and Finance*, *35*(7), 1736–1752. https://doi.org/10.1016/j.jbankfin.2010.12.008

Türkcan, K., & Erkuş-Öztürk, H. (2020). The impact of economic and political crises on the survival of tourism-related firms: Evidence from Antalya. *Tourism Economics*, *26*(7), 1152–1174. https://doi.org/10.1177/1354816619868614

Tutz, G., & Schmid, M. (2016). *Modeling discrete time-to-event data*. Springer International Publishing. https://doi.org/10.1007/978-3-319-28158-2

Urtasun, A., & Gutiérrez, I. (2006). Hotel location in tourism cities: Madrid 1936-1998. *Annals of Tourism Research*, *33*(2), 382–402. https://doi.org/10.1016/J.ANNALS.2005.12.008

Varetto, F. (1998). Genetic algorithms applications in the analysis of insolvency risk. *Journal of Banking and Finance*, *22*(10–11), 1421–1439. https://doi.org/10.1016/S0378-4266(98)00059-4

Veganzones, D., & Severin, E. (2021). Corporate failure prediction models in the twenty-first century: A review. *European Business Review*, *33*(2), 204–226. https://doi.org/10.1108/EBR-12-2018-0209

Vivel-Búa, M., & Lado-Sestayo, R. (2023). Contagion effect on business failure: A spatial analysis of the hotel sector. *Journal of Hospitality and Tourism Research*, *47*(3), 482–502. https://doi.org/10.1177/10963480211023804

Vivel-Búa, M., Lado-Sestayo, R., & Otero-González, L. (2016). Impact of location on the probability of default in the Spanish lodging industry: A study of MSMEs. *Tourism Economics*, *22*(3), 593–607. https://doi.org/10.5367/te.2015.0461

Vivel-Búa, M., Lado-Sestayo, R., & Otero-González, L. (2018). Risk determinants in the hotel sector: Risk credit in MSMEs. *International Journal of Hospitality Management*, *70*, 110–119. https://doi.org/10.1016/j.ijhm.2017.11.004

Vivel-Búa, M., Lado-Sestayo, R., & Otero-González, L. (2019). Influence of firm characteristics and the environment on hotel survival across MSMES segments during the 2007–2015 period. *Tourism Management*, *75*, 477–490. https://doi.org/10.1016/j.tourman.2019.06.015

Voulgaris, F., Doumpos, M., & Zopounidis, C. (2000). On the evaluation of Greek industrial SME's performance via multicriteria analysis of financial ratios. *Small Business Economics*, *15*(2), 127–136. https://doi.org/10.1023/A:1008159408904

Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica*, *57*(2), 307–333. https://doi.org/10.2307/1912557

Waikar, V. G., & Fernandes, S. (2020). Distress analysis and risk score of hotels. *International Journal of Risk and Contingency Management*, *9*(3), 1–14. https://doi.org/10.4018/IJRCM.2020070101

Warner, J. B. (1977). Bankruptcy costs: Some evidence. *The Journal of Finance*, *32*(2), 337–347. https://doi.org/10.2307/2326766

Wertheim, P., & Lynn, M. L. (1993). Development of a prediction model for hospital closure using financial accounting data. *Decision Sciences*, *24*(3), 529–546. https://doi.org/10.1111/j.1540-5915.1993.tb01292.x

Westgaard, S., & Van Der Wijst, N. (2001). Default probabilities in a corporate bank portfolio: A logistic model approach. *European Journal of Operational Research*, *135*(2), 338–349. https://doi.org/10.1016/S0377-2217(01)00045-5

Weterings, A., & Marsili, O. (2015). Spatial concentration of industries and new firm exits: Does this relationship differ between exits by closure and by M&A? *Regional Studies*, *49*(1), 44–58. https://doi.org/10.1080/00343404.2012.726708

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, *48*(4), 817. https://doi.org/10.2307/1912934

Wieprow, J., & Gawlik, A. (2021). The use of discriminant analysis to assess the risk of bankruptcy of enterprises in crisis conditions using the example of the tourism sector in Poland. *Risks*, *9(4)*(78). https://doi.org/10.3390/risks9040078

Williams, R. L. (2000). A note on robust variance estimation for cluster-correlated data. *Biometrics*, *56*(2), 645–646. https://doi.org/10.1111/J.0006-341X.2000.00645.X

Wu, Y., Gaunt, C., & Gray, S. (2010). A comparison of alternative bankruptcy prediction models. *Journal of Contemporary Accounting and Economics*, *6*(1), 34–45. https://doi.org/10.1016/j.jcae.2010.04.002

Yamaguchi, K. (1991). *Event history analysis* (1st ed.). SAGE.

Yazdanfar, D., & Öhman, P. (2020). Financial distress determinants among SMEs: empirical evidence from Sweden. *Journal of Economic Studies*, *47*(3), 547–560. https://doi.org/10.1108/JES-01-2019-0030

Youn, H., & Gu, Z. (2010). Predicting Korean lodging firm failures: An artificial neural network model along with a logistic regression model. *International Journal of Hospitality Management*, *29*(1), 120–127. https://doi.org/10.1016/j.ijhm.2009.06.007

Yuan, K.-Q., Li, H., Liang, S., & Chen, Q.-X. (2023). Can inconsistent media coverage increase hotel survival? The bright side of controversy. *International Journal of Contemporary Hospitality Management*, *35*(3), 951–972. https://doi.org/10.1108/IJCHM-02-2022-0179

Zhai, S. S., Choi, J. G., & Kwansa, F. (2015). A financial ratio-based predicting model for hotel business failure. *Global Business and Finance Review*, *20*(1), 71–86. https://doi.org/10.17549/gbfr.2015.20.1.71

Zhang, D., & Tveterås, R. (2022). Influence of price variability and financial ratios on business failure in the Atlantic salmon industry. *Marine Resource Economics*, *37*(2), 183–200. https://doi.org/10.1086/718380

Zhang, D., & Xie, J. (2023). Influence of tourism seasonality and financial ratios on hotels' exit risk. *Journal of Hospitality and Tourism Research*, *47*(4), 714–733. https://doi.org/10.1177/10963480211016038

Zhang, Q., Vallascas, F., Keasey, K., & Cai, C. X. (2015). Are market-based measures of global systemic importance of financial institutions useful to regulators and supervisors? *Journal of Money, Credit and Banking*, *47*(7), 1403–1442. https://doi.org/10.1111/JMCB.12249

Zhang, X., Zhao, Y., & Yao, X. (2022). Forecasting corporate default risk in China. *International Journal of Forecasting*, *38*(3), 1054–1070. https://doi.org/10.1016/j.ijforecast.2021.04.009

Zheng, C., Li, Z., & (Snow) Wu, J. (2022). Tourism firms' vulnerability to risk: The role of organizational slack in performance and failure. *Journal of Travel Research*, *61*(5), 990–1005. https://doi.org/10.1177/00472875211014956

Zhou, F., Fu, L., Li, Z., & Xu, J. (2022). The recurrence of financial distress: A survival analysis. *International Journal of Forecasting*, *38*(3), 1100–1115. https://doi.org/10.1016/j.ijforecast.2021.12.005

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research*, *22*, 59–82. https://doi.org/https://doi.org/10.2307/2490859