UNIVERSIDADE DE LISBOA

ISEG - Lisbon School of Economics and Management

Essays in Agricultural Credit Risk

Mário Raúl Santiago do Céu

Orientadora: Professora Doutora Raquel Medeiros Gaspar

Tese especialmente elaborada para obtenção do grau de Doutor em Gestão

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2024

To my dear family.

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To the farmers, who face the immense challenge of feeding us all.

And finally, to Lili. Meow...

Preface

The papers that make up this thesis received valuable contributions through participation in various academic and scientific events.

The first paper, "A Review on Climate Change, Credit Risk, and Agriculture", was presented at the prestigious **4th Annual Conference of the European Academy of Management (EURAM 2024)**, held on June 25-28, 2024, organised by University of Bath, UK. This paper was published in **Rural Sustainability Research** edited by Latvia University of Agriculture under the DOI: 10.2478/plua-2024-0004.

The second paper, "Vegetative Cycle and Bankruptcy Predictors of Agricultural Firms", in its still preliminary version, was presented at the **1st Annual Meeting of the European Journal of Management Studies**, organised by Advance/CSG Research Center, which took place at ISEG, University of Lisbon on July 8, 2021. This same paper, with improvements, was also presented at the **International Conference on Agribusiness and Food Economics (IntAgricon 2021)** held at Konya Food and Agriculture University, Konya, Turkey, on August 12-14, 2021. The finalized article, co-authored with Raquel Medeiros Gaspar, has been published in **Agricultural Economics**, a monthly publication by the Czech Academy of Agricultural Sciences. This journal has been circulating since 1954 (formerly titled Zemědělská ekonomika until 1999) and is well-regarded in the academic community. Notably, Agricultural Economics is indexed in both Scopus and Web of Science. The article is accessible under the DOI: 10.17221/206/2022-AGRICECON.

The third paper, "Financial Distress in European Vineyards and Olive Groves", was presented at a prestigious scientific Finance event, the **12th Portuguese Finance Net-**

work Conference, held on July 5-7, 2023, at the University of Madeira, in Funchal (Portugal). Following its presentation, the paper, co-authored with Raquel Medeiros Gaspar, underwent a rigorous evaluation process and was accepted for publication in the renowned journal **New Medit, A Mediterranean Journal of Economics, Agriculture, and Environment**. Published by Bologna University Press, New Medit has a distinguished history in disseminating research in interdisciplinary fields since its inception. It is worth noting that New Medit is indexed in both Scopus and Web of Science, further enhancing the visibility and impact of the research. This paper is available under the DOI: 10.30682/nm2401c.

Lastly, the fourth paper, "Unveiling the Fragility of Small-Scale Agriculture", currently in the process of submission, contributes significantly to the diverse and impactful body of work presented in this comprehensive thesis. It was presented at the **5th Balkan Agricultural Congress**, held on September 20-23, 2023, organised by Trakya University in Edirne, Turkey, and also presented at the **2024 RCEA International Conference on Economics, Econometrics, and Finance**, held on May 20-22, 2024, organised by Brunel University of London.

Abstract (PT)

Esta tese explora a intrincada dinâmica do risco de crédito na atividade agrícola. A investigação integra conhecimentos de vários ângulos, abrangendo factores como o ciclo vegetativo, actividades agrícolas específicas como a viticultura e olivicultura, a dimensão económica e considerações relacionadas com as alterações climáticas. Utilizando um conjunto abrangente de dados de empresas agrícolas, o estudo examina os preditores de falência, estima modelos de predição e relata o estado da arte, através de quatro artigos originais.

Abordando as crescentes ameaças das alterações climáticas à produtividade agrícola, o primeiro artigo realiza uma revisão sistemática da literatura, identificando 39 artigos da Scopus e da Web of Science. Desta seleção, emergem três dimensões principais – (i) empréstimos agrícolas e risco de crédito, (ii) princípios verdes e sustentabilidade, e (iii) o contexto dos países em desenvolvimento. As conclusões sublinham a necessidade imperiosa de integrar as considerações climáticas nas políticas agrícolas e de crédito. São recomendadas estratégias proativas, abrangendo políticas de crédito personalizadas, melhor acesso ao crédito, capacitação financeira e combate às desigualdades sociais.

O segundo artigo destaca o papel crucial do ciclo vegetativo na diferenciação entre empresas agrícolas saudáveis e falidas. Os preditores baseados na liquidez revelam-se eficazes para culturas não perenes, enquanto os preditores de atividade demonstram uma precisão superior para culturas perenes.

O terceiro artigo estende o seu foco aos setores vitícola e olivícola de países mediterrânicos, apresentando 12 modelos adaptados para diferentes combinações de países e culturas. Os resultados sublinham a necessidade de modelos dedicados que tenham em conta as variações sectoriais e regionais para melhorar a precisão das previsões.

O quarto artigo explora as dificuldades financeiras das pequenas empresas agrícolas, que constituem a maior parte do sector. Aproveitando uma amostra de 9.891 empresas, são estimados modelos de regressão logística. Notavelmente, a dimensão da empresa surge como um factor significativo, com as empresas mais pequenas a enfrentar maiores dificuldades financeiras. O estudo defende a inclusão do tamanho da empresa como covariável, enfatizando a sua relevância nas diferentes classes de dimensão.

Esta análise multidimensional fornece um quadro abrangente para compreender e mitigar os desafios enfrentados pelas empresas agrícolas. A síntese destas diversas perspectivas oferece informações originais e valiosas para os decisores políticos, instituições financeiras e profissionais, abrindo caminho para uma melhor compreensão dos riscos financeiros, particularmente os riscos de crédito que estas empresas enfrentam num cenário de grande incerteza e desafios relacionados com a segurança alimentar e riscos climáticos.

Palavras-Chave: Ciclo Vegetativo, Dificuldades Financeiras, Predição de Falência, Pequena Agricultura, Alterações Climáticas.

Abstract (ENG)

This thesis explores the intricate dynamics of credit risk in agricultural activity. The research integrates knowledge from various angles, covering factors such as the vegetative cycle, specific agricultural activities such as vineyards and olive groves, the economic size and considerations related to climate change. Utilizing a comprehensive dataset from agricultural firms, the study examines bankruptcy predictors, estimates prediction models, and reports on state of the art through four original papers.

Addressing the escalating threats of climate change to agricultural productivity, the first paper conducts a systematic literature review, identifying 39 articles from Scopus and Web of Science. From this selection, three major dimensions emerge — (i) agricultural lending and credit risk, (ii) green principles and sustainability, and (iii) the context of developing countries. Findings emphasize the need to integrate climate considerations into agricultural and credit policies. Proactive strategies are recommended, encompassing tailored credit policies, improved access to credit, financial empowerment, and addressing social inequalities.

The second paper highlights the crucial role of the vegetative cycle in differentiating between healthy and bankrupt agricultural firms. Liquidity-based predictors prove effective for non-perennial crops, while activity predictors demonstrate superior accuracy for perennial crops.

The third paper focuses on the vineyards and olive crops sectors in Mediterranean countries, presenting 12 tailored models for different combinations of countries and crops. Results underscore the necessity for dedicated models that account for sectoral and regional variations to enhance predictive accuracy.

The fourth paper explores the financial distress of small-scale agricultural firms, which constitute most of the sector. Logistic regression models are estimated using a sample of 9,891 firms. Noticeably, firm size emerges as a significant factor, with smaller firms experiencing higher financial difficulties. The study advocates for including firm size as a covariate, emphasizing its relevance across different size classes.

This multidimensional analysis provides a comprehensive framework for understanding and mitigating the challenges agricultural firms face. The synthesis of these diverse perspectives offers original and valuable information for policymakers, financial institutions and professionals, paving the way for a better understanding of the financial risks, particularly credit risks, that these firms face in a scenario of great uncertainty and challenges related to food security and climatic risks.

Keywords: Vegetative Cycle, Financial Distress, Bankruptcy Prediction, Small Farming, Climate Change.

Contents

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List of Acronyms

AUC - Area Under Curve

CAP - Common Agricultural Policy

EBITDA - Earnings Before Interest, Taxes, Depreciation, and Amortization

EU - European Union

FN - False Negatives

FP - False Positives

GCFI - Gross Cash Farm Income

NACE - Nomenclature Statistique des Activités Économiques dans la Communauté Européenne

ROC - Receiver Operating Characteristic

RGDP - Real Gross Domestic Product

SDG - Sustainable Development Goals

SO - Standard Output

SR - Systematic Review

TN - True Negatives

TP - True Positives

TPR - True Positive Rate

WoS - Web of Science

Chapter 1

Introduction and Research Overview

1.1 Overview and Relevance of the Study

The agricultural sector, fundamental to individual economies and global societies, is currently facing heightened scrutiny, primarily due to its crucial role in ensuring food security. Despite being a cornerstone of human survival, agriculture is confronted with unprecedented challenges as the world population reaches 8 billion, with projections soaring to 10 or 11 billion by 2050.

The imperative to enhance agricultural productivity clashes with the adverse impacts of climate change on essential natural resources such as water and soil. These changes extend to agro-climatic zones and cropping patterns. Simultaneously, businesses, especially those reliant on natural resources and susceptible to environmental elements, face multifaceted consequences of climate change. A critical concern revolves around the capacity of these agricultural firms to endure in an environment requiring substantial investments to mitigate climate change impacts. The repercussions will differ among farmers based on their agricultural practices, geographic regions, and financial structures.

Sustainable development in agriculture aims to meet present needs while ensuring that future generations can also fulfill theirs. Recognizing this, policymakers understood the need for global action. This led to the creation of the United Nations Sustainable Development Goals (SDGs), which offer a comprehensive framework to tackle global challenges, including those facing agriculture. Key SDGs, such as Zero Hunger (SDG 2), Clean Water and Sanitation (SDG 6), Climate Action (SDG 13), and Life on Earth (SDG 15), form the foundation of this approach.

This dissertation explores key themes central to the risks faced by agriculture, advancing knowledge on credit risk in the industry. It examines diverse aspects, from the vegetative cycles to the unique challenges of specific sectors like viticulture and olive growing, as well as more standard approaches assessing how the size of agricultural firms impacts financial difficulties.

Given the significant challenges and uncertainties in the agricultural sector, it is essential for stakeholders to understand the complexities of agricultural risks, particularly financial risks. This dissertation aims to address existing research gaps in this critical area, providing valuable insights to support informed decision-making in the field.

1.2 Procedures and Applied Methodologies

This dissertation employed a selection of methodological approaches to address the formulated hypotheses.

The underlying philosophy of the initial three articles aligns with positivism, adopting a deductive approach. Utilizing secondary quantitative data within a contemporary longitudinal period, the research is grounded in the insights of Saunders et al. (2019). This underscores the fundamental strength of longitudinal studies in capturing changes and developmental trends and references the positivist perspective. This perspective emphasizes reliance on objective facts to obtain robust scientific evidence through quantitative research methods, aligning with the epistemological stance inherent in these articles. The broad availability of quantitative data in databases enhances reliability compared to data obtained through alternative means.

In the fourth article, a comprehensive systematic literature review is undertaken.

Table 1.1 summarises the methodology and procedures applied in each of the empirical studies of this thesis, describing the databases, sources and number of observations used.

Table 1.1: Summary of procedures, methods, and data sources

Chapter	Procedures and Methods	Data Collected and Sources
Chapter 2	Systematic literature review Bibliometric analysis	Web of Science (WoS) and Scopus 1,109 articles screening 39 articles selected
Chapter 3	Collection of financial statements Econometric analysis using SPSS	Amadeus database (Bureau van Dijk) 2,228 firms (2,145 active, 83 bankrupt) - 1,039 Non-perennial crop firms - 1,189 Perennial crop firms
Chapter 4	Collection of financial statements Econometric analysis using SPSS Model estimation	Orbis database (Bureau van Dijk) 5,057 firms (4,085 healthy, 972 distressed) - 3,223 vineyards firms - 1,834 olive groves firms
Chapter 5	Collection of financial statements Econometric analysis using SPSS Model estimation	Orbis database (Bureau van Dijk) 9,891 firms (9,070 healthy, 821 distressed) - 191 microfarms - 595 small farms - 3,085 low-sales-farms - 2,283 moderate sales-farms - 3,764 medium large farms

Source: Own elaboration

1.3 Thesis Structure

The dissertation is structured into six chapters. The first chapter provides an introduction and research overview, its contribution to knowledge, and the procedures and methodologies applied.

The following chapters correspond to four ‘papers’ that address credit risk in agriculture. Thus, Chapter 2, *A Review on Climate Change, Credit Risk and Agriculture*, presents a bibliometric literature review of an unavoidable topic today and the risks that climate change poses to the economic activity of agriculture. Chapter 3, *Vegetative Cycle and Bankruptcy Predictors of Agricultural Firms*, introduces and highlights the importance of the vegetative cycle in predicting the bankruptcy of agricultural firms. Chapter 4, *Financial Distress in European Vineyards and Olive Groves*, is based on estimating financial distress models for European agricultural firms dedicated to viticulture and olive groves. Chapter 5, *Unveiling the Fragility of Small-Scale Agriculture*, addresses the importance of the size of agricultural firms, especially small-scale ones, in their financial survival.

Finally, Chapter 6 summarises the research’s conclusions, implications, emerging focuses and main limitations.

Chapter 2

A Review on Climate Change, Credit Risk and Agriculture

Abstract

Climate change significantly threatens agricultural productivity, presenting substantial challenges to the sector. This study aims to identify literary trends addressing risks for both agricultural firms and capital lenders. Employing a systematic literature review, we highlighted 39 articles from Scopus and Web of Science. Three major literary dimensions emerged: (i) agricultural lending and credit risk, (ii) green principles and sustainability, and (iii) the context of developing countries.

The findings stress the need to blend climate change into agricultural and credit policies. Policymakers and financial institutions should educate farmers on climate issues and encourage sustainable financial approaches. Anticipated climate risks will impact lenders' capital reserves, requiring portfolio adjustments. A deep understanding of climate change's interplay with agriculture lending and credit risk is vital, urging proactive policy and practice. Addressing climate challenges in agriculture requires a multifaceted strategy encompassing tailored credit policies, improved access to credit, financial empowerment, and addressing social inequalities.

Keywords: climate change, agricultural lending, sustainability, credit risk.

2.1 Introduction

The primary sources of uncertainty and risk in agriculture stem from production uncertainty, where unpredictable elements like weather impact output quality and quantity, further exacerbated by the significant time requirements dictated by biological processes (Moschini and Hennessy, 2001). Changes in temperature patterns, precipitation levels and extreme weather events can affect crop yields, water availability and livestock health. Farmers face the challenge of adapting their farming practices to these changing conditions to maintain productivity and profitability. This may involve implementing new technologies, diversifying crops or adopting more sustainable farming practices.

However, these adaptations often require financial resources that may not be readily available to farmers. Lenders providing loans to agricultural businesses need to assess the risk associated with the impacts of climate change on the borrower's ability to repay the loan. Furthermore, agriculture contributes to greenhouse gas emissions, further exacerbating climate change. To tackle these challenges, there is increasing pressure to embrace sustainable farming practices that mitigate climate change impacts and foster a circular economy. With the uncertainty and volatility brought on by climate change, lenders must assess the potential for crop failures, supply chain disruptions and reduced market demand to make informed decisions regarding loan terms, collateral requirements, and risk mitigation strategies.

The significance of the 2030 Agenda for Sustainable Development (United Nations, 2015), adopted by all member countries, is clear. This global agenda establishes priorities and aspirations for sustainable development, aiming to mobilise worldwide efforts towards shared goals and targets. A key tool in this context is the Paris Agreement (United Nations Environment Programme, 2015), established during the 2015 United Nations Climate Change Conference (COP 21). Its objective is to restrict the global temperature increase to below 2 degrees Celsius and strive for a limit of 1.5 degrees Celsius above pre-industrial levels. By aligning with the Paris Agreement, financial institutions can aid the shift to a low-carbon agricultural economy and mitigate credit risks linked to climate-related events.

Furthermore, integrating the Sustainable Development Goals (SDGs) into financial decision-making empowers financial institutions to contribute to the goals of the Paris Agreement. By promoting sustainable agriculture, facilitating the adoption of renewable energy, and encouraging energy-efficient practices, financial institutions can mitigate climate risks, strengthen agricultural resilience, and foster a transition toward a more environmentally conscious and economically sustainable future. Of the 17 SDGs adopted, there are several that depend on best practices in agricultural activity, which promote food security, actions to mitigate the impact of climate change, protect the forest, combat soil degradation, and conserve ecosystems and biodiversity.

The coming years will present significant agricultural challenges, which could be considered the most comprehensive yet. Farmers must provide enough food for a population of nearly 10 billion people by 2050 while also employing around 2 billion individuals and addressing environmental concerns such as land degradation, water scarcity, and the adverse impacts of climate change (Searchinger et al., 2019). Forecasts for future food demand vary, yet even the most hopeful projections necessitate a minimum of 50% growth in food production. The surge in demand for agricultural and food commodities, driven by expanding population and evolving consumption habits, is anticipated to reach its zenith in the next half-century (Baulcombe et al., 2009).

There is also an imperative need for agricultural activity to reinvent itself to meet the SDGs. Climate change is expected to negatively impact crop production worldwide. Researches indicate that crop yields have already been affected, and future climate conditions are projected to decrease further yields (Tilman et al., 2011; Vermeulen et al., 2012; Ray et al., 2019; Molotoks et al., 2021).

Climate change forecasts play a crucial role in determining economic losses, with benign forecasts resulting in economic benefits for society, while more severe forecasts lead to substantial losses (Adams et al., 1995). Capasso et al. (2020) examined how exposure to climate change affects a firm's credit risk and found that the distance-to-default is lower for firms with higher carbon emissions and carbon intensity, indicating that the market sees such firms as having a greater likelihood of default. Furthermore, the impacts of climate change on crop yield levels and variances are not uniform across all types of crops, as they manifest in a crop-specific manner. Specifically, increases in rainfall and temperature positively influence both the yield level and variability of sorghum. Conversely, the effects of precipitation and temperature on corn yield levels and variability exhibit contrasting patterns (Chen et al., 2004).

Other studies address the impact of climate change on poverty by 2030 due to the increase in prices of basic foodstuffs in low-productivity scenarios, which will consequently affect farmers' incomes (Hertel et al., 2010).

Depending on the region, the impacts of climate change are indeed alarming. Projections indicate that, under the most severe scenario, Australian farm profits could decline by as much as 50% compared to the latter half of the last century. Moreover, given the diverse responses of regions and countries to climate change, the international competitiveness of farmers might also be compromised (Hughes et al., 2022).

The gradual deterioration of business liquidity, accompanied by an increased default rate caused by climate change-induced destruction of capital and reduced profitability, poses potential risks to the financial and non-financial sectors (Dafermos et al., 2018). While studies based on thermal stress have indicated a direct relationship between extreme heat and elevated credit delinquency rates, primarily within the agricultural sector, this raises the discussion of whether long-term climate changes will also impact the credit quality provided to agricultural businesses (Aguilar-Gomez et al., 2024).

Some questions take work to answer between a sustainable planet and a sustainable economic activity. Farmers may resist the adoption of organic agriculture due to concerns about its economic viability compared to conventional methods, or policymakers must consider the financial and social costs before promoting or demanding potentially more environmentally friendly but less economically efficient agricultural practices (Lien et al., 2007).

The intricate relationship between climate change, agricultural loans, and credit risk is paramount in understanding the vulnerabilities and dynamics of the agricultural sector.

Climate change has a profound impact on agricultural productivity, and this, in turn, affects loan repayment abilities and credit risk. This literature review seeks to provide a comprehensive understanding of the interconnectedness of climate change, agricultural loans, and credit risk and its implications for policy, finance, and sustainable agricultural development. By analysing and synthesising existing literature, we aim to identify key findings and research gaps and highlight areas for future research. By clarifying credit risk in agriculture, we aim to improve understanding of its implications for sustainable development, enabling informed decision-making and policy interventions in this crucial area.

The remainder of this article is organised as follows: Section 2.2 outlines the research methodology, Section 2.3 discusses the results of the bibliometric analysis, and Section 2.4 provides the study's conclusions, implications, and suggestions for future research.

2.2 Data and Methods

2.2.1 Study Selection

This review aims to analyse the impact of climate change and sustainability policies on the credit risk of agricultural firms. We conducted a systematic review (SR) using the most reputable electronic bibliographic data sources, namely Scopus and Web of Science (WoS). Considering the theme of climate change and its contemporary relevance, we refrained from imposing temporal constraints on our search to encompass the entirety of the bibliographic essence from its inception to August 2023. Only articles submitted to the peer-review process were considered, so we excluded conference papers, systematic reviews, book chapters and other reports. We performed an extensive database search using specified keywords to link agriculture, credit risk and climate change. To identify the most relevant studies for our purpose, we conducted an advanced search using the boolean functions 'AND' and 'OR', combining them to make the search more efficient (see Table 2.1).

Table 2.1: Search criteria in Scopus and Web of Science (WoS)

Source	Search Criteria
Scopus	TITLE-ABS-KEY (("credit risk" OR "financial distress" OR insolvency OR bankruptcy OR default OR loan OR indebtedness) AND (agriculture OR agricultural) AND ("climate change" OR "climate risk" OR sustainability)) AND (LIMIT-TO (DOCTYPE , ar"))
WoS	((TS=("credit risk" OR "financial distress" OR insolvency OR bankruptcy OR default OR loan OR indebtedness)) AND ALL=(agriculture OR agricultural)) AND ALL=("climate change" OR "climate risk" OR sustainability) AND Article (Document Types)

Source: Own elaboration

2.2.2 Screening and Eligibility Process

Our search yielded 1,109 bibliographic references, all of which underwent screening. We conducted a comprehensive review involving a bibliometric analysis and a systematic content analysis of the selected articles. The schematic representation of the SR methodology is shown in Figure 2.1.

There were 282 duplicate articles between Scopus and WoS, so they were removed. Next, we made an exhaustive selection by title and abstract reading, and then those we considered candidates underwent a full-text assessment. To reach the ultimate selection, a meticulous analysis was conducted on the articles, where in the assessment encompassed aspects such as content relevance, employed methodologies, novel discoveries, contributions to the existing literature, and implications for researchers and policymakers. The literature on agriculture is broad and is essentially linked to agronomic conditions and practices. Hence, the association between finance, climate change and agriculture is difficult to isolate from the bibliometric noise, and of the initial 827 references (after removing duplicates), 39 remained that were considered relevant for this study. To bet-

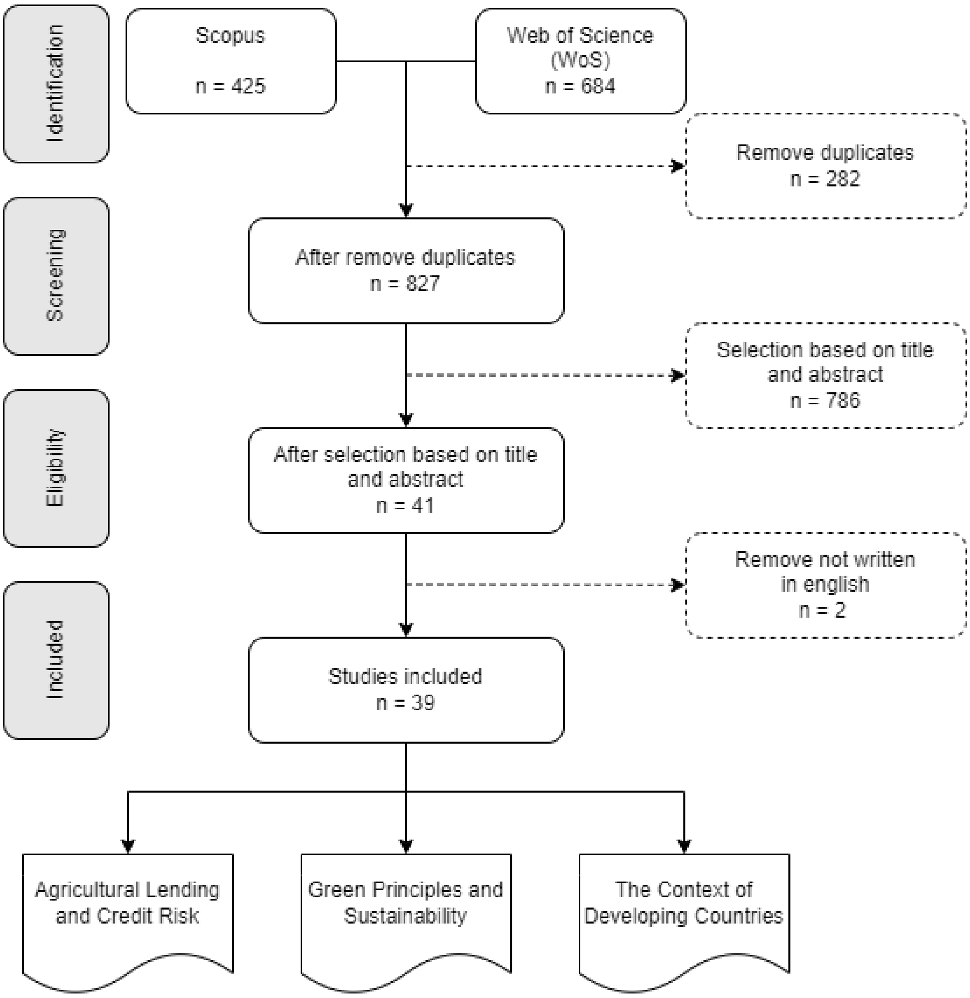

Figure 2.1: Diagrammatic flow of the selection process. Source: Own elaboration.

ter understand the keywords used in this final selection, we show a word cloud diagram (Figure 2.2).

The analysis of Figure 2.3 shows that only since 2020 has the production of research relating to the theme of this systematic literature review demonstrated a notable increase in interest. Prior to 2009, no scientific production on the topic had been identified. In 2023, until August, five articles had already been recorded, indicating a continuation of interest and academic production in the area. "It is important to note that the significant growth in research production from 2020 on the topic of this systematic literature review may be directly related to the influence of the 2030 Agenda for Sustainable Development (United Nations, 2015) and the Paris Agreement (United Nations Environment Programme, 2015) marking an important milestone in global discussions on sustainability and climate change.

Figure 2.2: Most frequently used keywords. Source: Own elaboration.

In our analysis of research-related publications, we found an average of 12.2 citations per document. Specifically, 17 articles had 10 or more citations (see Table 2.2). Additionally, Table 2.3 displays the distribution by Publisher, illustrating the number of publications associated with each identified Publisher.

2.3 Results and Discussion

2.3.1 Agricultural Lending and Credit Risk

Climate Sensitivity in Loan Recovery

There is a crucial interconnection between agricultural loans and agricultural productivity, highlighting their strong dependence on climatic conditions. Climate change asymmetrically affects the recovery of agricultural loans, i.e., negative sensitivities result in lower recoveries, while positive sensitivities lead to improved recoveries (Wahab et al., 2023). Climate-driven shifts in productivity strongly impact how borrowers in rural credit markets manage their loan repayments. This dynamic heightens the chances of defaults

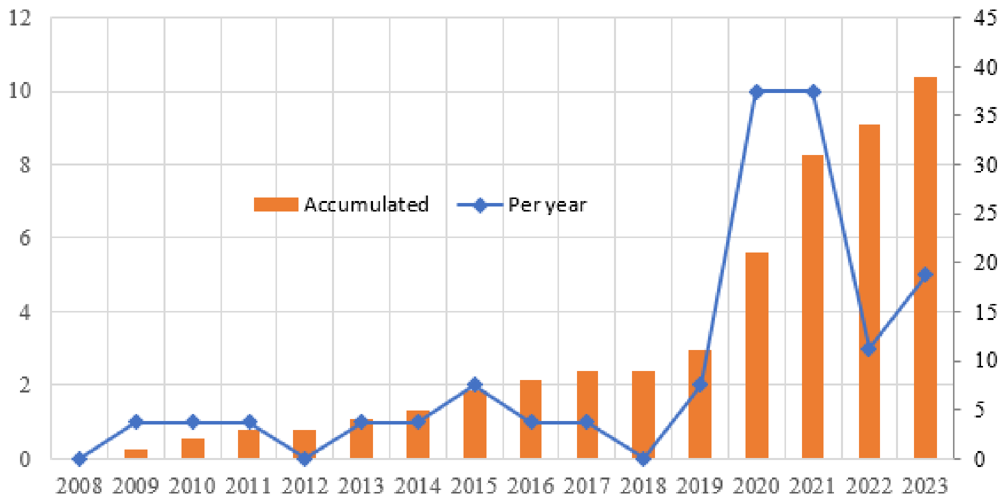

Figure 2.3: Number of publications per year. Source: Own elaboration.

Table 2.2: Authors with the highest number of citations per publication

Article	Local Citations	Countries of the author's affiliation
Lázár et al. (2015)	78	United Kingdom, Bangladesh
Sofoluwe et al. (2011)	70	Nigeria
Ojo and Baiyegunhi (2020)	29	South Africa, Nigeria
Mwinjaka et al. (2010)	27	Kenya, Netherlands
Islam et al. (2020)	26	Bangladesh, United Kingdom
Möllmann et al. (2020)	24	Germany
Vo et al. (2021)	22	Vietnam, Japan
Hochrainer et al. (2008)	22	Austria
Ndegwa et al. (2020)	18	United Kingdom, United States
Ali et al. (2020)	17	Togo, Nigeria, Ghana
Chandio et al. (2020)	16	China
Anugwa et al. (2021)	13	Nigeria, United Kingdom
Carranza and Niles (2019)	12	United States
Pauline et al. (2016)	11	Tanzania, South Africa
Enete et al. (2016)	11	Nigeria
Odhong et al. (2019)	10	Germany, Kenya
Castro and Garcia (2014)	10	Colombia

Source: Own elaboration

and exacerbates market failures. Remarkably, even the existence of credit information exchange systems, such as credit bureaus designed to boost financial inclusivity, fails to

Table 2.3: Distribution of publications by publisher

Publisher	Qty.
MDPI	7
SPRINGER	7
TAYLOR FRANCIS	7
ELSEVIER	5
EMERALD	4
FRONTIERS	2
ACADEMIC JOURNALS	1
ACCSCIENCE	1
OXFORD ACADEMY	1
ROYAL SOCIETY OF CHEMISTRY	1
WILEY	1
WORLD SCIENTIFIC	1
Dr. R. S. Yadab	1

Source: Own elaboration

mitigate these outcomes. These insights are important in light of climate change's adverse effects on agricultural productivity, particularly in vulnerable communities with limited capacity to cope. (Adjognon et al., 2019).

Emphasising the importance of lenders understanding natural capital risks, if the risk premium for agricultural loans is not well understood, it could become misaligned, and potentially cause net losses in the lender's portfolio. On the other hand, setting a premium that is too high could burden borrowers with excessive costs and limit the availability of financing for sustainable scaling efforts (Ascui et al., 2021).

An analysis of past climate events was conducted to develop a stress-testing methodology aimed at predicting future droughts. The research highlighted significant macroeconomic impacts in specific regions of the United States, particularly regarding Real Gross Domestic Product (RGDP), resulting in job losses and property devaluation. Lenders have experienced varying effects based on their geographic diversification, concluding that it is important to have access to historical data on localised weather events so that lenders can assess the resilience of their portfolios against such impacts (Breeden, 2023).

Examining the impact of climate change on credit risk within the agricultural sector, Brar et al. (2021) presented a structured framework. The study explored various climate change scenarios, assessing their influence on agricultural loan portfolios. Temperature increases from 0°C to 4°C were used as scenarios for evaluation. Employing a case study approach, the research analyzed agricultural loan portfolios dedicated to maize producers across diverse regions of Ontario, Canada, considering distinct climate change conditions. The findings emphasized the importance of integrating climate change considerations for a more resilient loan portfolio compared to disregarding climate effects. The methodology involved simulating corn productivity under varying climate change scenarios, allowing an evaluation of its impact on agricultural income and loan losses. The study's conclusions showcased significant risk reductions achievable through applying climate change models, contingent on the chosen modeling strategy. The study's implications extend to the adaptability of the framework across different crops and regions. Furthermore, it suggests the potential for future research to encompass a broader range of climate change impacts beyond just temperature escalation, including phenomena such as severe weather patterns.

Castro and Garcia (2014) studied the effects of commodity price volatility and climate variations on a default risk model. The findings reveal statistical significance for both price volatility and climate factors, yet their economic relevance is eclipsed by macroeconomic conditions and intermediate input prices. Moreover, the suggested model enables stress testing through risk scenarios, highlighting the dominance of climate-related risks over those arising from commodity price volatility. Bergman et al. (2020) employed random weather shocks as an exogenous source of variation in farm cash flow, revealing that these shocks had significant effects on multiple sectors of the economy of Iowa, United States. During the crisis, cash injections positively influenced land values, but also increased loan default rates and the number of bank failures, indicating that climate shocks can play a significant role in economic dynamics.

The age and education of farmers are also a covariate associated with agricultural credit risk. Spicka (2020) reveals that due to climate change and the associated risks in agriculture, younger, unmarried, and less educated farmers have a significantly higher propensity for risk-taking, potentially making them risky clients for banks.

Resilience and Mitigation Strategies

In a study by Ranjan (2013) regarding credit constraints for farmers and their connection to drought resilience, the significance of credit access in promoting water-saving technologies during droughts and groundwater depletion is underscored. The study explores the influence of credit costs and their interaction with various farmer constraints. Shorter repayment periods are suggested to encourage prudent water resource management, while excessively high-interest rates may lead to harmful approaches. The study emphasizes the need for timely credit access to address the increasing frequency of droughts, advocating for its integration with other strategies to support productive investments and ensure food security. However, it acknowledges challenges such as farmers' risk aversion and the necessity for innovative credit mechanisms. Moreover, the study highlights the potential of timely credit availability in promoting the adoption of water-saving technologies during droughts, while recognising the negative impact of high credit costs and the risk of recurring droughts on groundwater sustainability. Additionally, the study underscores the role of the loan duration in shaping farmers' groundwater utilisation strategies, emphasizing the potential for financial institutions to encourage sustainable outcomes.

Ali et al. (2020) assessed the willingness of Togolese farmers to pay for insurance based on weather indices as a market option to share climate risks. Although the results indicate that respondents are willing to pay, this option must be interconnected with other factors, including loans to organised groups of farmers. This study presents a very interesting perspective, opening the horizons for composite financial products associated with climate data, which in a certain way could mitigate the associated credit risk.

Jones et al. (2015) suggests that agricultural lenders should transition from using uniform credit risk assessment models to ones that comprehend the specificities of organic farms. Additionally, farmers should better understand credit risk assessment principles to effectively advocate with lenders and compete for terms that are not disadvantageous compared to conventional loans.

In a study about crowdfunding to support climate change mitigation practices, Kragt et al. (2021) interviewed 443 Norwegian farmers with low knowledge about crowdfunding. Those who are interested prefer subsidy or reward models that cover all mitigation costs. Factors such as agricultural financial stability and responsibility for climate change increase interest in crowdfunding. There is, however, farmer hesitancy to be publicly identified as a recipient of funding, suggesting that joint campaigns managed by intermediary organizations are an effective approach. It concludes that, despite the limitations, well-planned crowdfunding can involve groups of farmers in mitigating climate change.

2.3.2 Green Principles and Sustainability

The impact of green credit policies reveals significant improvements in profits and supply chain efficiency. Implementing green credit policies can improve profits for participants in the agricultural supply chain while allowing banks to reduce interest rates, which increases the overall utility of the supply chain, contributing to efficiency and sustainable development (Deng et al., 2021). Financial institutions aligned with environmental concerns provide loans to agriculture based on the principles of the green economy and circular economy, fostering sustainable societal development. However, insufficient information poses a critical challenge for lenders. Addressing this, implementing a hierarchical blockchain model proves beneficial in ensuring the reliability, security, and traceability of data in rural green credit research (Tan and Zhang, 2021).

Market niches have been emerging in response to the demand for environmentally friendly agriculture that promotes a more sustainable economy. Organic farms are acknowledged for enhancing the resilience of agricultural systems to climate change by creating more stable ecosystems and even mitigating their effects through the use of fertilizers, resulting in reduced greenhouse gas emissions. However, on the flip side, organic farms might be more susceptible to extreme and unpredictable weather events and patterns, potentially affecting the productivity of these green units. Xia et al. (2022) highlights the efficacy of agricultural supply chain finance in resolving farmers' loan difficulties. The study takes a comprehensive approach to evaluating risk decisions in the realm of green agriculture and categorizes farm households into four credit-needing groups, evaluating their risk profiles. The findings confirm the indicator system's appropriateness for fostering green agricultural development and providing valuable guidance for financial decision-makers. Moreover, the study's insights can be extrapolated to different agricultural supply chain contexts, offering broader applicability.

2.3.3 The Context of Developing Countries

Credit Constraints and Vulnerability

Climate change presents significant challenges to farmers in developing nations, affecting their ability to adapt and thrive. Among the myriad of challenges, credit constraints emerge as a critical factor hindering farmers' efforts to mitigate the impacts of climate change and implement necessary adaptation strategies. The inadequate access to financial resources severely compromises small-scale agriculture, emphasizing the need for appropriate credit policies to address these challenges, particularly in vulnerable areas (Ojo and Baiyegunhi, 2020). The vulnerability of the poorest farmers is evident in their limited access to credit and insurance schemes due to low credit ratings, designating them as high-risk debtors by traditional banking institutions (Mwinjaka et al., 2010). This low credit accessibility hampers their capacity to implement adaptation strategies, including the utilisation of climate-smart agricultural technologies vital for sustainable agriculture and ensuring food security amidst climate change (Anugwa et al., 2021). Sofoluwe et al. (2011) concluded that the lack of capital is the second most commonly reported issue by Nigerian farmers in their efforts to adapt to climate change. Therefore, access to loans plays a significant role in adaptation strategies, thus emphasizing the importance of facilitating credit access.

In contexts where adverse weather events significantly impact smallholder farmers' vulnerability, hindering adequate credit access, as exemplified in less developed countries, Möllmann et al. (2020) explored the influence of remotely-sensed vegetation health indices on credit risk for agricultural loans in Madagascar. The study highlighted that these indices notably elucidate credit risk, particularly in higher-risk scenarios, underscoring their potential value for microfinance institutions in managing loan portfolio risk. The authors advocated for the adoption of index insurance based on these indices, envisioning potential benefits such as reduced interest rates, enhanced credit accessibility, and a positive contribution to sustainable development in the region.

Market conditions significantly affect farmers' economic sustainability, particularly in climate-vulnerable countries such as Bangladesh, where agricultural costs often surpass income, necessitating loans to sustain operations. However, profits from agriculture frequently fall short of repaying the loans, perpetuating a cycle of debt for farmers and stakeholders involved (Lázár et al., 2015).

Studies conducted in diverse geographical regions shed light on the intricate relationship between climate change, credit access, and vulnerability. For instance, in Kenya, climate risk-induced rationing hampers credit-seeking behaviour among small-scale farmers (Ndegwa et al., 2020). Similarly, in arid and semi-arid regions of India, climate change adversely affects family debt, exacerbating existing socioeconomic disparities (Kandikuppa and Gray, 2022).

Formal Credit and Informal Credit

Formal credit institutions, when effectively targeted and distributed, have the potential to empower farmers and enhance resilience in the face of climate change. The study by Chandio et al. (2020) underscores the necessity of aligning formal credit services with the specific needs of farmers and advocates for global cooperation in providing loan guarantees to small farmers, safeguarding funds and promoting climate change adaptation strategies

While both formal and informal credit show positive associations with climate change adaptation strategies, farmers encounter significant barriers to accessing formal credit. Stringent requirements, lack of operational flexibility, and high-interest rates deter farmers, often leading them to turn to informal credit sources such as loans from social networks and Farmer-Based Organiations. The misalignment of formal credit with the informal nature of agricultural activities accentuates these challenges (Ankrah et al., 2023).

In the smallholder farming community, there is growing interest in accessing climate finance to support resilient agricultural development and the introduction of climate change mitigation practices. However, challenges prevail in accessing climate finance through formal financial institutions at market rates. In a study related to the dairy sector, obstacles are highlighted not only as risks in Kenyas's dairy sector but also as weak links between farmers and formal financial institutions (Odhong et al., 2019).

Microfinance Institutions

Microfinance institutions play a crucial role in providing essential liquidity to affected communities and mitigating natural disasters linked to climate change (Sseruyange and Klomp, 2021). However, caution is warranted, as microfinance products for climate adaptation can inadvertently create debt cycles due to adverse weather conditions, offering short-term solutions without addressing underlying vulnerabilities (Guermond et al., 2023).

Various climate-induced precipitation scenarios were analysed in a study examining climate change's impact on microinsurance programs for impoverished farmers in Malawi. Despite data uncertainties, this research's findings unveil vulnerabilities and risks associated with these programs in a more distant future, specifically from 2070-2080. The revelations from this study have sparked discussions concerning the potential influence of uncertainties on capital requirements and insurance premiums. While this investigation does not establish a direct link to the credit risk of agricultural firms, it underscores the critical importance of addressing climate change (Hochrainer et al., 2008).

The potential of microcredit, conceived in the previous century, is now being explored as a strategy to tackle climate change. While vulnerable populations resort to microcredit in response to climate shocks, its ability to mitigate sustained effects remains restricted due to limited outreach, supply obstacles, and a lack of alternative credit options. Alongside this limitation, microcredit contributes to the issue of over-indebtedness, potentially placing individuals on a trajectory of heightened risk in the face of future climate shocks. This can lead to loan defaults and the liquidation of assets, which are often sold to repay debts (Jordan, 2020).

Gender Disparities and Mental Health

Gender disparities further compound challenges in low-income countries, affecting small farmers' credit access. Male-headed households tend to have greater access to formal loans, directing resources differently than female-headed households. This has varied short and long-term impacts on the ability of small farmers to adapt to climate change (Carranza and Niles, 2019).

The impacts of climate change extend beyond the economic realm, affecting the mental health of farmers. Studies demonstrate a link between adverse weather conditions, agricultural losses, debt, and an increased risk of suicidal thoughts among farmers (Swami et al., 2020). Rising temperatures, directly affecting agricultural productivity, are associated with a notable increase in farmer suicide rates (Barve et al., 2021).

Strategies for Addressing Climate Change Impacts

Selling assets and taking loans are often strategies employed to address the catastrophic impacts of climate change (Enete et al., 2016; Islam et al., 2020; Patel et al., 2020). However, the ability of developing countries to do so is compromised due to various challenges faced by these communities). These challenges include the lack of knowledge to access loans and financial support, the poor economic condition of farmers, the absence of suitable environmentally-friendly technologies for rural farmers, and a general lack of information about climate change, ranking as the top concerns expressed by farmers (Pauline et al., 2016; Kath and Kanagasabapathi, 2020). Other studies indicate that access to official loans does not significantly impact farmers' adaptation decisions regarding climate change, attributing this to inefficiencies in loan capital management. Consequently, it is suggested that policymakers should establish preferential loan programs with stringent oversight to ensure efficient fund utilisation and prevent misuse by beneficiaries (Vo et al., 2021). A study on climate change adaptation in Iran revealed that "delaying loan repayment" ranked lowest among 31 adaptation strategies. Villagers preferred alternative approaches, such as creating new employment opportunities and sources of income, as more immediate solutions to address the challenges of climate change. This finding highlights a preference for non-financial strategies over deferring loan repayments in climate change adaptation efforts (Sarvestani and Shahraki, 2023).

2.4 Conclusion

This literature review offers valuable insights into climate risk management across three main dimensions: (i) *agricultural lending and credit risk*, (ii) *green principles and sustainability* and (iii) *context of developing countries*.

In the field of *agricultural lending and credit risk*, climate change strongly influences loan recovery, requiring prudent risk assessments and stress testing methodologies based on historical climate events. Lenders should align risk premiums with climate risks to ensure portfolio resilience while avoiding undue burdens on borrowers.

About *green principles and sustainability*, aligning of financial institutions with the principles of the green and circular economy is fundamental to promoting sustainable agricultural development. Implementing green credit policies in the agricultural supply chain not only increases overall efficiency but also increases profits for supply chain participants.

Understanding the impact of climate change on *developing countries* has been widely studied due to the intensity with which these countries feel the consequences. Climate change presents profound challenges for farmers in these regions. Insufficient access to credit amplifies vulnerability, making it difficult to implement essential adaptation strategies. Closing these gaps requires adapted credit policies, enhanced access to formal and informal credit, and addressing gender disparities in access to credit.

These findings highlight the need to integrate climate change considerations into agricultural and credit policies. Policymakers and financial institutions must prioritize climate education for farmers and advocate for sustainable financial practices. Climate risk is expected to be a crucial factor in creditors' capital reserves, requiring adjustments to investment portfolios. A comprehensive understanding of the interaction between climate change, agricultural lending, and credit risk is essential, and a proactive approach to policies and practices is advocated.

In conclusion, addressing the challenges of climate change in the agricultural sector requires a multifaceted approach, which includes specific credit policies, increased access to credit, financial empowerment and addressing social disparities. This review highlights the need for proactive strategies to mitigate climate risks and ensure a resilient agricultural sector. More research and policy interventions are imperative to navigate the complex landscape of climate change impacts on agriculture.

Chapter 3

Vegetative Cycle and Bankruptcy Predictors of Agricultural Firms

Abstract

The characterisation of agricultural activity depends on what firms produce. In this article, we introduce the importance of the vegetative cycle in the prediction of bankruptcy of agricultural firms, analysing the financial ratios proposed by the classical models of Altman (1983), Ohlson (1980) and Zmijewski (1984). We consider 2 228 Portuguese firms, 83 defaulting between 2015 and 2019. The findings confirm that the differences between healthy and bankrupt firms depend on their vegetative cycle. Although predictors based on liquidity are helpful only in predicting the bankruptcy of non-perennial crop firms, activity predictors are better in identifying healthy perennial crop firms. In addition, we show substantial statistical differences in liquidity and profitability, but only in healthy firms. The results encourage the topic of the vegetative cycle to be more present in the construction of more accurate bankruptcy prediction models.

Keywords: agriculture, bankruptcy prediction, financial ratios, non-perennial, perennial.

3.1 Introduction

In an agricultural project, different investment needs and risks depend on the longevity of the crops. The vegetative cycle is related to the risk of exposure to natural phenomena, specific cultivation practices, and threats transversal to other activity sectors. Alone or together, they can affect the survivability of the business.

Agricultural activity is going through challenging times. Even though agricultural productivity increases have belied Malthusian predictions, food shortages remain a severe threat because of the finitude of available arable land (Lanz et al., 2017). Also, climate change is now dominating the concerns and agendas of world leaders. Results from one study of the effects of the climate crisis, using latest-generation crop and climate models, suggest significant effects on the production of different crops, with a 24% decrease in corn but a 17% increase in wheat (Jaegermeyr et al., 2021). Although farmers recognize the negative effect of these climate changes on the productivity of some crops, the predictions are that if they cannot adapt to land use, there will be substantial losses in various economic outcomes (Burke and Emerick, 2016)

However, the need for agriculture to adapt to a sustainable development model and thus avoid global biodiversity loss is on the political agenda, particularly in the European Union (EU). Citizens are pressing for the Common Agricultural Policy to focus more on sustainable production methods. The European Commission established a European Green Deal, with a target of at least 25% of the EU's agricultural land under organic farming (European Commission, 2021).

Agriculture is an activity of diversified practices with different investment needs depending on the crops. Agricultural firms rely on indebtedness to acquire land, machinery, and technology or manage working capital needs. Some of them, in this modernisation effort, succumb and go bankrupt. Also, for world governments to define better policies, particularly how support to the agricultural sector should be structured, it is necessary to deepen the knowledge of its characteristics.

It is essential to understand that certain decisions related to the vegetative cycle of crops may be associated with some financial fragility. Some farmers prefer annual crops because they generate income in their first year, whereas non-perennial crops may require several years before the first harvest. Farmers making these choices demonstrate different risk behaviours (Özerol and Bressers, 2017).

Creditors need to identify bankruptcy predictors to categorise borrowers' risk of default. Agricultural firms also depend on their vegetative cycle, which affects the investment cycle and, thus, their capital requirements. For example, the investment needed to plant a vineyard is significant, and the first harvest is obtained only years later. The same goes for a producer of olives or oranges. These perennial crops are characterised by a vegetative cycle that does not necessarily end with the death of the plant as soon as crops are harvested. Firms dedicated to these crops typically have high planting costs and lower maintenance investments in subsequent years.

Conversely, farmers who grow wheat, rice, or vegetables must renew their investment at the end of the season. Therefore, these non-perennial crops require a shorter asset turnover than perennial crops. We illustrate the vegetative cycle of crops in Figure 3.1

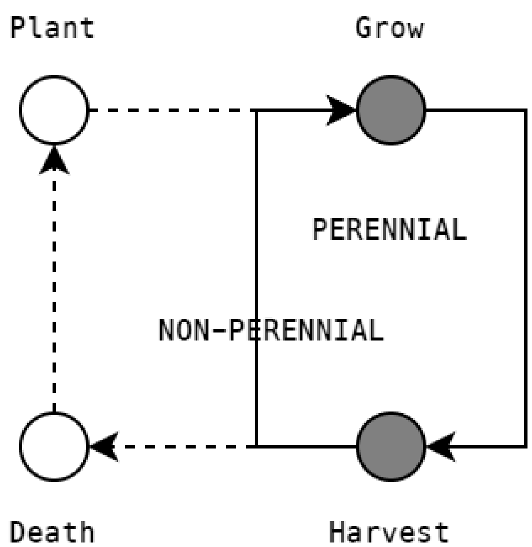

Figure 3.1: Vegetative cycle of crops. Source: Own elaboration.

Dorohan-Pysarenko et al. (2021) state that a long production cycle of some agricultural products can be a severe threat, as it makes the firm unable to react quickly to changes in market conditions. Supposing a considerable time gap between investment and its associated return, inflationary conditions or rising interest rates can cause a firm to go bankrupt. Despite this possibility, most agricultural credit score models tend not to differentiate firms according to their growing cycle and understand them as having similar financial structures in terms of liquidity, solvency, leverage, activity, and profitability. Here, we demonstrate that relying on this assumption can be risky, as the values of traditional bankruptcy predictors fluctuate with the vegetative cycle.

This article analyses the financial variables traditionally used to predict corporate bankruptcy. Besides looking into the difference between healthy and bankrupt firms, we focus on how different these variables are according to their vegetative cycle. Concretely, for Portuguese agricultural firms, we distinguish between firms dedicated to growing non-perennial crops and firms dedicated to growing perennial crops. We use the European Community statistical classification of the Nomenclature of Economic Activities NACE (Nomenclature statistique des activités économiques dans la Communauté européenne) Rev. 2 (European Commission, 2008b), according to the vegetative cycle of crops.

3.2 Literature Review

Because of its unique characteristics, agriculture has been widely studied in the credit risk literature. Focussed on understanding the predictors of the financial health of agricultural firms, researchers have been looking for more specific variables linked to the rural world.

Krause and Williams (1971) studied the behavioural personality of farmers. Limsombunchai et al. (2005) estimated a credit risk model for farm lending, introducing dummy variables distinguishing regions and the farm type (horticulture, orchard/vegetable, livestock/aquaculture and others). Rusiana et al. (2017) looked into how experience, age of farmers, and farm size relate to firms' financial strength. In another approach, Dinterman et al. (2018) concluded that some macroeconomic factors are strong predictors of farm bankruptcies. Investigators of some studies, such as Hardy and Weed (1980) and Zech and Pederson (2002), looked into qualitative and quantitative variables but concluded that only the quantitative variables tended to be statistically significant. More recently, and aware of the influence of climate on agricultural productivity and consequently on the likely financial strength of agricultural firms, Römer and Musshoff (2018) introduced a climate variable in a credit scoring model for the first time. Their main conclusion was that the variable did not improve the model's accuracy. However, it remains to be seen whether the conclusions would not have been different if this climate variable had been affected by the type of agriculture and the vegetative cycle.

Through time, however, investigators of most studies still focussed mainly on quantitative variables and, among them, on financial ratios. See, for instance, Johnson and Hagan (1973), Whittington (1980), Barry and Ellinger (1989), Laitinen (1993), De Jager and Swanepoel (1994), Lukason (2014), Klepac and Hampel (2017), Valaskova et al. (2020), and Chen et al. (2021). Financial ratios provide essential information about a firm's past performance, predicting a firm's future performance prospects, assessing management's decision-making, and risk assessment, and are a critical tool employed in lending agreements to control a firm's activities (Faello, 2015). Among particularly well-known studies in this category, Altman (1968) and Altman (1983) used multivariate discriminant analysis and considered both listed and non-listed firms, respectively; Ohlson (1980) used the logistic scoring model; Zmijewski (1984) used a probit model.

The literature on credit risk in the agricultural sector deserves a deeper understanding of the unique characteristics of its bankruptcy predictors. In particular, we aim to understand better how the vegetative cycle of plantations is a factor to be considered in determining the survival of the non-listed agricultural business. Our analysis is based on a Portuguese data set. To our knowledge, it is also the first study on Portuguese agricultural bankruptcy predictors. We test the following hypotheses:

H_1: The distribution of financial ratios between bankrupt and healthy firms is the same.

H_2: In the subsample of non-perennial crop firms, the distribution of financial ratios between bankrupt and healthy firms is the same.

H_3: In the subsample of perennial crop firms, the distribution of financial ratios between bankrupt and healthy firms is the same.

H_4: The distribution of financial ratios between non-perennial and perennial crop firms is the same.

H_5: In the subsample of healthy firms, the distribution of financial ratios between non-perennial and perennial crop firms is the same.

H_6: In the subsample of bankrupt firms, the distribution of financial ratios between non-perennial and perennial crop firms is the same.

We consider the predictors used in the key references of Altman (1983), Ohlson (1980) and Zmijewski (1984) and categorise the financial ratios used into five groups: *i)* liquidity ratios show the ability of firms to use short-term assets to pay their short-term obligations, *ii)* solvency ratios refer to a firm's ability to honour long-term obligations and continue operating in the future, *iii)* leverage ratios measure debt levels, *iv)* activity ratios measure how well a firm can turn its resources into sales, and *v)* profitability ratios measure the ability to generate gains through efficient resource management.

3.3 Data and Methods

3.3.1 Data Sources

In this study, we focussed on financial predictors for Portuguese agricultural firms. We considered a firm bankrupt if one of three occurrences happened: *i)* bankruptcy at the firm's request, with a court decision, *ii)* bankruptcy at the lender's request, with a court decision, and *iii)* bankruptcy at the firm's request or the lender's request but without a court decision (see Table 3.1).

Table 3.1: Bankrupt firms by bankruptcy type

	2015	2016	2017	2018	2019	Totals
Firm's request	4	6	6	11	14	41
Lender's request	6	1	6	7	7	27
Without court decision	4	3	1	3	4	15

Source: Own elaboration

The data source is the Amadeus database, provided by Bureau van Dijk (2021).

To identify which firms were bankrupt from 2015 to 2019, we consulted Iberinform (a subsidiary of Crédito y Caución, a leading global credit insurance operator).

We considered as healthy all Portuguese agricultural firms with complete financial sheets and income statements from 2014 to 2018. We excluded firms that did not comply with their reporting obligations during that period. We selected the last financial statements available before the bankruptcy for bankrupt firms and the 2018 financial statements for healthy firms. Of the total of 2 228 firms, 83 were considered bankrupt. Also, 1 039 were classified as growing non-perennial crops, and 1 189 were classified as growing perennial crops, according to the statistical classification of economic activities in the European Community (NACE Rev. 2). Table 3.2 presents the firms' distributions according to these classifications.

Table 3.2: Distribution of financial statements

	Healthy	Bankrupt	Totals
Non-perennial crop firms	985	54	1 039
Perennial crop firms	1 160	29	1 189
Total	2 145	83	2 228

Source: Own elaboration

In terms of bankruptcy predictors, we analysed the ratios proposed by Altman (1983), Ohlson (1980) and Zmijewski (1984) listed in Table 3.3. For descriptive statistics, see Table 3.4

3.3.2 Methodology

The emphasis of the analysis is not on obtaining a bankruptcy estimation model. Empirically the tests were performed to analyse the differences between financial ratios according to financial health (bankrupt versus non-bankrupt firms) and the vegetative cycle (non-perennial crop versus perennial crop firms). Our main goal was to test differences in bankruptcy predictors.

From a statistical point of view, removing outliers is an acceptable practice. Including a few outliers could result in the sample's mean and variance and regression's variable

Table 3.3: Investigated financial ratios

Ratios	Description	Altman (1983)	Ohlson (1980)	Zmijewski (1984)
-Liquidity				
WCTA	Working capital / Total assets	x	x	
LIQ	Current assets / Current liabilities			x
CLCA	Current liabilities / Current assets		x	
FUTL	Funds provided by operations / Total liabilities		x	
-Solvency				
RETA	Retained earnings / Total assets	x		
BVEBVL	Book value of equity / Book value of total liabilities	x		
-Leverage				
TLTA (FINL)	Total liabilities / Total assets		x	x
OENEG	1 if total liabilities exceeds total assets, 0 otherwise		x	
-Activity				
STA	Sales / Total assets	x		
-Profitability				
EBITTA	EBIT / Total assets	x		
ROA (NITA)	Net income / Total assets		x	x
INTWO	1 if net income negative last two years, 0 otherwise		x	
CHIN	$(NI_t - NI_{t-1}) / (\lvert NI_t \rvert + \lvert NI_{t-1} \rvert)$		x	
-Dimension				
SIZE	Log (Total assets / GNP price-level index)		x	

GNP – gross national product; *NI* – net income; *EBIT* – earnings before interest and taxes
Source: Own elaboration

coefficients being significantly different from the results that are truly representative of the data set' (Faello, 2015). However, that is not the case for bankruptcy studies. Hossari et al. (2007) analysed 46 different studies on bankruptcy prediction and found that the outliers were not removed in 39 (85%). In this study, we also chose to maintain outliers. Financial ratios tend to present skewed distributions, although some have a shape similar to the normal distribution. Figure 3.2 shows distribution charts and Table 3.5 shows standard Kolmogorov-Smirnov test results confirming our expectations about the non-normality of ratios.

To compare financial ratios across subsamples and given the descriptive analysis described, we performed a non-parametric test proposed by Mann and Whitney (1947). The Mann-Whitney U test can be considered the non-parametric version of the parametric t-test and tests the null hypothesis that a randomly selected value from one sample is likely to be significantly greater or less than a randomly selected value from a second sample. For this purpose, the samples must be independent, which is the case. The U statistic is defined as follows:

Table 3.4: Descriptive statistics of variables

	according to the financial health							according to the vegetative cycle						
	N	*	Mean	Median	Std.Dev.	Min.	Max.	N	*	Mean	Median	Std.Dev.	Min.	Max.
WCTA	2145	H	0.162	0.210	0.529	-5.739	0.983	1039	NP	0.150	0.229	0.786	-16.810	0.973
	83	B	-0.389	0.002	2.016	-16.810	0.997	1189	P	0.133	0.188	0.515	-4.923	0.997
LIQ	2145	H	5.670	2.140	10.115	0.017	95.718	1039	NP	5.152	1.920	9.272	0.000	95.718
	82	B	12.063	0.959	77.408	-0.689	699.301	1188	P	6.564	2.142	22.810	-0.689	699.301
CLCA	2145	H	1.092	0.467	2.756	0.010	60.039	1039	NP	3.202	0.521	68.060	0.010	2191.624
	83	B	41.210	0.997	254.793	-1.452	2191.624	1189	P	2.049	0.466	23.558	-1.452	780.443
FUTL	2145	H	0.357	0.126	1.203	-5.989	29.811	1027	NP	0.310	0.127	0.901	-5.989	9.634
	64	B	-0.093	0.000	0.381	-1.549	1.112	1182	P	0.374	0.114	1.392	2.652	29.811
RETA	2145	H	0.203	0.301	0.916	-23.618	0.978	1039	NP	0.155	0.300	1.172	-23.618	0.978
	83	B	-0.720	-0.015	2.541	-16.117	0.886	1189	P	0.180	0.286	0.904	-14.690	0.976
BVEBVL	2145	H	2.789	0.618	16.365	-0.958	646.009	1039	NP	2.225	0.577	6.224	-0.958	73.873
	83	B	0.480	0.076	2.301	-0.941	18.265	1189	P	3.121	0.591	21.210	-0.934	646.009
TLTA	2145	H	0.706	0.618	0.859	0.002	24.034	1039	NP	0.767	0.634	1.122	0.013	24.034
	83	B	1.511	0.930	2.153	0.052	16.976	1189	P	0.708	0.629	0.770	0.002	15.156
OENEG	2145	H	0.123	0	0.329	0	1	1039	NP	0.139	0	0.346	0	1
	83	B	0.446	0	0.500	0	1	1189	NP	0.132	0	0.339	0	1
STA	2145	H	0.028	0.028	0.169	-2.630	2.011	1036	NP	0.015	0.031	0.210	-2.630	1.004
	64	B	0.558	0.251	0.0670	0.008	3.537	1183	P	0.410	0.296	0.476	0.000	7.344
EBITTA	2145	H	0.028	0.028	0.169	-2.630	2.011	1036	NP	0.015	0.031	0.210	-2.630	1.004
	78	B	-0.249	-0.051	0.540	-3.365	0.535	1187	P	0.021	0.023	0.192	-3.365	2.011
ROA	2145	H	0.012	0.016	0.162	-2.630	1.833	1036	NP	-0.002	0.016	0.204	-2.630	0.878
	78	B	-0.269	-0.067	0.544	-3.383	0.442	1187	P	0.006	0.013	0.188	-3.383	1.833
INTWO	2145	H	0.152	0	0.360	0	1	1025	NP	0.160	0	0.367	0	1
	63	B	0.476	0	0.503	0	1	1183	P	0.163	0	0.370	0	1
CHIN	2145	H	-0.053	-0.053	0.646	-1	1	1024	NP	-0.032	-0.012	0.631	-1	1
	62	B	-0.177	-0.203	0.662	-1	1	1183	P	-0.077	-0.093	0.659	-1	1
SIZE	2145	H	0.608	0.569	0.608	-1.220	3.381	1039	NP	0.592	0.583	0.595	-1.220	2.905
	83	B	0.511	0.583	0.701	-1.148	2.905	1189	P	0.614	0.554	0.626	-1.161	3.381

* H (healthy firms), B (bankrupt firms), NP (non-perennial crop firms), P (perennial crop firms)
Source: Own elaboration

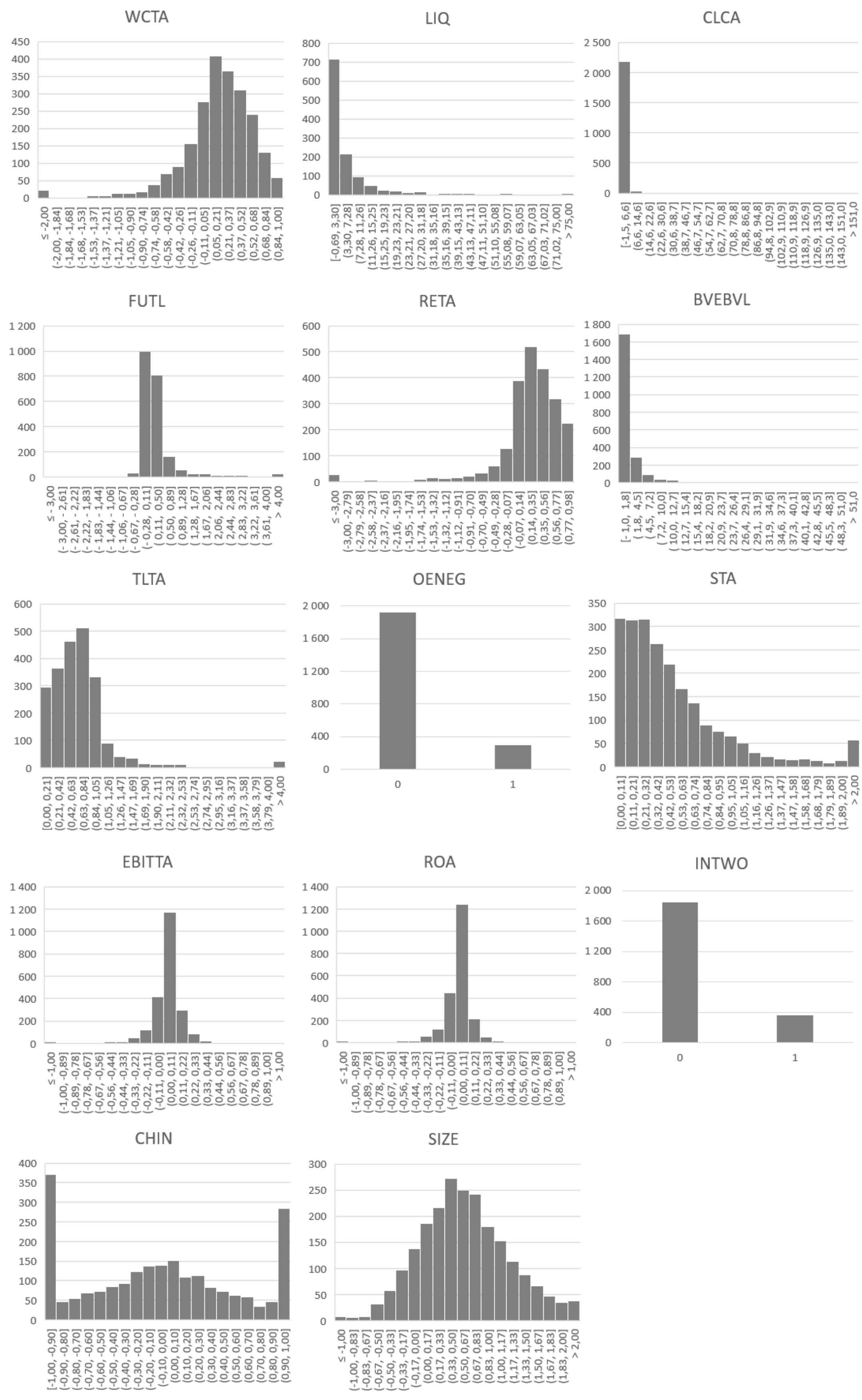

Figure 3.2: Frequency distribution of financial ratios (full sample). Source: Own elaboration.

Table 3.5: One-sample Kolmogorov-Smirnov test

	N	Normal Parameters Mean	Std.Dev.	Test Statistics	p-Value (2-tailed)
WCTA	2228	0.1410	0.6556	0.161	0.000***
LIQ	2227	5.9055	17.8336	0.370	0.000***
CLCA	2228	2.5866	49.5525	0.479	0.000***
FUTL	2209	0.3440	1.1894	0.296	0.000***
RETA	2228	0.1683	1.0375	0.257	0.000***
BVEBVL	2228	2.7029	16.0696	0.410	0.000***
TLTA	2228	0.7356	0.9507	0.255	0.000***
OENEG	2228	0.1351	0.3419	0.519	0.000***
STA	2209	0.5403	0.6402	0.199	0.000***
EBITTA	2223	0.0184	0.2007	0.208	0.000***
ROA	2223	0.0020	0.1957	0.224	0.000***
INTWO	2208	0.1617	0.3682	0.508	0.000***
CHIN	2207	-0.0564	0.6464	0.072	0.000***
SIZE	2228	0.6040	0.6118	0.035	0.000***

***, **, * represent .01, .05, and .10 significance levels, respectively. WCTA – working capital : total assets; LIQ – current assets : current liabilities; CLCA – current liabilities : current assets; FUTL – funds provided by operations : total liabilities; RETA – retained earnings : total assets; BVEBVL – book value of equity : book value of total liabilities; TLTA – total liabilities : total assets; OENEG – 1 if total liabilities exceed total assets, 0 otherwise; STA – sales : total assets; EBITTA – EBIT : total assets; EBIT – earnings before interest and taxes; ROA – net income : total assets; INTWO – 1 if net income negative last two years, 0 otherwise; CHIN – $(NI_t - NI_{t-1}) / (|NI_t| + |NI_{t-1}|)$, where NI – net income; SIZE – log (total assets : GNP price-level index); GNP – gross national product. Source: Own elaboration

$$U = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1 \tag{3.1}$$

$$U = n_1 n_2 + \frac{n_2(n_2+1)}{2} - R_2 \tag{3.2}$$

where n_1 corresponds to the number of observations available from the first population and n_2 to the number of observations from the second. R_1 and R_2 denote the sum of the ranks of the observations from the first and second populations, respectively.

For variables *OENEG* (1 if total liabilities exceed total assets) and *INTWO* (1 if net income negative last two years), which assume binomial distributions, we performed a χ^2 test, defined as follows:

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \tag{3.3}$$

where k corresponds to the number of classes, O_i stands for expected frequencies, E_i stands for expected frequencies, and i is the total number of independent observations.

3.4 Results and Discussion

One factor that assumes importance in interpreting the results is that the financial ratios are not evenly distributed around the mean. Thus, except for the OENEG and CHIN [$(NI_t - NI_{t-1}) / (|NI_t| + |NI_{t-1}|)$] variables, we performed non-parametric tests to compare medians of subsamples.

Table 3.6 and Table 3.7 summarise the Mann-Whitney U and χ^2 tests for the comparison of healthy and bankrupt firms.

Table 3.8 and Table 3.9 summarise the Mann-Whitney U and χ^2 tests results for the vegetative cycle, considering whether the firms were bankrupt or healthy.

Table 3.10 summarises the results of the Mann-Whitney U and χ^2 tests in terms of significance. The left-hand side shows differences in predictors of healthy and bankrupt firms (in the full sample and for the different vegetative cycles). The right-hand side shows differences in predictors according to firms' vegetative cycle (in the full sample, just healthy or bankrupt firms).

The results imply that we reject the null hypotheses (H_1, H_2 and H_3) for almost all financial ratios. Except for STA (sales : total assets), SIZE [log(total assets : GNP price-level index)] and CHIN, most financial ratios were statistically different when comparing healthy and bankrupt firms. The results obtained support the thesis that the bankruptcy predictors used by Altman (1983), Ohlson (1980) and Zmijewski (1984) usefully discriminate between bankrupt and non-bankrupt agricultural firms. The importance of financial

Table 3.6: Mann-Whitney U test according to financial health of firms

	Full sample (H_1)			Non-Perennial Crop Firms (H_2)			Perennial Crop Firms (H_3)		
	Mann-Whitney U	Z-Score	*p*-Value (2-tailed)	Mann-Whitney U	Z-score	*p*-Value (2-tailed)	Mann-Whitney U	Z-score	*p*-Value (2-tailed)
WCTA	63158	-4.497	0.000***	17320	-4.320	0.000***	13269	-1.944	0.052
LIQ	58875	-5.087	0.000***	16647	-4.633	0.000***	12027	-2.348	0.019**
CLCA	63165	-4.496	0.000***	16647	-4.633	0.000***	14347	-1.354	0.176
FUTL	29142	-7.855	0.000***	7516	-6.995	0.000***	6707	-3.816	0.000***
RETA	48072	-7.120	0.000***	11860	-6.863	0.000***	11812	-2.742	0.006***
BVEBVL	47973	-7.137	0.000***	12839	-6.407	0.000***	10876	-3.254	0.001***
TLTA	47973	-7.137	0.000***	12839	-6.407	0.000***	10876	-3.254	0.001***
STA	63692	-0.984	0.325	19124	-0.575	0.565	10089	-2.004	0.045**
EBITTA	41283	-7.609	0.000***	11179	-6.690	0.000***	8885	-3.848	0.000***
ROA	38793	-8.056	0.000***	10513	-7.009	0.000***	8497	-4.068	0.000***
CHIN	58888	-1.541	0.123	15977	-1.786	0.074*	12580	-0.470	0.639
SIZE	84605	-0.767	0.443	24004	-1.207	0.228	16141	-0.372	0.710

***, **, * represent .01, .05, and .10 significance levels, respectively. WCTA – working capital : total assets; LIQ – current assets : current liabilities; CLCA – current liabilities : current assets; FUTL – funds provided by operations : total liabilities; RETA – retained earnings : total assets; BVEBVL – book value of equity : book value of total liabilities; TLTA – total liabilities : total assets; STA – sales : total assets; EBITTA – EBIT : total assets; EBIT – earnings before interest and taxes; ROA – net income : total assets; CHIN – $(NI_t - NI_{t-1}) / (|NI_t| + |NI_{t-1}|)$, where NI – net income; SIZE – log (total assets : GNP price-level index); GNP – gross national product. Source: Own elaboration

Table 3.7: Chi-Square test according to financial health of firms

	Full sample (H_1)				Non-Perennial crop Firms (H_2)				Perennial crop Firms (H_3)			
	N	Chi-Square	df	*p*-Value (2-tailed)	N	Chi-Square	df	*p*-Value (2-tailed)	N	Chi-Square	df	*p*-Value (2-tailed)
OENEG	2228	71.218	1	0.000***	1039	68.867	1	0.000***	1189	8.245	1	0.004***
INTWO	2208	47.325	1	0.000***	1025	41.267	1	0.000***	1183	8.944	1	0.003***

***, **, * represent .01, .05, and .10 significance levels, respectively. OENEG – 1 if total liabilities exceed total assets, 0 otherwise; INTWO – 1 if net income negative last two years, 0 otherwise. Source: Own elaboration

ratios based on liquidity, solvency, and leverage in differentiating between healthy and bankrupt firms was confirmed. Only the CHIN ratio does not reject the null hypothesis in profitability ratios. This ratio analyses the change in earnings in two consecutive years, so a firm in financial difficulties would be expected to show a more significant negative change than a healthy firm. We also noticed that the differences in the SIZE ratio between bankrupt and healthy firms was not statistically significant, regardless of whether they were perennial or non-perennial crop firms. In addition, the WCTA (working capital : total assets) and CLCA (current liabilities : current assets) financial ratios showed statistically significant differences at 1% in non-perennial crop firms. However, they did not show differences in the group of perennial crop firms. The CLCA ratio was strongly

Table 3.8: Mann-Whitney U test according to vegetative cycle of crops

	Full sample (H_4)			Healthy Firms (H_5)			Bankrupt Firms (H_6)		
	Mann-Whitney U	Z-score	*p*-Value (2-tailed)	Mann-Whitney U	Z-score	*p*-Value (2-tailed)	Mann-Whitney U	Z-score	*p*-Value (2-tailed)
WCTA	574771	-2.833	0.005***	522908	-3.385	0.001***	700	-0.793	0.428
LIQ	599414	-1.173	0.241	561321	-0.698	0.485	738	-0.176	0.860
CLCA	598375	-1.275	0.202	561321	-0.698	0.485	684	-0.946	0.344
FUTL	583475	-1.570	0.116	539029	-2.258	0.024**	363	-1.399	0.162
RETA	605595	-0.798	0.425	547516	-1.664	0.096*	5930	-1.815	0.070*
BVEBVL	602509	-1.002	0.316	567645	-0.256	0.798	595	-1.796	0.073*
TLTA	602509	-1.002	0.316	567645	-0.256	0.798	595	-1.796	0.073*
STA	426066	-12.094	0.000***	400070	-11.979	0.000***	317	-2.162	0.031**
EBITTA	586971	-1.848	0.065*	534390	-2.582	0.010***	625	-0.667	0.505
ROA	599079	-1.046	0.296	545489	-1.806	0.071*	618	-0.740	0.459
CHIN	579544	-1.755	0.079*	543722	-1.933	0.053*	431	-0.256	0.798
SIZE	617149	-0.035	0.972	568579	-0.190	0.849	699	-0.802	0.422

***, **, * represent .01, .05, and .10 significance levels, respectively. WCTA – working capital : total assets; LIQ – current assets : current liabilities; CLCA – current liabilities : current assets; FUTL – funds provided by operations : total liabilities; RETA – retained earnings : total assets; BVEBVL – book value of equity : book value of total liabilities; TLTA – total liabilities : total assets; STA – sales : total assets; EBITTA – EBIT : total assets; EBIT – earnings before interest and taxes; ROA – net income : total assets; CHIN – $(NI_t - NI_{t-1}) / (|NI_t| + |NI_{t-1}|)$, where NI – net income; SIZE – log (total assets : GNP price-level index); GNP – gross national product. Source: Own elaboration

Table 3.9: Chi-Square test according to vegetative cycle of crops

	Full sample (H_4)				Healthy Firms (H_5)				Bankrupt Firms (H_6)			
	N	Chi-Square	df	*p*-Value (2-tailed)	N	Chi-Square	df	*p*-Value (2-tailed)	N	Chi-Square	df	*p*-Value (2-tailed)
OENEG	2228	0.204	1	0.652	2145	0.476	1	0.490	83	3.309	1	0.069*
INTWO	2208	0.040	1	0.841	2145	0.7457	1	0.388	63	1.046	1	0.306

***, **, * represent .01, .05, and .10 significance levels, respectively. OENEG – 1 if total liabilities exceed total assets, 0 otherwise; INTWO – 1 if net income negative last two years, 0 otherwise. Source: Own elaboration

associated with liquidity, so it was a strong candidate for predicting bankruptcies for agricultural activities dedicated to crops with a shorter vegetative cycle. However, the STA ratio was statistically different at a significance level of 5% according to financial health in perennial crop firms. However, it did not show any difference in non-perennial crop firms. In other words, the STA ratio did not predict bankruptcy for agricultural firms involved in short-cycle plantations.

When we subdivided according to the vegetative cycle (hypotheses H_4, H_5 and $H_{6)}$, the STA ratio, which measures the relationship between sales and total assets, presented solid statistical evidence (at 1% significance) depending on the vegetative cycle. This finding is understandable, given the greater expression that this ratio assumed in firms engaged

Table 3.10: Summary table

Ratios	According to Financial Health			According to Vegetative Cycle		
	Full Sample	Non-Perennial Crop Firms	Perennial Crop Firms	Full Sample	Healthy Firms	Bankrupt Firms
- *Liquidity*						
WCTA	***	***		***	***	
LIQ	***	***	**			
CLCA	***	***				
FUTL	***	***	***		**	
- *Solvency*						
RETA	***	***	***		*	*
BVEBVL	***	***	***			*
- *Leverage*						
TLTA	***	***	***			*
OENEG	***	***	***			*
- *Activity*						
STA			**	***	***	**
- *Profitability*						
EBITTA	***	***	***	*	**	
ROA	***	***	***		*	
INTWO	***	***	***			
CHIN		*		*	***	
- *Activity*						
SIZE						

***, **, * represent .01, .05, and .10 significance levels, respectively. WCTA – working capital : total assets; LIQ – current assets : current liabilities; CLCA – current liabilities : current assets; FUTL – funds provided by operations : total liabilities; RETA – retained earnings : total assets; BVEBVL – book value of equity : book value of total liabilities; TLTA – total liabilities : total assets; OENEG – 1 if total liabilities exceed total assets, 0 otherwise; STA – sales : total assets; EBITTA – EBIT : total assets; EBIT – earnings before interest and taxes; ROA – net income : total assets; INTWO – 1 if net income negative last two years, 0 otherwise; CHIN – $(NI_t - NI_{t-1}) / (|NI_t| + |NI_{t-1}|)$, where NI – net income; SIZE – log (total assets : GNP price-level index); GNP – gross national product. Source: Own elaboration

in non-perennial crops compared with those engaged in perennial crops. In other words, the transformation of assets into sales was higher in plantations with a shorter vegetative cycle. Interestingly, some financial ratios showed statistically significant differences when firms were healthy. However, they lost some significance when firms went bankrupt. This is the case of the WCTA, FUTL (funds provided by operations : total liabilities), STA, EBITTA [earnings before interest and taxes (EBIT) : total assets], ROA (net income : total assets) and CHIN. We can infer that only when firms are in regular operation, without difficulties that affect their survival, can they show different financial structures according to the vegetative cycle of the plantations. The WCTA ratio, which in the group of healthy firms presented solid statistical evidence of the differences between firms with different vegetative cycles, lost all significance in the bankrupt ones. We can infer that when a firm is bankrupt, the vegetative cycle does not affect the short-term cash balance measured by this ratio that measures short-term financial health. This is an interesting finding, because working capital measures a firm's ability to meet its current liability commitments by using current assets. Furthermore, EBITTA, which was strongly differentiated between the vegetative cycles of healthy firms, lost this differentiation in the bankrupt firms. This finding suggests that, for agricultural firms that are financially stable, the profitability ratio varies depending on the vegetative cycle. However, for firms that are bankrupt, the profitability ratio does not show any significant variation based on the vegetative cycle. This suggests that for bankrupt firms, other factors are likely influencing their financial performance, rather than the crop cycle itself.

We found some similarities with other studies concerning the characterisation of plantations, but never specifically to the vegetative cycle. This similarity is the case of the study by Hardy and Weed (1980), who covered plantations and livestock, and Limsombunchai et al. (2005), who considered not only vegetables but even aquaculture.

Structural, climatic and biophysical characteristics can be decisive in bankruptcy prediction. Exposure to uncertainty varies depending on the lifespan of the plantations. For example, the probability of a vineyard being affected by a climatic phenomenon during its long life differs from that of a rice plantation that lasts only one year. Also, the charges are different depending on the crop cycle. Thus, we must assess whether a model for predicting bankruptcy should not consider these differences, knowing that some financial ratios are also different.

Our findings suggest that the vegetative cycle can affect the differentiation between healthy and bankrupt firms, which motivates several reflections. Vegetative cycle considerations are absent from previous studies on bankruptcy in the agricultural sector. The analysis we presented here exposes that as a limitation. Indeed, model accuracy can be improved by considering different vegetative cycles. In terms of future studies contextualised with the threat of climate change and its influence on farmers' preferences for different vegetative cycles of crops, it is essential to create credit risk models sensitive to cycles. Finally, although not always transversal between economic blocks or countries, the structures for classifying economic activities should allow for the identification of the vegetative cycle.

Agricultural firms, the healthy ones more than the bankrupt ones, presented statistically different ratios between vegetative states, mainly regarding liquidity and profitability. These findings, extrapolated to other areas of economic study, open a great potential for new findings unrelated to bankruptcy prediction.

3.5 Conclusion

In this article, we conducted an empirical analysis on a substantial sample of firms within the Portuguese agricultural sector. We performed a cross-analysis, comparing different financial ratios as originally studied by Altman (1983), Ohlson (1980), and Zmijewski (1984). This comparison was carried out based on the financial health of firms and the vegetative cycle of plantations.

Our results identify how useful the classical predictors are for differentiating the financial health of agricultural firms dedicating themselves to crops with different vegetative cycles. Some ratios revealed the ability to differentiate between two categories (perennial crop and non-perennial crop firms). However, others revealed this ability in only one of the groups studied. Our findings indicate that the financial predictors of bankruptcy generally differed between groups of firms according to their category (liquidity, solvency, leverage, profitability, and dimension). In liquidity ratios, statistical evidence was lacking in differentiating healthy firms from bankrupt ones when they were dedicated to plantations with a vegetative cycle renewed annually (non-perennial crop firms). However, the activity ratio was different only in perennial crop firms. In the second group of findings, we obtained statistical evidence that some liquidity and profitability ratios differed in differentiating the vegetative cycles only when firms were healthy. In none of the tests performed did the size of the firms show any statistical ability to differentiate the financial condition of the firms.

Implications for theory, practice and policy makers. Stakeholders must understand agriculture as an activity full of specifics that react differently to exogenous factors. Economic policies also have a significant effect on farm profitability. Farmers, when faced with difficulties, adapt quickly to differentiated agronomic practices. However, the results depend on investment cycles, and the uncertainty increases the longer the vegetative cycle. In the future, the effect of climate change on farmers' investment decisions can be significant, including from a credit risk perspective. Farmers can opt for crops with more resilient vegetative cycles for economic survival. Understanding how the predictors of financial distress are revealed among different cycles is an essential tool for those who support agricultural activity, whether financial institutions, suppliers or policymakers, regardless of whether they are in economic blocks, as is the case of the EU.

Limitations. Some limitations should be considered when interpreting these results. The first limitation is that the variables studied are not necessarily those that could be the most significant in a statistical estimation context. We took the predictors from the previous literature. Another area for improvement is the fact that we focussed on Portugal alone. The national context and the potential mismatch of transnational realities owing to the heterogeneity of the agricultural sector require care when extrapolating to other situations.

This article emphasizes the importance of incorporating the vegetative cycle when predicting bankruptcy, demonstrating how agricultural cycles affect financial stability. Future bankruptcy models could benefit from including this factor, along with key macroeconomic variables. These macroeconomic factors are essential for understanding the broader economic conditions that influence the financial health of businesses, especially in the agricultural sector.

Additionally, expanding the empirical analysis to a transnational context could provide valuable insights by examining how local agricultural cycles interact with global economic trends. The study could also go beyond just the vegetative cycle type, exploring specific crops and their distinct vulnerabilities to market fluctuations and climate variability. Finally, incorporating the impact of European agricultural policies on the financial health of agricultural firms would further strengthen the analysis.

Chapter 4

Financial Distress in European Vineyards and Olive Groves

Abstract

This study focuses on predicting the financial distress of agricultural firms operating in the vineyards and olive crops sectors in Mediterranean countries, specifically in Portugal, Spain, and Italy, which are crucial to producing these crops. The study sample size is 5,057 firms.

Twelve models are presented, estimated from subsamples of combinations between countries and crops. Logistic regression is used for the estimation of these models. The accuracy of the models is evaluated, considering the importance of misclassification costs. Additionally, the areas under the ROC curves are calculated and compared in a dynamic of possible combinations between crops and countries. The study concludes that there are differences between the two sectors, as well as across countries, and suggests that dedicated models for each country or crop may improve the models' accuracy.

Keywords: agriculture, financial distress, prediction models, ROC curves.

4.1 Introduction

The similarities between the Mediterranean regions in biophysical, climatic, and structural conditions are widely recognised. From this similarity, agronomic practices also evolved, predominantly for certain plantations, namely cultivating vineyards and olive groves (Caraveli, 2000). "In the Mediterranean basin, the olive along with the vine constituted the equivalent of the rural industries of the North. This equivalence is important, if not for the volume of income, at least for the number of people they engaged, since the 16th century and on, whenever an increase of the cultivation of the olive is observed" (Loumou and Giourga, 2003, p.90). In 2020, the European Union (EU) explored 3.2 million hectares of vineyards and 5.1 million hectares of olive groves, corresponding to 45% of the world's wine-growing area and 40% of the olive-growing area. From 1962, when the first common market organization was created, until 2013, the last reform was revised, the wine sector became more competitive, with simpler and more balanced market rules. European policies over this half century have significantly transformed the sector through diversified interventionist measures, initially supporting divestments (grubbing up) and then supporting firms in financing the restructuring of most of the current vineyards. In 2014, the eight largest EU wine-producing countries accounted for 94% of the EU's wine exports and 65% of global wine exports (Correia et al., 2019). Concerning the production of olives, mainly destined for the extraction of olive oil, the Mediterranean countries have had almost absolute dominance in the world due to their unique and highly favourable climate for this culture. In the European Union, Spain, Italy, Greece, and Portugal emerge as the primary contributors to this market, accounting for a substantial 99% of the EU-27[1] and 40% of the world, respectively (FAO, 2022). Through Figure 4.1, it is possible to verify the largest producers of grapes and olives in the European Union.

While these crops play a crucial role in European agriculture and the economy, uncertainties loom over their future. Due to climate change, Fraga et al. (2019) refer to risks to these countries' economic sustainability of vineyards and olive groves. Further-

[1]The 27 European Union countries after the UK left the EU.

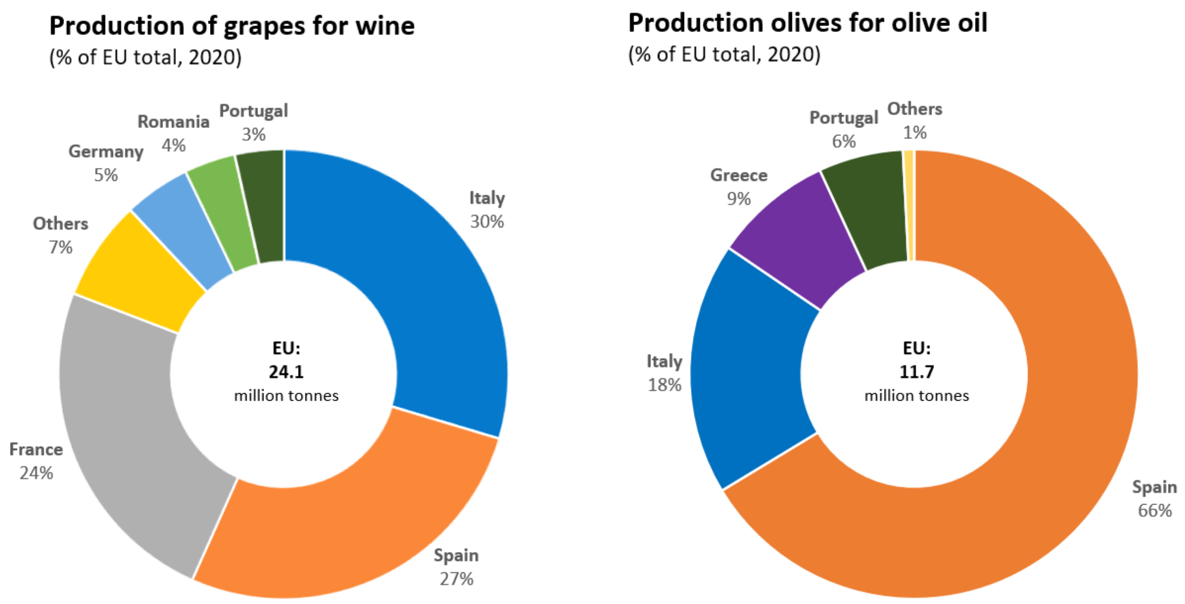

Figure 4.1: Production of grapes and olives in EU. Source: Eurostat.

more, within the olive sector, there is a coexistence of modern and traditional farms, exhibiting significant disparities in productivity, management practices, economic performance, contributions, and sustainable values, raising concerns about the adaptability and survival prospects of traditional family farms (Mokrani et al., 2022). The prevalence of small-scale agriculture also impacts firm viability, wherein farm size and distribution are intrinsically linked to efficiency, with larger farms demonstrating greater productivity and technological advantage, enhancing their survival prospects (Ruz-Carmona et al., 2023).

On the other hand, the Mediterranean countries, compared to Northern Europe, suffer from an ageing agricultural population and poor farm training, which negatively impacts their financial performance. The reformulation of direct payments under the CAP (Common Agricultural Policy), added to the impact of climate change and the liberalisation of agricultural trade, places these rural economies in the South more exposed to financial risks (Giannakis and Bruggeman, 2015).

The similarities in the geography and agronomic practices of Portugal, Spain and Italy are widely studied (Arnalte-Alegre and Ortiz-Miranda, 2013; Beopoulos, 2017). However, this does not mean that we can consider a single financial distress prediction model for agricultural firms from different countries and crops.

The paper aims to examine the financial sustainability and risk of agricultural firms, particularly vineyards and olive groves in Portugal, Spain, and Italy. These crops play a vital role in the region's agriculture and economy. However, uncertainties and challenges threaten their future, including climate change risks, disparities between modern and traditional farms, and the impact of policy changes on financial performance. While studying similarities in geography and agronomic practices, a one-size-fits-all approach may not be suitable due to unique economic, social, and environmental factors influencing the financial health of these farms. Hence, financial distress prediction tools for each of these dimensions are presented.

The remainder of the paper is organised as follows. Section 4.2 addresses the literature on the definition of financial distress, particularly in agriculture, and the relevance of the ROC (receiver operating characteristic) curve to measuring the accuracy of predictive models. Section 4.3 describes the data and methodology, and section 4.4 presents and discusses the results. Finally, Section 4.5 presents the conclusions and limitations.

4.2 Literature Review

After the seminal study by Beaver (1966), the prediction of bankruptcy and financial distress has been a subject of significant interest and research among scholars. While bankruptcy is a legal action that decrees the end of business activity, financial distress results from financial difficulties compromising the firm's ability to honour its commitments. We can define financial distress as a stage before a court decrees bankruptcy. Fitzpatrick (1934) characterizes five moments in the life of a firm until bankruptcy: (i) incubation, (ii) embarrassment, (iii) financial insolvency, (iv) total insolvency, and (v) confirmed insolvency. Altman et al. (2019) goes deeper into the different concepts and list six reasons that alone or together can contribute to corporate failure, namely (i) poor operating performance and high financial leverage, (ii) lack of technological innovation, (iii) liquidity and funding shock, (iv) relatively high new business formation rates in specific periods, (v) deregulation of key industries, and (vi) unexpected liabilities. The duration between a firm showing signs of financial distress and its bankruptcy being declared is imprecise. However, the years before this failure show predictors of this failure. Chan and Rotenberg (1988) estimated this duration to be four years in the Canadian agricultural sector. However, financial distress does not necessarily imply bankruptcy, and many firms prosper after going through moments of financial difficulty.

In the credit risk literature, there are different approaches to defining financial distress, as if it were a singular state dependent on numerous internal or external variables, in addition to different interactions with the local policies and economies in which they operate. “A firm is in financial distress at a given point in time when the liquid assets of the firm are not sufficient to meet the current requirements of its hard contracts“ (Hotchkiss et al., 2008, p.6). Wruck (1990) defines financial distress as an insufficient cash flow to cover current obligations. Asquith et al. (1994) bases the entire definition on interest coverage ratios, classifying the firm in financial distress if, for two consecutive years, EBITDA (earnings before interest, taxes, depreciation, and amortization) is less than interest expenses or if in one year, EBITDA is less than 80 per cent of its interest expenses. Whitaker (1999) reports this state for the first year in which cash flow is less than current long-term debt maturities. However, one thing is for sure, “distinguishing between financially distressed and healthy companies is more difficult than the traditional comparison between bankrupt and healthy companies“ (Platt and Platt, 2006, p.155).

There are characteristics of the markets and sectors of activity in which firms operate which can compromise the effectiveness of insolvency prediction models. Research on these differences is well known and focuses on various aspects such as cultural, legal, regulatory, or macroeconomic. The financial health of firms must be examined in loco within the local macro environment (Khoja et al., 2019). Nevertheless, within similar markets, depending on the sector of activity, there may be variables that stand out as affecting the financial health of firms. In the European Union (EU-27), public policies are shared in the agricultural sector, and even in countries that share similar climates and favourable conditions for the exploitation of certain agricultural products, this does not mean that firms in these countries have similar levels of financial distress.

The lack of a formal definition of financial distress, unlike bankruptcy, which the court defines on a specific date, motivated researchers to propose concepts that somehow characterise the financial strength of firms but emphasise the subjectivity about the most appropriate variables for the definition of this state of the financial health of firms. The transnational specificities or agricultural products cultivated are only sometimes analysed in the research repository on financial distress in agriculture. The data is collected across territories without any differentiation. Klepac and Hampel (2017) tested 250 agriculture business firms in the EU (forestry and logging, fishing, and aquaculture), of which 62 reported the default of payment or insolvency proceedings. Vavřina et al. (2013) were concerned with homogenizing the data, limiting the choice of 2,581 active and 71 bankrupted agribusiness firms in the Visegrad Group countries (Czechia, Hungary, Poland, and Slovakia). Other studies selected firms from agricultural subsectors without proper homogenization criteria. Karas et al. (2017) selected 450 active and 25 bankrupt firms. Data were obtained from cereals, rice, grapes, plant propagation, raising of sheep and goats, and mixed farming subsectors. In this selection, they mixed small samples from such subsectors as non-perennial crops, perennial crops and livestock.

Literary approaches that compare predictive models of bankruptcy or financial difficulties in agriculture across various countries and crop combinations still need to be improved. A great diversity of agronomic practices influences the business structures themselves. The risk of failure for a farmer who produces olives may differ from another farmer who explores vineyards. The same is valid for many other combinations. This research opens a reflection on the subject and aims to contribute to filling this gap.

4.3 Data and Methods

4.3.1 Data and Definition of Financial Distress

The financial data used in this study is sourced from the Orbis database, provided by Bureau van Dijk. This database is a reputable and widely utilized financial resource, consolidating information from diverse sources, including firm reports, regulatory filings, and other publicly available records. It offers extensive financial data for a vast number of firms worldwide. Within the scope of our research, we employed this database to collect financial information about firms operating in the viticulture and oliviculture sectors across European countries. Only firms that have not failed to publish financial statements in the years 2018, 2019 and 2020 are considered. We excluded firms that did not have known operating revenue (turnover) in these three years. Of the European countries dedicated to viticulture and oliviculture, only Italy, Spain, and Portugal had sufficient financial data available[2]. Table 4.1 presents the distribution of firms according to the above classifications. We divided data into two groups: just 2018 and both 2019 and 2020. Following the same procedure devised by Platt and Platt (2008), we implemented a two-step procedure to categorize firms according to their financial health. To belong to the healthy group, firms had to register three positive variables in 2019 and 2020. If any of these metrics failed, they would be placed in the financially distressed group; otherwise, they are categorized as healthy. The variables chosen were (i) EBITDA to interest coverage, (ii) EBIT (earnings before interests and taxes), and (iii) Net income before special items[3]. The financial ratios used to estimate the models are obtained from the 2018 financial statements. This methodology allows us to retrospectively define the status of firms, knowing their performance in the following two years.

Table 4.1: Distribution of financial statements

	Vineyards			Olive Groves			Totals		
	H	FD	% FD	H	FD	% FD	H	FD	% FD
Portugal	738	117	13.7%	351	51	12.7%	1089	168	13.4%
Spain	426	87	17.0%	471	83	15.0%	897	170	15.9%
Italy	1456	399	21.5%	643	235	26.7%	2099	634	23.2%
Totals	2620	603	18.7%	1465	369	20.1%	4085	972	19.2%

Healthy (H), Financial Distressed (FD), (% FD) Proportion of distressed.
Source: Own elaboration

[2]Although there were 399 growing grapes French firms, there were only two firms in olive culture. In Greece, only 4 growing grapes firms were available.

[3]To calculate this last variable and consider the lack of uniformity between the accounting standards, we adopted the formula of extracting extraordinary items (revenue and expenses) from net income.

Table 4.2 presents descriptive statistics of applying the two-step procedure to the variables that define the categorization of firms between healthy and financially distressed.

4.3.2 Method and Hypotheses

Although the methodology of discriminant analysis gained popularity with Altman (1968), it was from the 1980s onwards that logistic regression came to be preferred by researchers and is even used in the overwhelming majority of bank scorecards (Nyitrai and Virág, 2019). Ohlson (1980) as at the origin of this popularity with his seminal work in the literature on credit risk. In this study, given the characteristics of the sample, namely the disproportion between healthy firms and firms in financial distress, we use binary logistic regression.

In logistic regression or a probit model, the model's predictive capacity also depends on defining a cutoff to separate healthy firms from the rest. There is no single way to determine the optimal cutoff. Ohlson (1980) states that previous prediction studies have two assumptions present. First is the presentation of a (mis)classification matrix. Second, an additive property in which the best cutoff point is the one that minimizes the sum of type I (classify a distressed firm as healthy) and type II (classify a healthy firm as distressed) percentage errors. However, it must be considered that comparing models, predictors, and data sets in different periods is exceptionally difficult. Also, the costs are not equal. Classifying a distressed firm as healthy implies losing the return on investment, and classifying a healthy firm as distressed means losing the investment opportunity (Agarwal and Taffler, 2008). Other authors have tried other approaches. Hsieh (1993) defines type I error as the opportunity cost of holding a long position in equity securities of failing firms. In turn, the type II error is defined as the opportunity cost of selling short securities of healthy firms. Aware of this importance, Dopuch et al. (1987) and Koh (1992) studied the misclassification costs of type I and type II Errors through proportions from 1:1 to 20:1 and 1:1 to 500:1, respectively. The analysis of type I and type II Errors is very present in the literature. It is indispensable in this kind of research, having the great advantage of being easy to interpret, even for those who do not

Table 4.2: Descriptive statistics of the firms categorization procedure

		EBITDA interest coverage[a] 2019		EBITDA interest coverage 2020		EBIT 2019		EBIT 2020		net income before special items[b] 2019		net income before special items 2020	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Italy													
Vineyards	FD	-141.92	-60.52	-144.30	-52.19	-216.33	-97.97	-259.77	-95.47	-232.76	-101.58	-263.18	-99.96
	H	260.08	31.70	226.62	21.74	130.41	14.30	92.02	8.06	82.91	3.34	62.69	1.63
Olive grows	FD	-52.73	-16.29	-55.14	-15.86	-82.54	-27.03	-88.73	-27.20	-86.59	-28.66	-89.93	-29.60
	H	31.97	4.41	28.65	3.54	-3.21	1.83	9.40	2.67	10.61	0.45	7.18	0.66
Portugal													
Vineyards	FD	-72.19	-19.13	-70.23	-20.89	-86.52	-27.78	-89.81	-30.40	-104.21	-31.50	-107.81	-31.56
	H	94.85	22.93	81.86	17.97	55.07	9.29	38.15	4.93	35.84	5.74	23.09	2.95
Olive grows	FD	-121.49	-51.84	-177.84	-39.05	-149.69	-102.96	-225.64	-62.55	-177.67	-111.17	-271.99	-64.29
	H	119.01	29.78	114.26	30.63	65.64	12.64	67.43	10.98	23.47	8.54	47.32	7.93
Spain													
Vineyards	FD	-61.54	-28.22	-57.07	-28.99	-94.27	-38.54	-87.15	-43.20	-80.69	-37.36	-74.12	-34.00
	H	125.57	29.35	129.40	19.20	82.78	14.71	86.99	6.91	68.92	8.51	65.37	3.70
Olive grows	FD	-71.36	-28.37	-73.77	-20.01	-85.83	-45.76	-88.40	-34.22	-74.47	-36.71	-79.13	-31.40
	H	88.46	29.52	61.67	20.51	59.51	15.77	31.93	10.68	38.85	9.62	59.20	5.84

Healthy (H), Financial Distressed (FD).
Source: Own elaboration

[a] EBITDA interest coverage = EBITDA - Financial expenses
[b] Net income before special items = Net income + Extraordinary and other expenses - Extraordinary and other revenue

have a high level of mathematics and statistics education (Čámská et al., 2016). In short, the accuracy of a model goes far beyond the simple calculation of the correct percentage of observation classifications. Moreover, minimizing total error probabilities is different from minimizing total error costs.

In this subjectivity, other powerful tools were adopted, such as the ROC curve representing the universe of possible events (Hanley and McNeil, 1982). In World War II, the ROC curve was first used to detect enemy objects on the battlefield. From then on, its expansion into other areas of knowledge was rapid, being widely recognized for its advantages, namely in biosciences, atmospheric forecasting, or finance. The analyses obtained through the ROC curve are considered powerful tools for validating the discriminatory power of a predictive model (Basel Committee on Banking Supervision, 2005). ROC Curve results from how the scores obtained from the prediction model are distributed between firms considered healthy and in financial distress and can be easily understood through Figure 4.2. A perfect model would not confuse the scores between financial health categories, but in the real world, there is an overlapping zone in which both coexist. Hence, a broad debate exists about the best cutoff point to consider in a financial distress prediction model.

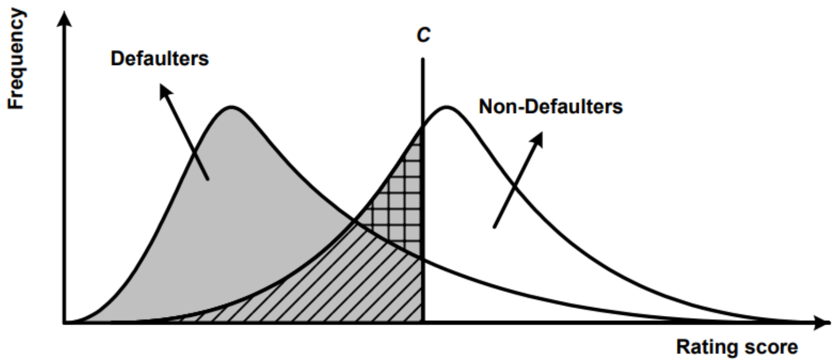

Figure 4.2: Distribution of scores according to financial health. Source: (Basel Committee on Banking Supervision, 2005, p.37).

This methodology, represented as a curve, is represented by an antagonistic relationship between sensitivity (the proportion of correctly classified non-failures) and specificity (the proportion of correctly classified failures) along a continuous scale of cutoff points. In other words, the area under the curve (AUC) summarises curve performance across all thresholds, and a cutoff point is a defined criterion to separate failed from healthy firms. The higher the AUC, where the x-axis represents (1-specificity) and the y-axis represents sensitivity, the greater the model's discriminatory power. The ROC curve conveys the conjugation of the type I and type II error curves along an axis. In practice, AUC is a measure of prediction accuracy, where 1 will represent a perfect model. On the contrary, an AUC equal to 0.5 will demonstrate the total ineffectiveness of the model in predicting an occurrence (Altman et al., 2010; Hanley and McNeil, 1982). Thus, a larger AUC indicates better predictability of the model.

The ROC curve is widespread in medical diagnosis, where there are demanding precision scales. For example, are expected AUCs between 0.80 and 0.90 for chest x-ray films and 0.80 to 0.90 for mammography. In weather forecasting, are accepted values from 0.75 for rain forecast and 0.65 for temperature intervals or fog Swets (1988). In one of the unavoidable references in the literature, Lemeshow et al. (2013) does not mention an optimal scale to describe the quality of discrimination, but in general, is used the following rule: (i) no discrimination if AUC is equal to 0.5, (ii) poor, if between 0.5 and 0.7, (iii) acceptable, if between 0.7 and 0.8, (iv) excellent, if between 0.8 and 0.9, and (v) outstanding if it is above 0.9. About financial distress prediction models in agriculture, Klepac and Hampel (2017) mentions 4 classifications: (i) eligible if AUC is between 0.50 and 0.75, (ii) good if between 0.75 and 0.92, (iii) very good if between 0.92 and 0.97, and (iv) perfect if it is above 0.97. Valaskova et al. (2020) defines five levels of accuracy: (i) inappropriate for bankruptcy prediction if below 0.6, (ii) poor if between 0.6 and 0.7, (iii) fair if between 0.7 and 0.8, (iv) good if between 0.8 and 0.9, and (v) excellent if above 0.9.

This study analyzes the accuracy of the presented models by examining the areas under the ROC curves and, specifically, the differences between them. Through the interaction between the different subsamples and trying out various combinations, we tested the following null hypotheses:

- Interaction between the $GlobalModel$[4] and the $AggregateModels$[5]:

[4] The total sample, all types of crops and countries.
[5] Subsamples by type of crop, or by country.

H_1: Between the Global and Vineyards Models, there are no differences in the AUCs.

H_2: Between the Global and Olive Groves Models, there are no differences in the AUCs.

H_3: Between the Global and Portugal Models, there are no differences in the AUCs.

H_4: Between the Global and Spain Models, there are no differences in the AUCs.

H_5: Between the Global and Italy Models, there are no differences in the AUCs.

- Interaction between Crop Aggregates:

H_6: Between the Vineyards and Olive Groves Models, there are no differences in the AUCs.

- Interaction between Country Aggregates:

H_7: Between the Portugal and Spain Models, there are no differences in the AUCs.

H_8: Between the Portugal and Italy Models, there are no differences in the AUCs.

H_9: Between the Spain and Italy Models, there are no differences in the AUCs.

- Combined Interaction of $IndividualModels$[6]:

H_{10}: Between the Portugal Vineyards and Portugal Olive Groves Models, there are no differences in the AUCs.

H_{11}: Between the Spain Vineyards and Spain Olive Groves Model, there are no differences in the AUCs.

H_{12}: Between the Italy Vineyards and Italy Olive Groves Models, there are no differences in the AUCs.

H_{13}: Between the Portugal Vineyards and Spain Vineyards Models, there are no differences in the AUCs.

H_{14}: Between the Portugal Vineyards and Italy Vineyards Models, there are no differences in the AUCs.

H_{15}: Between the Spain Vineyards and Italy Vineyards Models, there are no differences in the AUCs.

[6]Individual interaction between crops and countries.

H_{16}: Between the Portugal Olive Groves and Spain Olive Groves Models, there are no differences in the AUCs.

H_{17}: Between the Portugal Olive Groves and Italy Olive Groves Models, there are no differences in the AUCs

H_{18}: Between the Spain Olive Groves and Italy Olive Groves Models, there are no differences in the AUCs.

4.3.3 Independent Variables

Table 4.3 contains 12 financial ratios to be tested as potential independent variables in the model according to those most commonly present in bankruptcy and financial distress prediction studies. For this study, we combine four categories of ratios. The structure of presentation in this paper revolves around four key aspects: (i) liquidity ratios, assessing firms' capacity to fulfill short-term obligations; (ii) solvency (leverage) ratios, linked to the level of indebtedness and the ability to meet both short-term and long-term payment commitments, ensuring sustained operation; (iii) profitability ratios, gauging the ability to generate income through efficient resource management; and (iv) activity/other ratios, measuring the composition of fixed assets and the operational activity of agricultural firms.

We chose to exclude financial ratios that presented inconsistent values with the expected sign in this list by logical intuition. For example, the profitability ratio that measures the relationship between earnings and equity (return on equity) could simultaneously contain negative signals in the numerator and denominator. That would result in a positive and erroneously good ratio, and we found 418 firms in this condition on our preliminary data. Also, the solvency ratio, which measures the relationship between total liabilities and equity (debt-to-equity), could be affected by negative equity found in 489 firms in our data. The result would be contrary to the perception that this ratio will worsen the greater the relationship between the numerator and denominator.

Table 4.3: Initial set of financial ratios

	Ratios	Description	Observations
Liquidity	CCL	Cash and equivalents / Current liabilities	Cash Ratio
	WCTA	Working capital / Total assets	
	CATA	Current assets / Total assets	
	CR	Current assets / Current liabilities	Current Ratio
Solvency/Leverage	RETA	Retained earnings / Total assets	
	EQTA	Equity / Total assets	Shareholder Equity Ratio
	TLTA	Total liabilities / Total assets	Debt-to-Assets Ratio
Profitability	EBITTA	EBIT / Total assets	
	CFTA	(Net income + Deprec + Amortiz) / Total Assets	
	ROA	Net income / Total assets	Return on Assets
Activity/Others	STA	Sales / Total assets	Total Asset Turnover
	FATA	Fixed assets / Total assets	

Source: Own elaboration

4.3.4 Model Development

This study presents 12 models divided into two groups. The first group of six is based on aggregated data, considering all data as a whole or aggregating them according to crops or countries. The second group of six subdivides the data by countries and crops. The data considered in estimating these models are from 2018 because 2019 and 2020 only classify firms according to their financial health.

We performed a binary logistic regression, a statistical method in which several assumptions must be observed. The first is that the dependent variable is measured on a dichotomous scale. The probability of a given observation falling into one of 2 possible categories is predicted: healthy firm or distressed firm. The second assumption is the existence of several independent variables. The third assumption is the independence of observations, thus being mutually exclusive and exhaustive categories. Finally, the fourth assumption is that there must be a linear relationship between any continuous independent variables and the logit transformation of the dependent variable. We performed the Box-Tidwell transformation in SPSS for this last assumption, which confirmed that this assumption is not violated. The logistic model is given by:

$$P_i = \frac{1}{1 + e^{-(\beta_0 + \beta_{i1} X_{i1} + \beta_2 X_{i2} + \ldots + \beta_n X_{in})}} \tag{4.1}$$

where, P_{i} = probability of financial distress, $X_{ij} = j^{th}$ variable of the i^{th} firm, and β_j

= estimated coefficient for the j^{th} variable.

4.3.5 Models Accuracy

This article presents several forecasting models and analyses their explanatory power. We employ the confusion matrix (Table 4.4) to scrutinize type I and II errors and the area under the ROC curve (AUC) to analyze the occurrence of misclassifications. This matrix shows the number or percentages of false positives (FP, type I error), false negatives (FN, type II error), true positives (TP, sensitivity) and true negatives (TN, specificity). Let us assume that the *negatives* are the healthy firms and the *positives* are financially distressed firms:

Table 4.4: Confusion matrix

		Predicted	
		Healthy	Financial Distressed
Observed	Healthy	True negative	False positive
	Financial Distressed	False negative	True positive

Source: Own elaboration

The accuracy of the classification process is based on the relationship between sensitivity and specificity, according to the following equations:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.2}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{4.3}$$

$$Specificity = \frac{TN}{TN + FP} \tag{4.4}$$

where, TP = true positive, TN = true negative, FP = false positive, and FN = false negative.

The AUC equation is given by:

$$AUC = \int_0^1 TPR(FPR^{-1}(\theta))d\theta \tag{4.5}$$

where, TPR represents the true positive rate, FPR = false positive rate = $(1 - Specificity)$, $FPR^{-1}(\theta)$ represents the classification threshold value that corresponds to a given θ, and θ varies from 0 to 1, representing the proportion of positive samples that are correctly classified out of the total positive samples.

100(1- α)% confidence interval can be calculated using the standard normal distribution, that is:

$$AUC \pm z_{\alpha/2} SE(AUC) \tag{4.6}$$

According to Hanley and McNeil (1982), the standard error of the area under the curve is given by:

$$SE(AUC) = \sqrt{\frac{AUC(1 - AUC) + (n_{FD} - 1)(Q1 - AUC^2) + (n_H - 1)(Q2 - AUC^2)}{n_{FD}.n_H}} \tag{4.7}$$

where, AUC = area under the ROC curve, n_{FD} = number of financial distressed firms, n_{H} = number of healthy firms, $Q1$ = AUC/(2-AUC), and Q2 = 2AUC^2/(1+AUC).

The test statistic is given as follows:

$$z = \frac{AUC}{SE(AUC)} \tag{4.8}$$

where z = standard normal variate.

Although there is no criterion to determine the optimal cutoff for several reasons (misclassification costs, efficiency, etc.), the Youden Index (J) provides a criterion to determine an optimal threshold value (Fluss et al., 2005), which it is maximized the equation:

$$J = Max_c(Sensitivity_c + Specificity_c - 1) \tag{4.9}$$

where c = optimal cutoff.

In this study, for simplicity, we assume that sensitivity and specificity are equally important or desirable.

We use the same method as Hanley et al. (1983) to assess the differences between the AUC of the different models. This method performs a two-sided test for differences between AUCs that analyzes the proportion of positive and negative cases and the respective AUC of each model. The test returns a p-value that determines the significance of the difference between the two curves. The statistical test is as follows:

$$z = \frac{AUC_1 - AUC_2}{\sqrt{(SE(AUC_1))^2 + (SE(AUC_2))^2 - 2.r.SE(AUC_1).SE(AUC_2)}} \tag{4.10}$$

where, z = standard normal variate and r = correlation between AUCs.

4.4 Results and Discussion

4.4.1 Statistical Results

To understand how variables are revealed when forming different subsamples depending on the financial health of firms and across countries, we present the respective descriptive statistics Table 4.5 and Table 4.6. The median serves as the appropriate measure of central tendency, particularly given the inclusion of outliers and the non-uniform distribution of the sample. As expected, and for the generality of the results, the medians are higher in healthy firms, regardless of the type of the crops. There are, however, some exceptions that deserve to be highlighted when the analysis considers countries. In Portugal and Italy, all ratios are consistent depending on whether firms are healthy or in financial distress. However, in Spain, CR, EQTA, and TLTA ratios present higher values in Spanish financial distress firms than in healthy firms. In Portugal and Italy, all ratios are consistent depending on whether firms are healthy or in financial distress.

Confirming previous studies on the violation of the assumption of normality in the distribution of financial ratios (Deakin, 1976; Frecka and Hopwood, 1983), we performed a standard Kolmogorov-Smirnov test, where, unsurprisingly, we found that none of the financial ratios presents a normal distribution (Table 4.7).

A Spearman correlation matrix is performed to observe the correlations between covariates (Table 4.8). Considering that we are using a non-uniformly distributed distribution, it is preferable to the Pearson correlation matrix (Bol et al., 2012). The Spearman correlation coefficient uses the order values of the observations. Thus, this coefficient is not sensitive to distribution asymmetries nor the presence of outliers, not requiring that the data come from two normal populations. Given the typology of each ratio, it is intended to select one or at most two ratios in each category. The selection of ratios to be included in the final model goes through several combinations between variables from different categories to potentially reduce multicollinearity. In the discrimination between healthy and distressed firms, the numerical comparison is expected to be consistent with previous studies.

Performing a Mann-Whitney U-Test (Table 4.9), it is possible to verify that the differences in the financial ratios of healthy firms for those in financial distress are only sometimes consistent across crops or countries. Some ratios only express such differences in one of the crops (e.g., CCL in vineyards), and others depend on the country (e.g., FATA in olive groves in Italy).

For countries, and since there are three independent groups, we performed a Kruskal-Wallis test (Table 4.10), a non-parametric statistical method suitable for comparing more than two independent groups, which also dispenses the assumption of normality. This test evaluates whether at least one of the groups differs significantly from the others in terms of the distribution of the variable. The null hypothesis of equal distributions across groups was rejected for all financial ratios, indicating that there are significant differences in the financial data based on country (see Figure 4.3).

Table 4.5: Descriptive statistics of variables according to crops

			Healthy Firms						Financial Distressed Firms					
Type	Ratio	Crops	N	Mean	Median	Std.Dev.	Min.	Max.	N	Mean	Median	Std.Dev.	Min.	Max.
I	CCL	V	2592	851.93	0.17	42728.5	-133.8	2175351	595	2.98	0.08	17.15	0.00	260.9
		OG	1438	5.33	0.25	41.2	0.00	975.4	367	6.28	0.19	48.34	0.00	749.9
	WCTA	V	2620	0.09	0.10	0.46	-9.94	1.37	603	-0.05	0.04	0.95	-18.3	1.00
		OG	1465	0.04	0.06	0.47	-5.36	1.00	369	-0.76	0.01	12.68	-243.3	0.97
	CATA	V	2620	0.45	0.40	0.29	0.00	1.00	603	0.33	0.21	0.29	0.00	1.00
		OG	1465	0.37	0.27	0.31	0.00	1.00	369	0.29	0.15	0.30	0.00	1.00
	CR	V	2592	1730.51	1.55	86133.7	-146.8	4385009	595	10.40	1.53	85.70	0.00	1983.4
		OG	1438	17.70	1.46	155.7	0.00	3616.7	367	13.73	1.08	70.58	0.00	1082.1
II	RETA	V	2620	0.18	0.19	1.27	-56.8	1.00	603	0.02	0.06	1.29	-19.57	0.99
		OG	1465	0.16	0.14	0.76	-17.6	1.00	369	-2.12	0.02	40.53	-778.3	0.99
	EQTA	V	2620	0.35	0.32	0.51	-9.94	1.00	603	0.21	0.25	1.19	-17.8	1.00
		OG	1465	0.38	0.36	0.48	-5.34	1.00	369	-0.38	0.23	12.68	-242.9	1.00
	TLTA	V	2620	0.65	0.68	0.51	0.00	10.94	603	0.79	0.75	1.19	0.00	18.79
		OG	1465	0.62	0.64	0.48	0.00	6.34	369	1.38	0.77	12.68	0.00	243.9
III	EBITTA	V	2620	0.02	0.01	0.32	-12.88	2.18	603	-0.09	-0.03	0.29	-4.27	0.61
		OG	1465	0.01	0.01	0.24	-3.27	2.30	369	-0.08	-0.03	0.31	-3.47	0.83
	CFTA	V	2620	0.04	0.03	0.32	-12.88	2.21	603	-0.07	-0.02	0.28	-4.31	0.47
		OG	1465	0.03	0.02	0.25	-4.10	2.40	369	-0.06	-0.02	0.29	-3.47	0.83
	ROA	V	2620	0.01	0.01	0.32	-12.88	2.09	603	-0.09	-0.04	0.29	-4.31	0.46
		OG	1465	0.00	0.00	0.25	-4.11	2.30	369	-0.08	-0.03	0.30	-3.47	0.83
IV	STA	V	2620	0.38	0.21	0.83	0.00	33.19	603	0.16	0.05	0.34	0.00	4.19
		OG	1465	0.30	0.11	0.53	0.00	6.74	369	0.18	0.02	0.62	0.00	7.55
	FATA	V	2620	0.55	0.60	0.29	0.00	1.00	603	0.67	0.79	0.29	0.00	1.00
		OG	1465	0.63	0.73	0.31	0.00	1.00	369	0.71	0.85	0.30	0.00	1.00

I (Liquidity), II (Solvency/Leverage), III (Profitability), IV (Activity/Others); V (Vineyards), OV (Olive Groves)
Source: Own elaboration

Table 4.6: Descriptive statistics of variables according to countries

			Healthy Firms						Financial Distressed Firms					
Type		Country	N	Mean	Median	Std.Dev.	Min.	Max.	N	Mean	Median	Std.Dev.	Min.	Max.
I	CCL	PT	1071	2057.34	0.38	66471.9	-133.8	2175351	168	4.96	0.28	23.68	0.00	260.9
		ES	892	5.20	0.39	37.96	0.00	860.5	168	9.28	0.31	59.58	0.00	749.9
		IT	2067	3.77	0.10	51.09	0.00	1699.0	626	2.69	0.07	23.33	0.00	522.2
	WCTA	PT	1089	0.16	0.20	0.53	-9.94	1.37	168	-1.49	0.10	18.80	-243.3	0.98
		ES	897	0.10	0.09	0.40	-5.36	1.00	170	-0.10	0.06	1.49	-18.32	0.96
		IT	2099	0.02	0.06	0.44	-4.68	1.00	634	-0.07	0.01	0.46	-3.19	1.00
	CATA	PT	1089	0.46	0.43	0.28	0.00	1.00	168	0.42	0.39	0.31	0.01	1.00
		ES	897	0.37	0.31	0.28	0.00	1.00	170	0.31	0.23	0.27	0.01	1.00
		IT	2099	0.42	0.33	0.32	0.00	1.00	634	0.28	0.16	0.30	0.00	1.00
	CR	PT	1071	4134.04	2.50	133991	-146.8	4385009	168	12.53	2.17	39.12	0.00	335.2
		ES	892	15.59	1.69	137.3	0.00	3616.8	168	18.48	1.77	90.47	0.01	1082.1
		IT	2067	33.61	1.26	953.5	0.00	42821.7	626	9.61	1.08	85.37	0.00	1983.4
II	RETA	PT	1089	0.23	0.27	0.69	-12.88	1.00	168	-4.90	0.02	60.05	-778.3	0.97
		ES	897	0.23	0.18	0.42	-5.39	0.99	170	-0.08	0.01	1.61	-19.57	0.99
		IT	2099	0.11	0.11	1.44	-56.77	1.00	634	0.11	0.05	0.68	-6.43	0.99
	EQTA	PT	1089	0.35	0.37	0.62	-9.94	1.00	168	-1.59	0.20	18.81	-242.9	1.00
		ES	897	0.51	0.55	0.43	-5.34	1.00	170	0.38	0.59	1.49	-17.79	1.00
		IT	2099	0.30	0.24	0.44	-8.22	1.00	634	0.30	0.19	0.40	-3.06	1.00
	TLTA	PT	1089	0.65	0.63	0.62	0.00	10.94	168	2.59	0.80	18.81	0.00	243.9
		ES	897	0.49	0.45	0.43	0.00	6.34	170	0.62	0.41	1.49	0.00	18.79
		IT	2099	0.70	0.76	0.44	0.00	9.22	634	0.70	0.81	0.40	0.00	4.06
III	EBITTA	PT	1089	0.02	0.02	0.44	-12.88	0.93	168	-0.13	-0.04	0.39	-3.47	0.53
		ES	897	0.05	0.02	0.15	-2.21	1.14	170	-0.03	-0.02	0.21	-1.73	0.65
		IT	2099	0.00	0.01	0.23	-3.41	2.30	634	-0.09	-0.03	0.28	-4.27	0.83
	CFTA	PT	1089	0.05	0.05	0.44	-12.88	0.98	168	-0.10	-0.02	0.39	-3.47	0.49
		ES	897	0.06	0.04	0.19	-4.10	1.14	170	-0.01	0.00	0.19	-1.33	0.73
		IT	2099	0.02	0.02	0.24	-3.76	2.40	634	-0.07	-0.02	0.28	-4.31	0.83
	ROA	PT	1089	0.00	0.01	0.44	-12.88	0.92	168	-0.14	-0.05	0.39	-3.47	0.46
		ES	897	0.03	0.02	0.19	-4.11	1.14	170	-0.03	-0.02	0.19	-1.38	0.63
		IT	2099	-0.01	0.00	0.24	-3.76	2.30	634	-0.09	-0.04	0.28	-4.31	0.83
IV	STA	PT	1089	0.34	0.22	0.50	0.00	6.14	168	0.17	0.07	0.25	0.00	1.63
		ES	897	0.38	0.20	0.52	0.00	6.48	170	0.27	0.08	0.54	0.00	4.19
		IT	2099	0.35	0.13	0.91	0.00	33.19	634	0.14	0.02	0.48	0.00	7.55
	FATA	PT	1089	0.54	0.57	0.28	0.00	1.00	168	0.58	0.61	0.31	0.00	0.99
		ES	897	0.63	0.69	0.28	0.00	1.00	170	0.69	0.77	0.27	0.00	0.99
		IT	2099	0.58	0.67	0.32	0.00	1.00	634	0.72	0.84	0.30	0.00	1.00

I (Liquidity), II (Solvency/Leverage), III (Profitability), IV (Activity/Others), PT (Portugal), ES (Spain), IT (Italy)
Source: Own elaboration

Table 4.7: One-sample Kolmogorov-Smirnov test

			Normal Parameters		Test	Asymp. Sig.
		N	Normal Mean	Std. Dev.	Statistic	(2-tailed)
I	CCL	4992	444.698	30789.257	0.499	0.000***
	WCTA	5057	-0.001	3.468	0.386	0.000***
	CATA	5057	0.398	0.303	0.109	0.000***
	CR	4992	905.882	62066.191	0.498	0.000***
II	RETA	5057	-0.015	11.004	0.463	0.000***
	EQTA	5057	0.288	3.479	0.419	0.000***
	TLTA	5057	0.712	3.479	0.419	0.000***
III	EBITTA	5057	-0.003	0.296	0.279	0.000***
	CFTA	5057	0.016	0.300	0.290	0.000***
	ROA	5057	-0.014	0.301	0.289	0.000***
IV	STA	5057	0.319	0.699	0.324	0.000***
	FATA	5057	0.602	0.303	0.109	0.000***

I (Liquidity), II (Solvency/Leverage), III (Profitability), IV (Activity/Others)
***. **. * represent .01. .05. and .10 significance levels. respectively.
Source: Own elaboration

Table 4.8: Spearman's rho coefficients

		CCL	WCTA	CATA	CR	RETA	EQTA	TLTA	EBITTA	CFTA	ROA	STA	FATA
I	CCL	1.00											
	WCTA	0.57	1.00										
	CATA	0.22	0.59	1.00									
	CR	0.70	0.88	0.36	1.00								
II	RETA	0.24	0.36	0.08	0.33	1.00							
	EQTA	0.35	0.44	0.05	0.42	0.72	1.00						
	TLTA	-0.35	-0.44	-0.05	-0.42	-0.72	-1.00	1.00					
III	EBITTA	0.18	0.28	0.25	0.18	0.40	0.27	-0.27	1.00				
	CFTA	0.21	0.29	0.28	0.20	0.41	0.27	-0.27	0.91	1.00			
	ROA	0.20	0.30	0.24	0.21	0.42	0.30	-0.30	0.98	0.92	1.00		
IV	STA	0.08	0.24	0.53	0.07	0.19	0.05	-0.05	0.45	0.52	0.42	1.00	
	FATA	-0.22	-0.59	-1.00	-0.36	-0.08	-0.05	0.05	-0.25	-0.28	-0.24	-0.53	1.00

I (Liquidity), II (Solvency/Leverage), III (Profitability), IV (Activity/Others)

For all ratios, the level of statistical significance of Spearman correlation coefficients is relevant at the 0.01 level.

Source: Own elaboration

Table 4.9: Mann-Whitney U test according to financial condition

		Vineyards				Olive Groves			
		Mann-Whitney U	Wilcoxon W	Z	Asymp.Sig. (2-tailed)	Mann-Whitney U	Wilcoxon W	Z	Asymp.Sig. (2-tailed)
CCL	PT	36889.0	43792.0	-2.347	0.019**	8682.0	10008.0	-0.052	0.959
	ES	15421.5	19076.5	-2.070	0.038**	17343.0	127558.0	-1.583	0.113
	IT	253446.5	330867.5	-3.173	0.002***	70412.0	97673.0	-0.813	0.416
WCTA	PT	38716.0	45619.0	-1.796	0.073*	7277.0	8603.0	-2.158	0.031**
	ES	16068.0	19896.0	-1.955	0.051*	18936.0	22422.0	-0.454	0.650
	IT	249482.0	329282.0	-4.324	0.000***	66464.0	94194.0	-2.732	0.006***
CATA	PT	38170.0	45073.0	-2.016	0.044**	8503.0	9829.0	-0.577	0.564
	ES	14944.5	18772.5	-2.847	0.004***	17622.0	21108.0	-1.431	0.152
	IT	206347.0	286147.0	-8.875	0.000***	57801.0	85531.0	-5.336	0.000***
CR	PT	40615.0	47518.0	-0.828	0.408	7508.0	8834.0	-1.603	0.109
	ES	17028.0	20683.0	-0.769	0.442	18068.0	128283.0	-1.042	0.297
	IT	266428.0	343849.0	-1.778	0.075*	67224.0	94485.0	-1.798	0.072*
RETA	PT	30866.0	37769.0	-4.959	0.000***	6563.0	7889.0	-3.079	0.002***
	ES	15203.0	19031.0	-2.641	0.008***	12434.0	15920.0	-5.290	0.000***
	IT	266071.5	345871.5	-2.574	0.010**	69106.0	96836.0	-1.938	0.053*
EQTA	PT	31448.0	38351.0	-4.724	0.000***	6948.0	8274.0	-2.583	0.010**
	ES	18243.0	109194.0	-0.229	0.819	18680.0	129836.0	-0.644	0.519
	IT	278862.0	358662.0	-1.225	0.221	69389.0	97119.0	-1.853	0.064*
TLTA	PT	31448.0	304139.0	-4.724	0.000***	6948.0	68724.0	-2.583	0.010**
	ES	18250.0	22078.0	-0.223	0.824	18680.0	22166.0	-0.644	0.519
	IT	278862.0	1339558.0	-1.225	0.221	69389.0	276435.0	-1.853	0.064*
EBITTA	PT	20589.0	27492.0	-9.100	0.000***	5291.0	6617.0	-4.720	0.000***
	ES	9995.0	13823.0	-6.775	0.000***	10145.0	13631.0	-6.992	0.000***
	IT	103624.0	183424.0	-19.712	0.000***	39476.0	67206.0	-10.844	0.000***
CFTA	PT	19560.0	26463.0	-9.514	0.000***	4899.0	6225.0	-5.225	0.000***
	ES	9430.0	13258.0	-7.223	0.000***	10893.0	14379.0	-6.436	0.000***
	IT	100853.0	180653.0	-20.004	0.000***	37230.0	64960.0	-11.519	0.000***
ROA	PT	20915.0	27818.0	-8.968	0.000***	5397.0	6723.0	-4.583	0.000***
	ES	10353.0	14181.0	-6.491	0.000***	10892.0	14378.0	-6.436	0.000***
	IT	105609.0	185409.0	-19.503	0.000***	40286.0	68016.0	-10.600	0.000***
STA	PT	29582.0	36485.0	-5.477	0.000***	4979.0	6305.0	-5.146	0.000***
	ES	12173.0	16001.0	-5.046	0.000***	14291.0	17777.0	-3.909	0.000***
	IT	159662.0	239462.0	-13.810	0.000***	52596.0	80326.0	-6.947	0.000***
FATA	PT	38170.0	310861.0	-2.016	0.044**	8503.0	70279.0	-0.577	0.564
	ES	14944.5	105895.5	-2.847	0.004***	17622.0	128778.0	-1.431	0.152
	IT	206347.0	1267043.0	-8.875	0.000***	57801.0	264847.0	-5.336	0.000***

PT (Portugal), (ES) Spain, (IT) Italy.
***, **, * represent .01, .05, and .10 significance levels, respectively.
Source: Own elaboration

Table 4.10: Kruskall-Wallis test[a,b]

		Global data				Vineyards				Olive Groves			
		Healthy		Fin. Distressed		Healthy		Fin. Distressed		Healthy		Fin. Distressed	
		Kruskal Wallis H	Asymp. Sig.	Kruskal Wallis H	Asymp. Sig.	Kruskal Wallis H	Asymp. Sig.	Kruskal Wallis H	Asymp. Sig.	Kruskal Wallis H	Asymp. Sig.	Kruskal Wallis H	Asymp. Sig.
I	CCL	251.706	0.000***	46.952	0.000***	163.055	0.000***	17.974	0.000***	77.390	0.000***	34.210	0.000***
	WCTA	128.879	0.000***	23.143	0.000***	97.105	0.000***	15.246	0.000***	48.545	0.000***	13.816	0.001***
	CATA	57.878	0.000***	38.300	0.000***	45.144	0.000***	25.661	0.000***	8.756	0.013**	14.473	0.001***
	CR	157.989	0.000***	29.482	0.000***	96.376	0.000***	14.691	0.001***	76.786	0.000***	22.379	0.000***
II	RETA	62.581	0.000***	13.788	0.001***	37.547	0.000***	8.159	0.017**	32.836	0.000***	6.667	0.036**
	EQTA	227.524	0.000***	51.655	0.000***	95.339	0.000***	23.242	0.000***	130.363	0.000***	31.017	0.000***
	TLTA	227.524	0.000***	51.470	0.000***	95.339	0.000***	23.111	0.000***	130.363	0.000***	31.017	0.000***
III	EBITTA	98.068	0.000***	24.208	0.000***	75.460	0.000***	16.903	0.000***	41.038	0.000***	7.173	0.028**
	CFTA	147.841	0.000***	37.044	0.000***	149.772	0.000***	26.618	0.000***	32.378	0.000***	12.263	0.002***
	ROA	113.206	0.000***	34.662	0.000***	86.118	0.000***	23.242	0.000***	45.545	0.000***	10.149	0.006***
IV	STA	61.860	0.000***	60.946	0.000***	75.855	0.000***	52.227	0.000***	26.313	0.000***	29.245	0.000***
	FATA	57.878	0.000***	38.300	0.000***	45.144	0.000***	25.661	0.000***	8.756	0.013**	14.473	0.001***

a. Grouping Variable: Portugal, Spain, Italy. b. 2 degrees of freedom.
***. **. * represent .01. .05. and .10 significance levels. respectively.
Source: Own elaboration

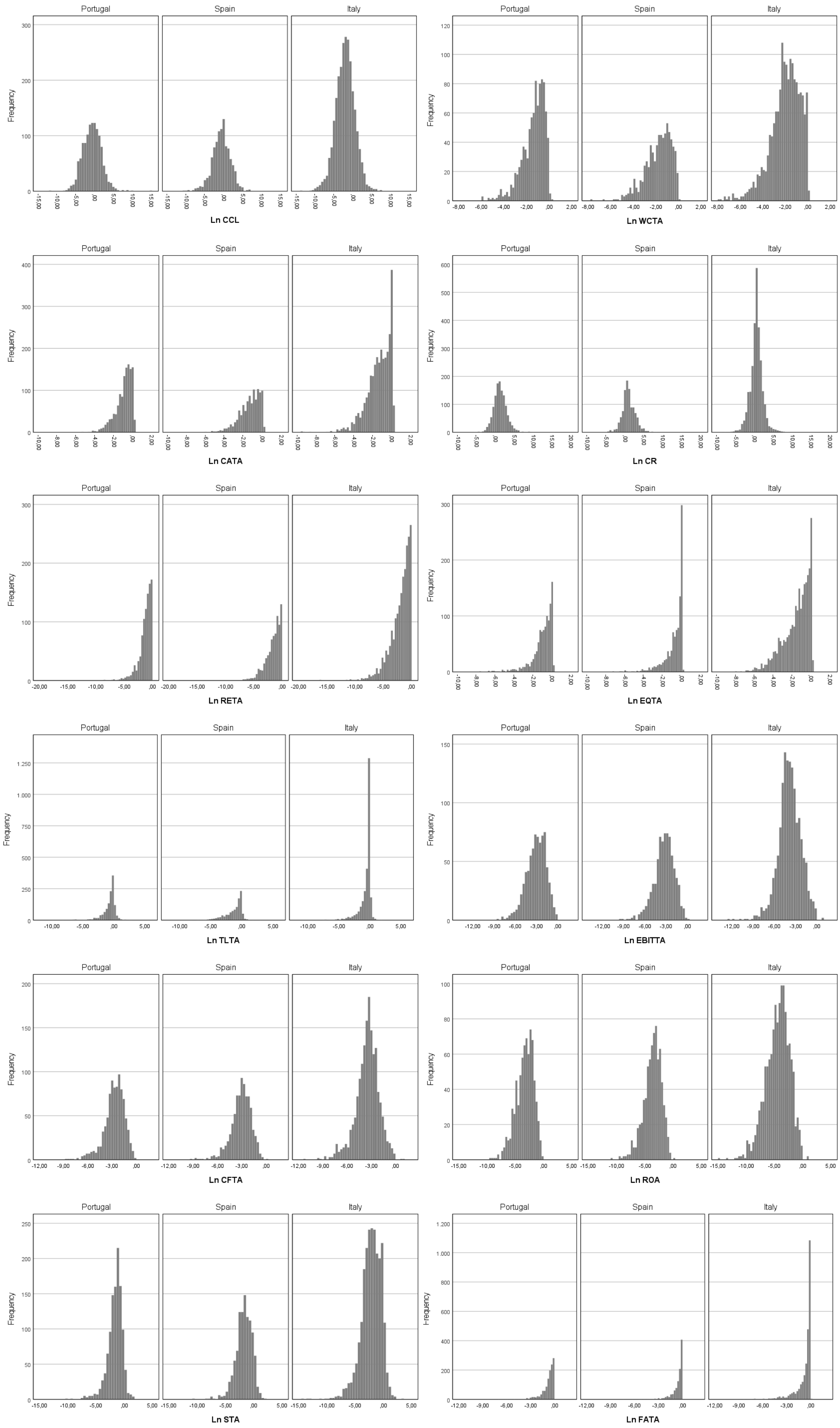

Figure 4.3: Distribution of frequencies by countries in natural logarithmic scale (ln). Source: Own elaboration.

The estimation of the logit model is summarised in Table 4.11 and Table 4.12. Excepted for STA in the Olive Groves aggregate model and EBITTA in the Spain Olive Groves individual model, all covariates were estimated with a p-value<0.05. However, with the p-value on the significance threshold, we chose to include them in the models as they improve the respective R^2. All estimated models exhibit a Chi-Square goodness of fit test with an associated probability below 0.01, indicating that the current models outperform the intercept models. In other words, it is concluded that the independent variables have a significant influence on the estimated models.

The accuracy and AUC are summarised in Table 4.13, which expresses the confusion matrix results. The optimal cutoff point in these models was determined using Youden's index.

Table 4.14 and Figure 4.4 present the test results comparing the areas under the ROC curve of the different models. The main result of the differences in the areas under the curve between aggregated models is that only the Vineyards model shows differences with the Olive Groves model. Neither the global model compared with the crop or country models nor the countries themselves showed statistically significant differences. The Vineyards model is more accurate (AUC of 0.752 against 0.695) despite the covariates chosen to be the same as the Olive Groves Model (CATA, EBITTA and STA).

Analysis of the individual models' differences results in the finding that the models sometimes present pretty significant differences. This is the case of comparing the models in Italy about Vineyards and Olive Groves. The statistical test has a $p-$value of less than 0.0001, the most robust rejection of the null hypothesis. In Italy, the Vineyards model has an AUC of 0.788, which is even the best AUC of all 12 models. In turn, the Olive Groves model from Italy has the lowest AUC of all models. In this model, the STA covariate is not included due to a lack of statistical significance, being a model with only two covariates in addition to the constant. Between different countries but with the same crops, there are also differences to be noted. The null hypothesis is also rejected in the Vineyards case between Portugal and Italy. The Italy model has the best accuracy (AUC of 0.788 against 0.696). Although both models contain the variable STA, Portugal

Table 4.11: Panel A: Aggregate models

		Global Model	Crops Models Vineyards	Crops Models Olive G.	Countries Models Portugal	Countries Models Spain	Countries Models Italy
	Constant	-1.055	-0.862	-1.085	-1.309	-1.338	-0.707
	p-Value	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
I	CCL						
	p-Value						
	WCTA						
	p-Value						
	CATA	-0.772	-0.654	-0.796			-0.985
	p-Value	(0.001)	(0.001)	(0.001)			(0.001)
	CR						
	p-Value						
II	RETA					-0.680	
	p-Value					(0.001)	
	EQTA						
	p-Value						
	TLTA	0.159			0.453		
	p-Value	(0.010)			(0.001)		
III	EBITTA	-1.352	-1.658	-1.356		-2.277	-1.587
	p-Value	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)
	CFTA						
	p-Value						
	ROA						
	p-Value						
IV	STA	-1.022	-1.646	-0.321	-2.014	-0.667	-0.980
	p-Value	(0.001)	(0.001)	(0.068)	(0.001)	(0.014)	(0.001)
	FATA						
	p-Value						
	χ^2 Model	274.614	225.754	62.495	69.785	53.647	188.385
	Model *p*-Value	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	Nagelkerke R^2	0.085	0.109	0.053	0.099	0.084	0.101
	-2loglikelihood	4,675.28	2,881.09	1,779.06	918.90	882.22	2,772.31
	N	5,057	3,223	1,834	1,257	1,067	2,733

I (Liquidity), II (Solvency/Leverage), III (Profitability), IV (Activity/Others)
Source: Own elaboration.

Table 4.12: Panel B: Individual models

		Vineyards			Olive Groves		
		Portugal	Spain	Italy	Portugal	Spain	Italy
	Constant	-1.695	-1.069	-0.712	-1.496	-1.638	-0.674
	p-Value	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	CCL						
	p-Value						
	WCTA						
I	*p*-Value						
	CATA			-0.659			-1.159
	p-Value			(0.008)			(0.001)
	CR						
	p-Value						
	RETA					-0.741	
	p-Value					(0.001)	
II	EQTA						
	p-Value						
	TLTA	0.401					
	p-Value	(0.001)					
	EBITTA			-2.579		-1.457	-0.927
	p-Value			(0.001)		(0.056)	(0.002)
III	CFTA		-6.365		-2.565		
	p-Value		(0.001)		(0.023)		
	ROA						
	p-Value						
	STA	-1.747	-0.802	-2.240	-3.036		
IV	*p*-Value	(0.001)	(0.029)	(0.001)	(0.009)		
	FATA						
	p-Value						
	χ^2 Model	40.732	45.561	191.285	33.915	20.049	31.909
	Model *p*-Value	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	Nagelkerke R^2	0.085	0.142	0.151	0.152	0.062	0.052
	-2loglikelihood	641.88	421.51	1,720.25	271.91	447.97	988.17
	N	855	513	1,855	402	554	878

I (Liquidity), II (Solvency/Leverage), III (Profitability), IV (Activity/Others)
Source: Own elaboration.

Table 4.13: Prediction accuracy of models

Model	AUC	Cutoff	Confusion Matrix Parameters				
			Accuracy	Sensitivity	Specificity	Type I Error	Type II Error
Global	0.724	0.2405	73.2%	59.3%	76.6%	40.7%	23.4%
Vineyards	0.752	0.2354	71.8%	66.3%	73.1%	33.7%	26.9%
Olive Groves	0.695	0.2397	73.8%	53.9%	78.8%	46.1%	21.2%
Portugal	0.706	0.1778	80.0%	50.6%	84.5%	49.4%	15.5%
Spain	0.694	0.2034	80.4%	49.4%	86.3%	50.6%	13.7%
Italy	0.739	0.2775	69.7%	67.5%	70.4%	32.5%	29.6%
Portugal Vineyards	0.696	0.1838	83.0%	46.2%	88.9%	53.8%	11.1%
Spain Vineyards	0.760	0.2341	80.7%	59.8%	85.0%	40.2%	15.0%
Italy Vineyards	0.788	0.2478	68.0%	79.7%	64.9%	20.3%	35.1%
Portugal Olives	0.762	0.1383	63.7%	78.4%	61.5%	21.6%	38.5%
Spain Olives	0.698	0.1627	78.2%	57.8%	81.7%	42.2%	18.3%
Italy Olives	0.669	0.3125	67.2%	58.7%	70.3%	41.3%	29.7%

AUC - Area under ROC curve
Source: Own elaboration

Table 4.14: Comparison of differences between areas under ROC curve

	Difference between AUCs	Std. error	z	p-value
H_1 Global Model ∼ Vineyards	0.028	0.0156	1.793	0.0730
H_2 Global Model ∼ Olive Groves	0.029	0.0191	1.515	0.1298
H_3 Global Model ∼ Portugal	0.018	0.0255	0.705	0.4808
H_4 Global Model ∼ Spain	0.030	0.0258	1.164	0.2446
H_5 Global Model ∼ Italy	0.015	0.0157	0.958	0.3382
H_6 Vineyards ∼ Olives	0.058	0.0196	2.930	0.0034^{***}
H_7 Portugal ∼ Spain	0.012	0.0333	0.359	0.7194
H_8 Portugal ∼ Italy	0.033	0.0257	1.262	0.2068
H_9 Spain ∼ Italy	0.045	0.0266	1.673	0.0942
H_{10} Portugal Vineyards ∼ Portugal Olives	0.065	0.0455	1.429	0.1530
H_{11} Spain Vineyards ∼ Spain Olives	0.062	0.0454	1.369	0.1711
H_{12} Italy Vineyards ∼ Italy Olives	0.119	0.0246	4.838	0.0001^{***}
H_{13} Portugal Vineyards ∼ Spain Vineyards	0.064	0.0423	1.502	0.1330
H_{14} Portugal Vineyards ∼ Italy Vineyards	0.092	0.0316	2.905	0.0037^{***}
H_{15} Spain Vineyards ∼ Italy Vineyards	0.028	0.0335	0.845	0.3979
H_{16} Portugal Olives ∼ Spain Olives	0.064	0.0485	1.315	0.1886
H_{17} Portugal Olives ∼ Italy Olives	0.092	0.0410	2.254	0.0242^{**}
H_{18} Spain Olives ∼ Italy Olives	0.029	0.0394	0.728	0.4663

AUCs - Areas under ROC curve
***. **. * represent .01. .05. and .10 significance levels. respectively.
Source: Own elaboration.

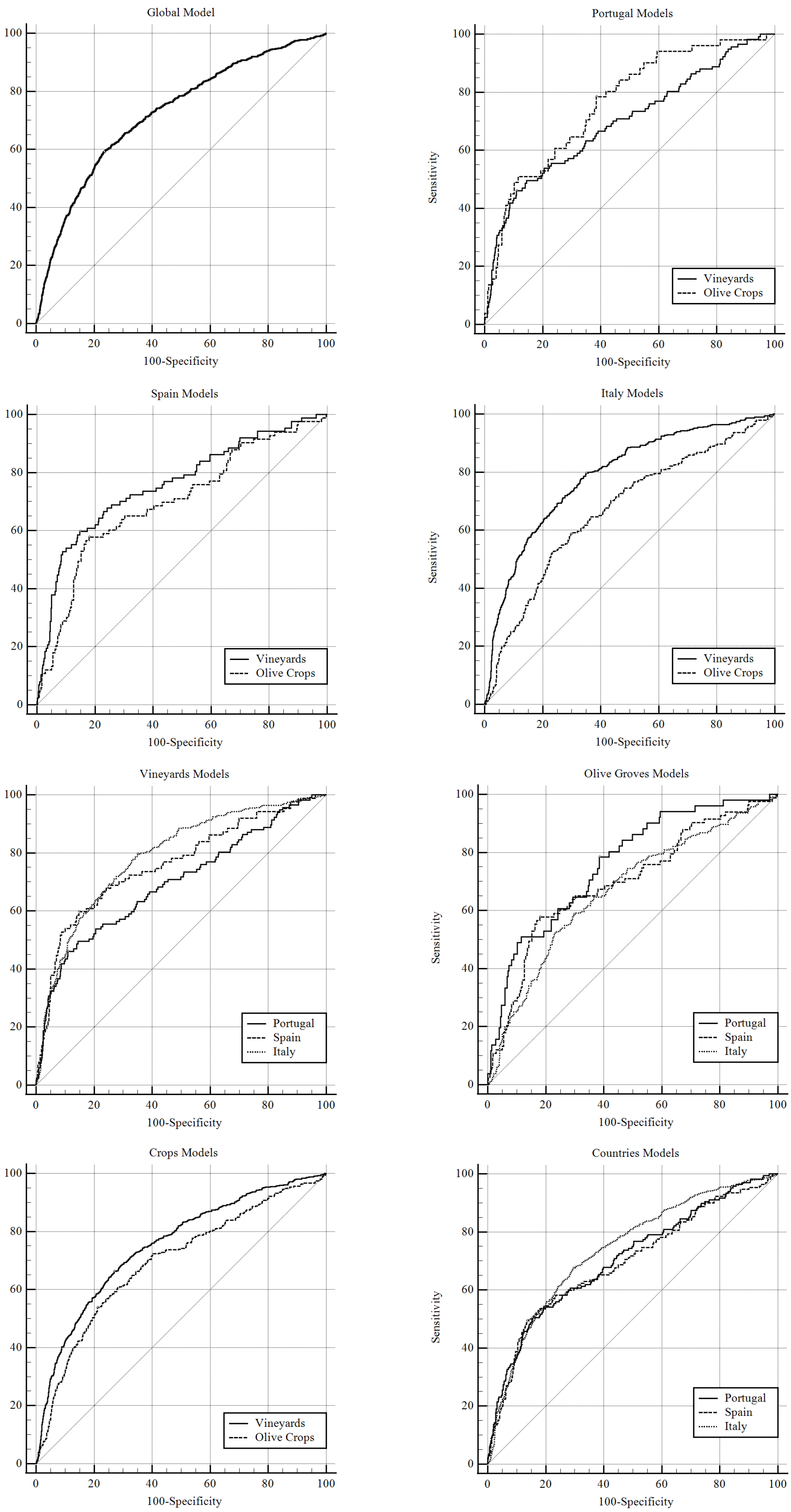

Figure 4.4: Comparison of ROC curves. Source: Own elaboration.

only has two covariates, while Italy also has the variable CATA. In the case of Olives Groves, the null hypothesis of differences between Portugal and Italy is also rejected. However, in this case, the opposite situation is registered, with Portugal registering an AUC of 0.762 while Italy is only 0.669. Interestingly, there is no covariate common to both models, highlighting that the Portuguese model uses a variable from the profitability category (CFTA) and another from the category of Activity (STA). In the case of Italy, a covariate of the liquidity category and another of profitability (EBITTA) is used.

4.4.2 Discussion

If, until now, studies dedicated to predicting bankruptcy or financial distress in agriculture generally considered agriculture as a whole, this study demonstrates that there are specificities that are open to the estimation of the models.

Although the dependent variable that determines the firm's state (healthy or distressed) is not based on variables that measure firms' activity, the STA ratio is a covariate in almost all the models presented. Only in the individual models of Spain and Italy referring to Olives Groves was this variable not shown to be statistically significant.

However, the models show a lower Nagelkerke R^2 compared to other studies. We must also consider that we did not remove outliers and limited the study to the most popular financial covariates in credit risk models. Thus, it is possible to improve the accuracy of the models by including qualitative and categorical variables. While the AUCs are not exceptional, they are still considered acceptable and comparable to those found in other studies, meaning the models are far from ineffective.

Financial costs by an imperfect estimation of the model, namely the cost of classifying a distressed financial firm as healthy, being higher than the inverse, are the backbone of the discussion in this paper. Therefore, and since it is possible to determine a specific cutoff to separate the two categories, it is essential to have a model that, for all possible thresholds, is as accurate as possible. Therefore, the area under curves obtained from the ROC Curve is of essential importance. Moreover, in the case of agricultural activity, in which different cutoffs may be associated depending on the country or crop, it is essential to have a model that presents the best accuracy along with the possible cutoffs.

The best accuracy of the model is only sometimes consistent with the highest AUC. Aggregate models of Portugal and Spain in which the accuracy based on the confusion matrix is among the highest of the aggregate models, but which, ambiguously, have the lowest AUCs. On the contrary, the Italian model has a low accuracy compared to the other aggregate models but has the highest AUC of the country models.

In individual models, we have similar cases. The Italy Vineyards model has the lowest confusion matrix accuracy but has the highest AUC of all the individual models. On the contrary, the Portugal Vineyards model has the highest accuracy of the individual models but the lowest AUC. In an undetermined optimal cutoff context, the AUC should be a preferable measure. However, when it is possible to determine an optimal cutoff, accuracy has the advantage of minimizing the sum of false positives and false negatives.

In comparing the accuracy of the models, we have identified statistically significant differences in the areas under the ROC curve (AUCs) for the following hypotheses, leading to the rejection of the null hypotheses:

H_6: The comparison between Vineyards and Olives models showed a statistically significant difference in AUCs.

H_{12}: The comparison between Italy Vineyards and Italy Olives models exhibited a highly significant difference in AUCs.

H_{14}: The comparison between Portugal Vineyards and Italy Vineyards models demonstrated a significant difference in AUCs.

H_{17}: The comparison between Portugal Olives and Spain Olives models resulted in a rejected hypothesis due to a significant difference in AUCs.

It is exciting that in the aggregate models, only between the aggregate model of Vineyards (0.752) against that of Olives groves (0.695), the differences are significant. All other aggregate models show no differences in accuracy. In the individual models, however, there are differences in some models, not only within the same country about crops (Italy) but also between different countries, although with the same crops. There are differences between Portugal and Italy in the AUCs, whether in the Vineyards or the

Olive Groves. These results suggest creating specific models if the agriculture practised differs at the level of crops or countries.

4.5 Conclusion

This study is based on the estimation of forecasting models of financial distress in vineyards and olive groves in Portugal, Spain and Italy, Mediterranean countries with similar characteristics and agronomic practices. For this purpose, we analyzed popular financial covariates commonly used in financial distress analysis. Our variables are related to liquidity, solvency, profitability, and activity of agricultural firms and are commonly used in credit risk models.

ROC curves and the corresponding areas under the curves (AUCs) allow us to conclude that, depending on the subsamples, significant differences suggest that credit risk in agriculture depends on the specifics of the agricultural activity itself. When comparing the differences in the areas under the ROC curve, we find significant variations between firms that cultivate olive groves and those that cultivate vineyards. The vineyard model is more predictive of financial distress, while the olive grove model is less accurate. However, no significant differences are observed among the various combinations of model comparisons across countries. The models that aggregate firms by country, namely Portugal, Spain, and Italy, show no significant variations. In Italy, the vineyard and olive grove models exhibit statistical differences. At the country and crop level, the difference in AUCs of firms that explore vineyards between Portugal and Italy is noticeable. This suggests that specific prediction models should be adopted in this countries depending on the categorization of agricultural firms. The results also show significant differences between Spain and Italy in the case of olive groves.

This study highlights the importance of adopting region-specific predictive models for assessing credit risk in agriculture. Policymakers in Portugal, Spain, and Italy should consider the distinct vineyard and olive grove cultivation characteristics when designing agricultural policies and financial support programs. Tailoring policies to specific crops can lead to more targeted and effective interventions to address financial distress and promote sustainable agricultural development. The distinct challenges faced by Mediterranean countries, together with the impact of climate change and agricultural trade liberalization, highlight the need for targeted interventions to address financial difficulties and improve the financial performance of rural economies in the South relative to Northern Europe. There is still to be considered the likely impacts of applying the new PAC 2023-2027 and its improved sustainability measures based on environmental and climate objectives through ecological schemes. These plans, based on significant budgets, if they consider the different characteristics of agricultural firms in different countries and crops, will certainly mitigate the factors related to financial distress. Farmers and business leaders in the agricultural sector can benefit from the insights provided by the study. Understanding the differences in credit risk prediction between vineyard and olive grove cultivation can help them make more informed financial decisions and risk management strategies. Farmers must recognise the factors influencing their financial health and take appropriate actions to enhance their financial sustainability. For the scientific community, this study highlights the importance of considering the specific characteristics of agricultural activities when developing credit risk models for the agriculture sector. This findings could prompt further research into refining and enhancing predictive models for different agricultural activities.

Limitations: There are limitations to consider when interpreting the results. The first limitation is the very definition of financial distress, which determines the dependent variable of logistic regression. While bankruptcy determines the end of the firm's activity, the severity of financial distress may not put the firm in real danger. Another limitation is that there needed to be an exhaustive exploration of predictor covariates. The study focuses on the dynamics of models between different countries and crops, having selected a few potential model-independent variables. If we had access to a combination of financial variables with others that are more qualitative and even specific to agricultural activity, the predictive power of the models could be better. Also, although this study is based on a large set of data, the business structure of agriculture in these countries is complex and leaves out all farmers who are not legally constituted as a firm. This is the case of individual entrepreneurs representing a broad spectrum of family farms and other small-scale agriculture.

Future research may introduce covariates linked to the rural world, especially those specific to different crops.

Chapter 5

Unveiling the Fragility of Small-Scale Agriculture

Abstract

The aim of this study is to predict financial distress in Iberian Peninsula farms, especially in small-scale agriculture, which dominates the agricultural sector.

Analyzing 9,891 firms, six logistic regression models are estimated, adapted to different economic sizes. Models exhibit high predictive accuracy, aiding in forecasting farm financial health. Binary logistic regression identifies eight key financial variables related to liquidity, leverage, profitability, and activity, as effective predictors of distress.

The conclusions expose the fragility of smaller firms. This emphasizes the significance of firm size in anticipating financial challenges, guiding policymakers towards tailored interventions for different-sized agricultural firms.

Keywords: agriculture, farm size, financial distress, prediction models, small farming.

5.1 Introduction

Following the green revolution that occurred in the previous century, which aimed to enhance agricultural production through the adoption of new technologies, fertilizers, pesticides, mechanization, and the use of adapted seeds, the focus has shifted to sustainable development. Small-scale farming has emerged as a crucial topic in conversations surrounding sustainability, economic and social growth, and global food security.

However, small farms face challenges in obtaining credit quickly and easily or providing payment guarantees because of their size. On the other hand, assessing credit risk for small agricultural operations can be challenging for creditors due to their distinct characteristics that demand careful analysis. Given small farms' significant challenges, including climate change, and the need to comply with regulations by adopting sustainable practices, developing credit risk models for these units is crucial. This study aims to address this challenge by presenting a credit risk model that predicts the financial difficulties of agricultural operations of different scales, emphasizing small farms.

The remaining paper is organised as follows. Section 5.2 addresses the literature on the characterization of credit risk associated with small-scale agriculture. Section 5.3 describes the data and methodology used, and section 5.4 presents and discusses the results. Finally, Section 5.5, presents the conclusions and limitations.

5.2 Literature Review

5.2.1 Farm Size and Economic Size

While small organizations have the advantage of being more flexible, having fewer problems monitoring managers and employees, and benefiting from more efficient intra-firm communication, they are less resilient to the shocks they may encounter (Dyrberg, 2004). However, larger firms, with more significant growth opportunities and investment in current assets, receive more financing from their suppliers (García-Teruel and Martínez-Solano, 2010). Small farms continue to play an essential role in fighting poverty. While larger farms tend to have suboptimal employment rates, small farms employ more people, often from their families and local communities. Moreover, small farms are still known for their higher productivity, greater efficiency, and lower capital intensity, especially in developing countries with limited availability of land and capital. However, as these countries get wealthier, and because labour productivity is typically lower than on large farms, it presents a long-term viability problem (Hazell et al., 2010; Hazell, 2011). Small farming is struggling with problems that are inseparable from its size. Retrograde management, the lack of adequate financing channels due to the lack of collateral, high financing costs compared to larger companies, and risk aversion on the part of commercial banks that are not well suited to supporting the primary sector (Yuan and Yang, 2018). Larger farms more easily meet lenders' requirements, are more successful in obtaining loans, and are less susceptible to sectorial downturns Rusiana et al. (2017). Small farms prevail in competition in an increasingly globalized and regulated market, facing difficulties consistent with their size. "Small-scale businesses operate under greater constraints due to more limited access to land and water, resources, information, technology, capital, and assets. They bear a double burden of vulnerability to risks and shocks: in addition to risks intrinsic to agriculture, they also face the risk of being excluded from productive assets and lucrative markets in the transformation process of food supply chains" (FAO, 2021, p.69) and face difficulties in accessing markets due to globalization of food chains and the concentration of power of large retailers (Al-Hassan et al., 2006).

"Most of the EU's farms are small in nature; two thirds were less than 5 hectares in size" (Cook, 2020, p.12) and of the more than 600 million farms worldwide, 84% are smaller than 2 hectares and are responsible for operating 12% of all agricultural land (Lowder et al., 2019, 2021). However, there is no universal definition of a small farm, which lacks a common understanding. In practice, each country adopts different definitions of this concept (Borychowski et al., 2020). Nonetheless, it is generally associated with the establishment of low-volume agricultural businesses. (Carlin and Crecink, 1979). Furthermore, it is not standardized around the 2-hectare dimension, depending a lot on the regions, and at the limit, 500 hectares can be considered a smallholding in Australia (Wolfenson, 2013). However, the characterization of small-scale agriculture cannot solely rely on questionable concepts such as arable land area. This is because intensive and super-intensive agricultural practices can generate high turnovers in relatively small areas, as seen in greenhouse farming. Hoppe et al. (2010) define a small farm as one with GCFI (gross cash farm income) less than USD 250,000 and a very small farm with less than USD 10,000. U.S Department of Agriculture categorizes small farms into two classes: (i) Low-sales: farms with GCFI less than USD 150,000 and (ii) Moderate-sales: farms with GCFI between USD 150,000 and USD 349,999 (Whitt et al., 2021). In the EU, standardized concepts were adopted. The economic size of farms, which until 2007 was measured by the standard gross margin, is now measured by the standard output (SO)[1] distributed in 14-dimensional classes. European Commission (2008a, 2018) has proposed two methods for categorizing economic size based on standard output. The first approach considers very small firms as those with a standard output of less than EUR 2,000 and small firms with an SO between EUR 2,000 and EUR 8,000. The second approach groups farms into quintiles based on their economic size measured by standard output, with the smallest farms having the lowest levels of economic output but cumulatively contributing to 20% of the total SO. Other sources point to a threshold of EUR 25,000 of SO to categorize a small farm, highlighting the difficulty of establishing a single definition (European Parliament, 2014).

According to data available from Bureau Van Dijk (2022), there are 122,701 agricultural firms with registered operational revenues (turnover), of which 83% can be considered as small and medium-sized agricultural holdings (less than EUR 350,000), with the majority (48%) in the range of EUR 8,000 to EUR 25,000. Only 3% of firms recorded turnovers below EUR 2,000, as many as those in the range of EUR 2,000 to EUR 8,000 (see Figure 5.1). These percentages may seem low, but it is important to note that most small farms are not structured as legal companies.

[1]Eurostat defines the standard output of an agricultural product as the average monetary value of the output, measured in euros per hectare (for crops) or head of livestock. A regional coefficient, based on an average value over a five-year reference period, is applied to each product. Adding up the standard outputs per hectare of crop and head of livestock for a farm provides a measure of the farm's overall economic size, expressed in euros.

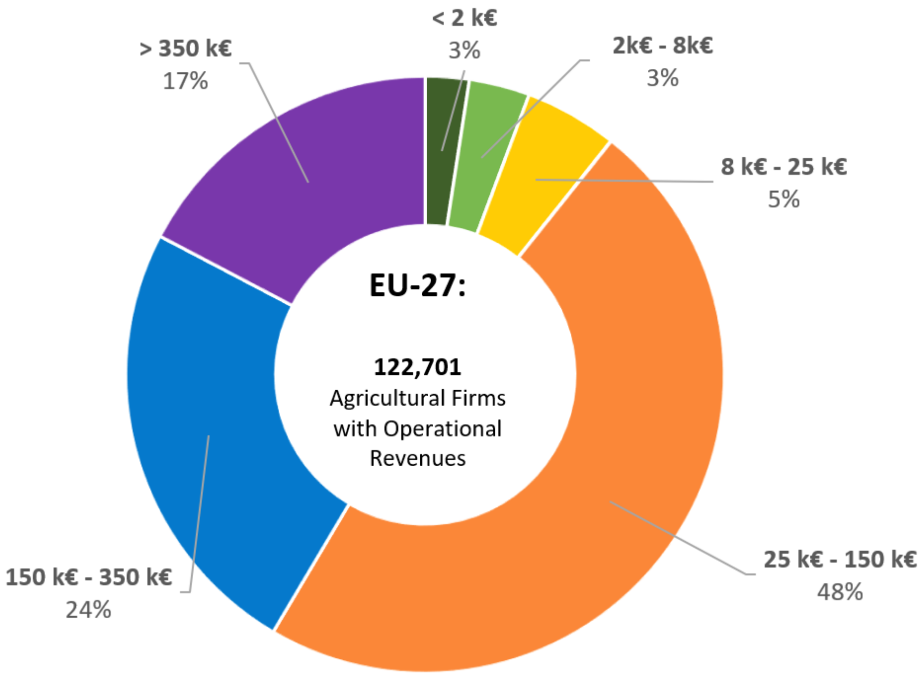

Figure 5.1: EU-27 agricultural firm sizes by 2021 revenues. Data sourced from Orbis (Bureau Van Dijk), accessed on 28 December 2022. https://orbis.bvdinfo.com

5.2.2 The Link between Financial Distress and Agricultural Activity

The subject of credit risk is multifaceted and covers various financial difficulties that businesses encounter. Furthermore, there is a need for consistent terminology to describe these financial issues. For example, some terms, such as "bankruptcy," carry legal implications and signify that a business cannot meet its obligations. Other terms, such as "insolvency," "default," and "financial distress," are more informal and suggest that a business is experiencing solvency problems that could lead to a loss for creditors. However, it is worth noting that these informal states' definitions must be more consistent across the literature and may differ based on the author's perspective. Since the seminal studies by Beaver (1966) and Altman (1968), there has been much research on bankruptcy, covering various methodological and conceptual approaches. However, contrasting with the objectivity associated with the concept of bankruptcy that is based on a court decision taken at a given time, financial distress can be a state that the firm feels with or without recurrence and that does not necessarily have to end in bankruptcy.

Agricultural firms are particularly susceptible to long cycles of activity that result in solvency problems and frustration for creditors who struggle to receive their loans under previously agreed conditions. Significant volatility of incomes characterizes agricultural activity. The European Union has attempted to reduce this volatility through direct payments, but standard deviations remain unchanged (Asseldonk et al., 2019).

Some studies interpret financial distress in agricultural firms as an informal state based on financial ratios. Valaskova et al. (2020) is based on the Slovak Commercial Code, which defines a firm at risk of bankruptcy when the equity-to-liability ratio is less than 8%. Furthermore, when the ratio of current assets to current liabilities is less than 1, the firm is also considered non-prosperous.

Alternative approaches were employed to categorize a firm as in financial difficulty, even in cases where financial information was unavailable. For example, if a firm had not provided financial statements for three consecutive years, it would be classified as part of the bankrupt group (Dietrich et al., 2005). Outside the agricultural sector, Platt and Platt (2006) interpret the state of financial distress when three criteria are verified simultaneously: (i) Negative EBITDA interest coverage, (ii) negative EBIT, and (iii) negative net income before special items. Other similar approaches, such as those by Whitaker (1999) highlight the insufficient relationship between cash flow and the current maturities of long-term debt and Asquith et al. (1994) based the definition on interest coverage ratios when presented as negative in one of two consecutive years.

The lack of studies that comprehensively analyze the concept of financial distress in agricultural firms and how this state manifests in various economic dimensions highlights the need to investigate this topic further. This need also motivates the developement and implementation of more suitable credit risk assessment models that capture the predictive variables of failure and more accurately evaluate the conditions under which loans should be made available. The organizational structures of small agricultural businesses, which are often less professional, pose challenges in credit risk modelling, and size is only occasionally considered a relevant variable.

The paper's contribution to the literature is to provide insights into predicting the financial difficulties of farms in the Iberian Peninsula, focusing on small-scale agriculture, which constitutes a significant portion of the agricultural business sector. This study has significant implications for policymakers and practitioners in the agricultural sector, particularly those dealing with small-scale agriculture.

5.3 Data and Methods

5.3.1 Sample Identification and Definition of Financial Distress

We obtained data from the ORBIS database provided by Bureau van Dijk. To classify the farms into different economic dimensions, we analyzed their financial statements and calculated their average operating revenues between 2020 and 2021, the most recent data available. We focused on 9,228 firms that are classified as "growing of perennial crops" and "growing of non-perennial crops" according to the statistical classification of economic activities in the European Community (NACE Rev. 2).

For our analysis, and in a practical approach to the various theoretical concepts related to the economic dimension of agricultural farms, we divided firms into five size categories:

- (i) *microfarms*, with operational revenue of up to EUR 8,000;
- (ii) *small farms*, with operational revenue between EUR 8,000 and EUR 25,000;
- (iii) *low-sales farms*, with operational revenue between EUR 25,000 and EUR 150,000;
- (iv) *moderate-sales farms*, with operational revenue between EUR 150,000 and EUR 350,000;
- (v) *Medium and Large farms*, with operational revenue above EUR 350,000.

This article focuses on firms that demonstrate persistent low solvency capacity. To avoid including firms that have experienced temporary difficulties in a single year, common in the agricultural sector, we verify the following criteria for two consecutive years.

Thus, in this study, a firm is classified as being in *financial distress* if two conditions co-occur for two consecutive years: (1) the *Insolvency Ratio* is negative, and (2) the Interest Coverage Ratio (*ICR*) is less than 1. If neither of these conditions is met, the firm is considered *healthy.* If no healthy, are in *financial distress* (FD). These two variables provide insight into the firm's solvency capacity and ability to pay interest using generated funds. The analysis is based on data from the years 2020 and 2021. These variables are formulated as follows:

$$Insolvency\ Ratio = 1 - \frac{total\ liabilities}{total\ assets} \quad (5.1)$$

$$ICR = \frac{EBIT}{Interests} \quad (5.2)$$

where, $EBIT$ = Earnings before interest and taxes, and $Interests$ = interest payable on any borrowings.

The distribution of firms according to their size and financial health is shown in Table 5.1.

Table 5.1: Distribution of samples

Firm's Size	H	FD	Total	% FD
Microfarms	129	62	191	32.5%
Small Farms	439	156	595	26.2%
Low-Sales Farms	2 690	368	3 058	12.0%
Moderate-Sales Farms	2 152	131	2 283	5.7%
Medium & Large Farms	3 660	104	3 764	2.8%
Total	9 070	821	9 891	8.3%

Healthy (H), Financial Distressed (FD)
Source: Own elaboration

5.3.2 Independent Variables

Table 5.2 contains 19 financial expressions commonly used as covariates in bankruptcy or financial distress prediction models. We categorize these candidate independent variables into four groups: (i) liquidity ratios measure a firm's ability to pay short debt obligations,

(ii) leverage ratios measure the indebtedness of a firm, (iii) profitability ratios determine the ability to generate income and (iv) activity/other ratios measure the operational activity of firms.

Table 5.2: Set of independent variables

Category	Variable	Acronym	Explanation
Liquidity	R01 Current Ratio	CR	Current Assets : Current Liabilities
	R02 Quick Ratio	QR	Cash Equivalents : Current Liabilities
	R03 Acid-Test Ratio	ATR	(Cash Equivalents + Receivables) : Current Liabilities
	R04 Working Capital to Assets	WCTA	Working Capital : Total Assets
Leverage	R05 Debt-to-EBITDA Ratio	DEBITDA	Total Debt : EBITDA
	R06 Gearing Ratio	TLEQ	Total Debt : Equity
	R07 Debt Ratio	TLTA	Total Debt : Total Assets
Profitability	R08 Return on Assets	ROA	Net Income : Total Assets
	R09 Ebit Margin Ratio	EBITTA	EBIT : Total Assets
	R10 EBITDA Margin	EBITDAM	EBITDA : Total Assets
	R11 Losses Recurrence	LR	1 if net income negative last two years, 0 otherwise
	R12 Net Income Change	NIC	$(NI_t - NI_{t-1}) / (\|NI_t\| + \|NI_{t-1}\|)$, where NI is net income
	R13 Interest to Sales	IES	Interest Expenses : Sales
	R14 Profit Margin	PM	Net Income : Sales
Activity/ Others	R15 Net Fixed Assets	NFA	Sales : Average Fixed Assets
	R16 Receivables Turnover	RT	Log (360 * (Net Credit Sales : Average Receivables))
	R17 Assets Turnover	STA	Sales : Average Total Assets
	R18 Size	SIZE	Log (Total Assets)
	R19 Firm's Age	AGE	Log (Firm's Age in days)

Source: Own elaboration

5.3.3 Model Development

This study employs models that are differentiated based on size classes. Specifically, in addition to a model encompassing all 9,891 firms, we present separate models for each of the five size classes. To analyze the data, we use logistic regression as the appropriate statistical method for a binary dependent variable, where 0 represents a healthy firm, and 1 denotes a financially distressed firm. The logistic model is expressed as follows:

$$P_i = \frac{1}{1 + e^{-(\beta_0 + \beta_{i1} X_{i1} + \beta_2 X_{i2} + \ldots + \beta_n X_{in})}} \tag{5.3}$$

where, P_{i} = probability of financial distress, $X_{ij} = j^{th}$ variable of the i^{th} firm, and β_j = estimated coefficient for the j^{th} variable.

5.3.4 Models Accuracy

To assess the accuracy of models, we evaluated the occurrence of Type I and Type II errors, and the Area Under the Receiver Operating Characteristic Curve (AUC) (Hanley and McNeil, 1982). The relationship between sensitivity and specificity is crucial in determining the proportion of the AUC, where a greater accuracy of the model corresponds to a larger area. Following Lemeshow et al. (2013), an AUC greater than 0.80 indicates the excellent discriminative ability of the model, while an AUC exceeding 0.90 is considered outstanding, and an AUC less than 0.70 indicates poor performance.

To evaluate the model's effectiveness, we utilized a confusion matrix (Table 5.3) to analyze the occurrence of Type I errors (false positives) and Type II errors (false negatives). In addition, we calculated confidence intervals to test the null hypothesis that the AUC is equal to zero. To determine the best threshold for distinguishing healthy and financially distressed firms, we identified the cutoff point that maximizes the Youden index, a commonly used metric for classification models.

Table 5.3: Confusion matrix

		Predicted	
		Healthy	Financial Distressed
Observed	Healthy	True negative	False positive
	Financial Distressed	False negative	True positive

Source: Own elaboration

5.3.5 Data Analysis

To further explore the financial performance of farms based on size, we analyzed several financial ratios in Table 5.4, Table 5.5, and Table 5.6. We emphasize the median due to the presence of outliers and note that the mean is not always a reliable central measure. As an illustration, financially distressed firms exhibit higher means in R01 (Current Ratio) and R02 (Quick Ratio) than healthy firms.

Some considerations stand out from the results. Regarding the variables R05 (Debt to EBITDA) and R06 (Gearing Ratio) variables, there is a potential for an ambiguous interpretation of how liabilities are expressed numerically in the ratio numerator. This contrast is especially noticeable in negative EBITDA or equity cases, typically associated with firms with weaker financial health.

Healthy microfarms tend to have an R13 variable, which measures the relationship between interest and sales, higher in healthy firms than in financially distressed ones, which does not happen in other size classes. This can be explained by the difficulty for microfarms to access credit, even more so as they are experiencing difficulties.

The variable R18 (Size) and the variable R19 (Age) have a greater expression in healthy firms than in firms in financial distress, which is consistent with the idea that economies of scale and experience positively influence a firm's ability to survive.

5.4 Results and Discussion

We start by referring a positive correlation between farms' economic scale and financial stability. The proportion of firms experiencing financial distress is shown to be inversely proportional to their size (Figure 5.2).

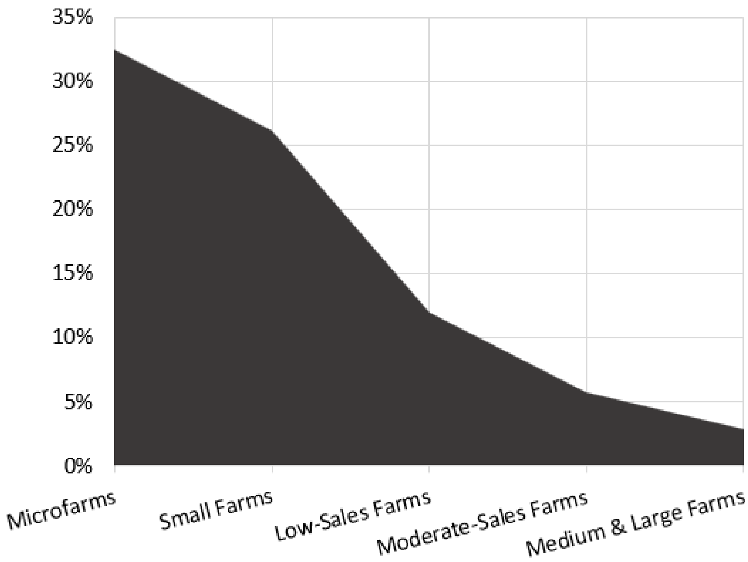

Figure 5.2: Percentage of agricultural firms in financial distress. Source: Own elaboration.

The results suggest that smaller farms are more likely to be financially distressed, with 32.5% of microfarms and 26.2% of small farms being classified as financially distressed.

Table 5.4: Descriptive statistics of variables - micro and small farms

		Microfarms						Small Farms					
	*	N	Mean	Median	Std. Dev.	Min.	Max.	N	Mean	Median	Std. Dev.	Min.	Max.
R01 Current Ratio	H	118	395.31	1.94	2611.95	0.00	26980.14	424	62.51	2.45	445.01	0.02	7662.05
	FD	59	551.15	0.29	2963.21	0.01	17348.72	154	5.58	0.42	18.92	0.01	129.64
R02 Quick Ratio	H	112	80.63	0.62	344.50	-0.09	3077.78	417	43.45	0.61	404.72	-0.08	7319.91
	FD	55	123.33	0.04	904.30	0.00	6707.82	150	2.41	0.06	11.69	0.00	96.12
R03 Acid-Test Ratio	H	112	78.04	0.32	341.07	-43.56	3077.78	417	40.93	0.42	392.28	-121.50	7027.58
	FD	55	-8.18	0.03	1339.42	-7203.19	6707.82	150	1.92	0.03	11.88	-23.53	96.12
R04 WCTA	H	129	0.09	0.09	0.73	-5.62	1.00	439	0.13	0.12	0.50	-3.24	1.00
	FD	62	-1.32	-0.50	3.15	-16.71	0.95	156	-1.15	-0.36	4.07	-40.58	0.90
R05 Debt to EBITDA	H	129	-10.65	-0.89	213.17	-2031.32	732.28	439	13.82	1.04	339.87	-3668.24	3340.16
	FD	62	9.24	-9.54	196.43	-294.40	1369.74	156	254.69	-4.76	1715.57	-294.48	15783.33
R06 Gearing Ratio	H	129	1.78	0.38	6.83	-32.11	37.91	439	1.07	0.57	36.69	-358.20	422.22
	FD	62	13.41	-2.15	126.92	-51.03	976.10	156	-5.24	-2.35	70.73	-809.18	244.83
R07 Debt Ratio	H	129	0.55	0.41	0.92	0.00	7.54	439	0.54	0.48	0.62	0.00	5.60
	FD	62	3.22	1.55	4.14	0.64	21.15	156	2.39	1.43	4.30	0.16	41.58
R08 Return On Assets	H	129	-0.07	-0.02	0.28	-2.35	0.44	439	-0.02	0.00	0.20	-2.85	0.76
	FD	62	-0.64	-0.15	1.38	-8.18	0.25	156	-0.55	-0.12	3.51	-43.15	0.79
R09 EBIT Margin Ratio	H	129	-0.07	-0.02	0.28	-2.35	0.44	439	-0.01	0.00	0.21	-2.85	0.77
	FD	62	-0.64	-0.15	1.38	-8.18	0.26	156	-0.55	-0.12	3.51	-43.15	0.84
R10 EBITDA Margin	H	129	-0.05	-0.01	0.28	-2.35	0.44	439	0.03	0.02	0.20	-2.62	0.77
	FD	62	-0.56	-0.05	1.39	-8.18	0.26	156	-0.46	-0.03	3.51	-43.15	1.01
R11 Losses Recurrence	H	129	0.52	1.00	0.502	0	1	439	0.34	0.00	0.48	0	1
	FD	62	0.85	1.00	0.355	0	1	156	0.73	1.00	0.44	0	1
R12 Net Income Change	H	129	-0.03	-0.06	0.63	-1	1	439	-0.12	-0.13	0.69	-1	1
	FD	62	-0.12	-0.10	0.54	-1	1	156	-0.01	-0.01	0.61	-1	1
R13 Interest to Sales	H	129	1.55	0.00	12.56	0.00	139.15	439	0.14	0.00	1.51	0.00	31.41
	FD	62	0.24	0.00	0.95	0.00	5.79	156	0.62	0.00	3.72	0.00	44.38
R14 Profit Margin	H	129	-21.49	-0.87	111.48	-976.65	9.60	439	-3.83	-0.06	43.55	-894.06	25.37
	FD	62	-28.19	-3.86	108.28	-790.00	0.87	156	-8.50	-1.13	44.03	-498.25	1.16
R15 Net Fixed Assets	H	124	2.42	0.04	19.92	0.00	221.39	420	13.73	0.11	244.57	0.00	5010.02
	FD	59	1.86	0.08	8.66	0.00	65.50	147	1.17	0.18	4.24	0.00	42.83
R16 Receivables Turnover	H	102	1.80	1.90	0.92	-0.94	4.52	370	2.17	2.19	0.80	-0.38	4.86
	FD	40	2.33	2.39	1.02	-0.28	4.68	115	2.36	2.36	0.82	-0.78	4.95
R17 Assets Turnover	H	129	0.09	0.02	0.17	0.00	1.15	439	0.18	0.07	0.32	0.00	3.61
	FD	62	0.22	0.05	0.43	0.00	2.18	156	0.35	0.13	0.86	0.00	7.99
R18 Size	H	129	1.97	2.06	0.68	0.24	3.23	439	2.09	2.01	0.57	0.71	3.83
	FD	62	1.59	1.60	0.67	-0.34	3.31	156	1.85	1.85	0.57	-0.12	3.57
R19 Age	H	129	3.58	3.54	0.35	2.91	4.34	439	3.59	3.55	0.33	2.91	4.36
	FD	62	3.42	3.42	0.30	2.94	4.10	156	3.48	3.46	0.29	2.93	4.12

* H (Healthy Firms), FD (Financial Distressed Firms)
Source: Own elaboration

Table 5.5: Descriptive statistics of variables - low-sales and moderate-sales farms

		Low-Sales Farms						Moderate-Sales Farms					
	*	N	Mean	Median	Std. Dev.	Min.	Max.	N	Mean	Median	Std. Dev.	Min.	Max.
R01 Current Ratio	H	2664	1767.00	2.38	89586.26	0.00	4623873.00	2147	24.83	2.11	612.09	0.01	28078.10
	FD	364	5.14	0.71	19.87	0.01	175.82	130	3.09	0.82	13.34	0.01	144.02
R02 Quick Ratio	H	2602	833.28	0.69	41446.17	-0.59	2114065.00	2096	6.99	0.56	59.34	-0.42	1683.30
	FD	355	1.80	0.10	10.01	-0.67	121.48	127	0.50	0.12	1.38	0.00	11.96
R03 Acid-Test Ratio	H	2602	831.87	0.48	41446.20	-373.48	2114065.00	2096	6.13	0.30	59.44	-132.88	1683.30
	FD	355	0.99	0.03	9.42	-19.46	121.48	127	0.03	0.03	2.04	-15.69	11.96
R04 WCTA	H	2690	0.19	0.18	0.42	-3.74	1.00	2152	0.20	0.19	0.35	-1.84	0.99
	FD	368	-0.40	-0.19	1.11	-13.95	1.00	131	-0.26	-0.09	0.68	-4.50	0.96
R05 Debt to EBITDA	H	2690	63.49	2.80	3624.52	-39821.67	182725.57	2152	5.39	3.61	199.10	-8152.82	3025.72
	FD	368	-61.62	-5.41	862.62	-16449.39	514.56	131	-16.19	-2.90	120.93	-1109.25	371.34
R06 Gearing Ratio	H	2690	4.16	0.73	48.23	-504.47	1725.04	2152	5.35	0.82	68.09	-1344.69	2178.61
	FD	368	11.72	-2.56	189.27	-275.43	3395.25	131	2.97	-3.01	37.23	-145.41	225.29
R07 Debt Ratio	H	2690	0.51	0.48	0.43	0.00	6.96	2152	0.51	0.50	0.37	0.00	5.18
	FD	368	1.57	1.24	1.17	0.33	14.51	131	1.32	1.08	0.78	0.49	6.88
R08 Return On Assets	H	2690	0.02	0.01	0.19	-5.06	0.95	2152	0.04	0.02	0.14	-1.67	2.46
	FD	368	-0.21	-0.12	0.36	-2.63	1.20	131	-0.14	-0.06	0.45	-4.52	0.46
R09 EBIT Margin Ratio	H	2690	0.03	0.02	0.20	-5.06	1.17	2152	0.06	0.03	0.16	-1.67	2.60
	FD	368	-0.20	-0.11	0.37	-2.63	1.61	131	-0.13	-0.05	0.46	-4.52	0.57
R10 EBITDA Margin	H	2690	0.08	0.05	0.21	-5.06	1.17	2152	0.10	0.07	0.16	-1.55	2.67
	FD	368	-0.13	-0.04	0.37	-2.58	1.66	131	-0.07	-0.01	0.45	-4.34	0.65
R11 Losses Recurrence	H	2690	0.18	0.00	0.383	0	1	2152	0.11	0.00	0.31	0	1
	FD	368	0.64	1.00	0.480	0	1	131	0.49	0.00	0.50	0	1
R12 Net Income Change	H	2690	-0.01	-0.02	0.69	-1	1	2152	0.02	0.01	0.66	-1	1
	FD	368	-0.15	-0.12	0.67	-1	1	131	-0.11	-0.13	0.71	-1	1
R13 Interest to Sales	H	2690	0.28	0.00	7.51	0.00	368.26	2152	0.06	0.00	0.59	0.00	17.75
	FD	368	0.50	0.00	4.92	0.00	69.59	131	0.22	0.02	0.86	0.00	6.97
R14 Profit Margin	H	2690	-0.90	0.05	20.61	-606.03	261.18	2152	-0.06	0.06	7.69	-259.76	145.77
	FD	368	-18.70	-0.45	223.94	-3909.59	8.43	131	-0.36	-0.15	5.01	-23.01	49.86
R15 Net Fixed Assets	H	2636	24.98	0.45	521.26	-226.41	21282.80	2130	27.45	0.78	534.93	0.00	19844.48
	FD	358	8.46	0.64	87.87	0.00	1631.54	131	14.53	0.83	79.58	0.00	756.58
R16 Receivables Turnover	H	2457	2.49	2.45	0.68	-0.91	7.24	2060	2.62	2.61	0.59	-0.70	7.46
	FD	331	2.56	2.47	0.68	-1.40	5.37	123	2.62	2.69	0.62	0.32	4.35
R17 Assets Turnover	H	2690	0.42	0.23	0.73	0.00	16.53	2152	0.59	0.37	0.87	0.00	24.45
	FD	368	0.60	0.31	0.90	0.00	8.48	131	0.77	0.47	1.08	0.00	8.40
R18 Size	H	2690	2.38	2.35	0.49	0.35	4.99	2152	2.73	2.67	0.46	0.82	4.67
	FD	368	2.18	2.16	0.52	0.65	3.99	131	2.67	2.59	0.55	1.19	4.25
R19 Age	H	2690	3.62	3.61	0.33	2.87	4.65	2152	3.65	3.67	0.34	2.88	4.65
	FD	368	3.52	3.51	0.31	2.87	4.51	131	3.53	3.50	0.32	2.91	4.26

* H (Healthy Firms), FD (Financial Distressed Firms)
Source: Own elaboration

Table 5.6: Descriptive statistics of variables - medium & large farms and full sample

	*	Medium & Large Farms N	Mean	Median	Std. Dev.	Min.	Max.	Full Sample N	Mean	Median	Std. Dev.	Min.	Max.
R01 Current Ratio	H	3655	10.00	1.85	278.95	0.01	16820.26	9008	540.67	2.06	48720.85	0.00	4623873.00
	FD	104	4.07	0.92	15.64	0.06	120.09	811	44.48	0.68	805.73	0.01	17348.72
R02 Quick Ratio	H	3549	2.77	0.41	19.56	-0.14	974.95	8776	252.94	0.54	22568.15	-0.59	2114065.00
	FD	99	0.35	0.10	0.66	0.00	3.89	786	10.03	0.09	239.36	-0.67	6707.82
R03 Acid-Test Ratio	H	3549	-1.08	0.15	185.04	-10961.14	974.95	8776	250.61	0.29	22568.47	-10961.14	2114065.00
	FD	99	-1.16	-0.02	9.15	-88.93	3.89	786	0.10	0.03	351.42	-7203.19	6707.82
R04 WCTA	H	3660	0.18	0.16	0.30	-1.02	0.99	9070	0.18	0.17	0.37	-5.62	1.00
	FD	104	-0.16	-0.02	0.58	-2.78	0.81	821	-0.56	-0.18	2.17	-40.58	1.00
R05 Debt to EBITDA	H	3660	8.20	3.97	172.02	-6529.46	5589.16	9070	23.94	3.42	1980.77	-39821.67	182725.57
	FD	104	33.49	-4.56	465.40	-1331.81	4044.59	821	23.13	-4.96	967.20	-16449.39	15783.33
R06 Gearing Ratio	H	3660	2.57	0.94	71.25	-2432.16	1707.73	9070	3.62	0.82	62.49	-2432.16	2178.61
	FD	104	-8.26	-3.57	176.41	-1475.25	698.25	821	4.70	-2.56	149.58	-1475.25	3395.25
R07 Debt Ratio	H	3660	0.50	0.51	0.31	0.00	2.69	9070	0.51	0.50	0.40	0.00	7.54
	FD	104	1.30	1.10	0.62	0.62	5.27	821	1.78	1.21	2.42	0.16	41.58
R08 Return On Assets	H	3660	0.05	0.03	0.13	-0.96	4.67	9070	0.04	0.02	0.16	-5.06	4.67
	FD	104	-0.13	-0.07	0.24	-1.22	0.75	821	-0.29	-0.10	1.61	-43.15	1.20
R09 EBIT Margin Ratio	H	3660	0.07	0.04	0.12	-0.79	1.67	9070	0.05	0.03	0.17	-5.06	2.60
	FD	104	-0.12	-0.05	0.26	-1.22	1.01	821	-0.28	-0.10	1.61	-43.15	1.61
R10 EBITDA Margin	H	3660	0.11	0.08	0.13	-0.73	1.78	9070	0.09	0.07	0.17	-5.06	2.67
	FD	104	-0.07	-0.02	0.26	-1.18	1.07	821	-0.21	-0.03	1.61	-43.15	1.66
R11 Losses Recurrence	H	3660	0.08	0.00	0.274	0	1	9070	0.14	0.00	0.34	0	1
	FD	104	0.52	1.00	0.502	0	1	821	0.63	1.00	0.48	0	1
R12 Net Income Change	H	3660	0.03	0.02	0.59	-1	1	9070	0.01	0.00	0.65	-1	1
	FD	104	-0.17	-0.24	0.71	-1	1	821	-0.12	-0.11	0.66	-1	1
R13 Interest to Sales	H	3660	0.08	0.01	3.06	0.00	184.91	9070	0.16	0.00	4.79	0.00	368.26
	FD	104	0.17	0.01	1.25	0.00	12.62	821	0.42	0.00	3.72	0.00	69.59
R14 Profit Margin	H	3660	0.12	0.05	2.96	-68.36	129.16	9070	-0.72	0.05	20.43	-976.65	261.18
	FD	104	-1.22	-0.13	8.41	-84.64	1.47	821	-12.34	-0.40	154.19	-3909.59	49.86
R15 Net Fixed Assets	H	3638	10.71	1.08	168.19	0.00	8288.01	8948	18.93	0.70	403.09	-226.41	21282.80
	FD	102	9.26	1.53	32.13	0.00	285.64	797	7.73	0.54	68.23	0.00	1631.54
R16 Receivables Turnover	H	3600	2.74	2.72	0.54	-0.44	9.30	8589	2.60	2.60	0.63	-0.94	9.30
	FD	102	2.83	2.80	0.72	1.59	6.35	711	2.56	2.53	0.74	-1.40	6.35
R17 Assets Turnover	H	3660	0.82	0.55	1.06	0.00	23.66	9070	0.60	0.35	0.91	0.00	24.45
	FD	104	1.14	0.70	1.45	0.00	8.44	821	0.62	0.28	1.01	0.00	8.48
R18 Size	H	3660	3.24	3.20	0.52	1.70	5.33	9070	2.79	2.77	0.65	0.24	5.33
	FD	104	3.04	3.05	0.51	1.76	4.26	821	2.26	2.23	0.69	-0.34	4.26
R19 Age	H	3660	3.71	3.76	0.33	2.87	4.99	9070	3.66	3.69	0.33	2.87	4.99
	FD	104	3.50	3.47	0.35	2.91	4.29	821	3.50	3.47	0.31	2.87	4.51

* H (Healthy Firms), FD (Financial Distressed Firms)
Source: Own elaboration

In contrast, the larger farms (medium & large farms) have the lowest percentage of financially distressed farms, with only 2.8%. This is consistent with the observation that larger farms have greater financial stability and management capabilities.

Table 5.7 displays the results of the Spearman correlation matrix. Given the non-normality of financial ratios (Deakin, 1976), we opted for Spearman's method over Pearson's, as recommended by Bol et al. (2012). The correlations between variables, except for some within the same category, such as liquidity, are generally low to moderate. To avoid multicollinearity, we plan to choose one or two ratios from each category based on their type and investigate different combinations of covariates across different categories.

The results of the logistic regression model estimation are presented in Table 5.8. According to the literature, all variables of the six models have coefficients with expected signs. Thus, the variables R07 and R11 have a positive sign, meaning that the greater the indebtedness or losses, the greater the probability of entering financial distress. It should be noted that only the covariate R07 is common to all models, so the level of indebtedness is statistically significant regardless of the size of the agricultural firm. The recurrence of losses, expressed by the variable R11, shows a more robust statistical significance in the samples of larger firms, and although it is present in the sample of microfarms, it is disregarded in the case of the sample of small farms. This leads us to conclude that small agricultural structures, family farms or partial occupancy can continue to accumulate losses without any relationship with financial distress. After all, small agricultural units often continue to be maintained over the years, without the farmers resorting to indebtedness (either due to difficulties in accessing or because they have activities that guarantee them supplementary livelihood) or there are even interest payments, which are the variables that characterize the state of financial distress in this study.

In contrast, the variables R04, R08, R09, R10, and R12 display a negative coefficient, indicating that a higher numerical expression corresponds to a lower probability of experiencing financial distress. Additionally, the variable R18, which gauges a firm's size, exhibits a negative coefficient, albeit only in the full sample. This suggests that, for

Table 5.7: Spearman's sho coefficients

	R01	R02	R03	R04	R05	R06	R07	R08	R09	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19
R01	1.00	.77**	.49**	.86**	-.18**	-.28**	-.54**	.20**	.18**	.14**	-.15**	.00	-.20**	.23**	.09**	-.07**	-.06**	.04**	.14**
R02		1.00	.78**	.63**	-.20**	-.30**	-.53**	.25**	.23**	.19**	-.15**	.03**	-.28**	.26**	.06**	.08**	-.02*	-.06**	.09**
R03			1.00	.38**	-.20**	-.27**	-.41**	.23**	.21**	.19**	-.11**	.04**	-.24**	.28**	.02	.03**	-.03**	-.11**	.02*
R04		Liquidity		1.00	-.14**	-.18**	-.47**	.31**	.30**	.26**	-.23**	.01	-.21**	.26**	.37**	-.04**	.16**	-.07**	.08**
R05					1.00	.40**	.27**	.08**	.11**	.14**	-.27**	.13**	.20**	.14**	01	.02*	.04**	.11**	-.00
R06						1.00	.45**	.02	.05**	.10**	-.12**	.03*	.24**	-.05**	.12**	.05**	.18**	.03**	-.16
R07			Leverage				1.00	-0.28	-.23**	-.14**	.20**	.01	.25**	-.33	.10**	.03**	.16**	-.21**	-.30
R08								1.00	.97**	.88**	-.57**	.49**	-.15**	.87**	.39**	.22**	40**	.00	-.06**
R09									1.00	.91**	-.56**	.47**	-.10**	.82**	.42**	.24**	.43**	-.02	-.08**
R10										1.00	-.50**	.42**	-.10**	.69**	.45**	.28**	.50**	-.11**	-.14**
R11											1.00	-.02*	.06**	-.59**	-.30**	-.12**	-.29**	-.05**	-.04**
R12												1.00	-.02*	.47**	.08**	.13**	.11**	-.01	-.04**
R13													1.00	-.10**	-.25**	-.06**	-.18**	.28**	.03**
R14							Profitability							1.00	.15**	.10**	.12**	.07**	.03**
R15															1.00	.29**	.90**	-.33**	-.19**
R16																1.00	.43**	-.04**	-.12**
R17																	1.00	-.27**	-.24**
R18																		1.00	.34**
R19								Activity / Others											1.00

* Correlation significant at the 0.05 level (2-tailed). ** correlation significant at the 0.01 level (2-tailed).

Source: Own elaboration

the global sample, larger firms are less likely to encounter financial distress. Notably, the statistical significance of size is only evident in the entire sample, indicating that size may be unjustly overlooked when the overall sample is divided into size categories. Consequently, the impact of size may be diminished in each subgroup. However, paradoxically, this finding underscores the significance of agricultural unit size in anticipating financial distress.

All of the independent variables demonstrate a statistical significance of less than 0.01. The Nagelkerke R^2 statistic values are approximately 0.5, indicating that the model explains approximately half of the variation in the dependent variable. The values are reasonably high, suggesting the model fits the data well. Additionally, all models exhibit a Chi-Square goodness of fit with a $p-$value below 0.001, suggesting that they surpass the intercept models in performance. Thus, it is concluded that all of the covariates significantly influence the models.

Figure 5.3 represents the areas under the ROC curve of the different models. All models show excellent discriminatory quality between healthy and bankrupt firms with AUC's greater than 0.93. Although not far apart, the models from the largest farms present the best values, with the "Medium & Large Farms" model being the best with a value of 0.959.

For a better comprehension of the distribution of variables relating to the financial well-being of firms, we have incorporated a logarithmic Dot Diagram for each model (Figure 5.4).

Table 5.9 presents the accuracy of the different logistic models according to the economic size of the farms, using the Area Under the ROC Curve (AUC) as an evaluation metric. Youden's index was utilized to identify the optimal cutoff point in these models (Youden, 1950). All models performed above 86% accuracy, indicating effectiveness in predicting financial distress. The model with the best performance is "Medium & Large Farms", with an AUC of 0.959 and an accuracy of 87.9%. This model also has the highest sensitivity (94.2%), which means it has the lowest false positive rate. However, generally, it can be said that any of the models have high levels of accuracy and the "Full Sample"

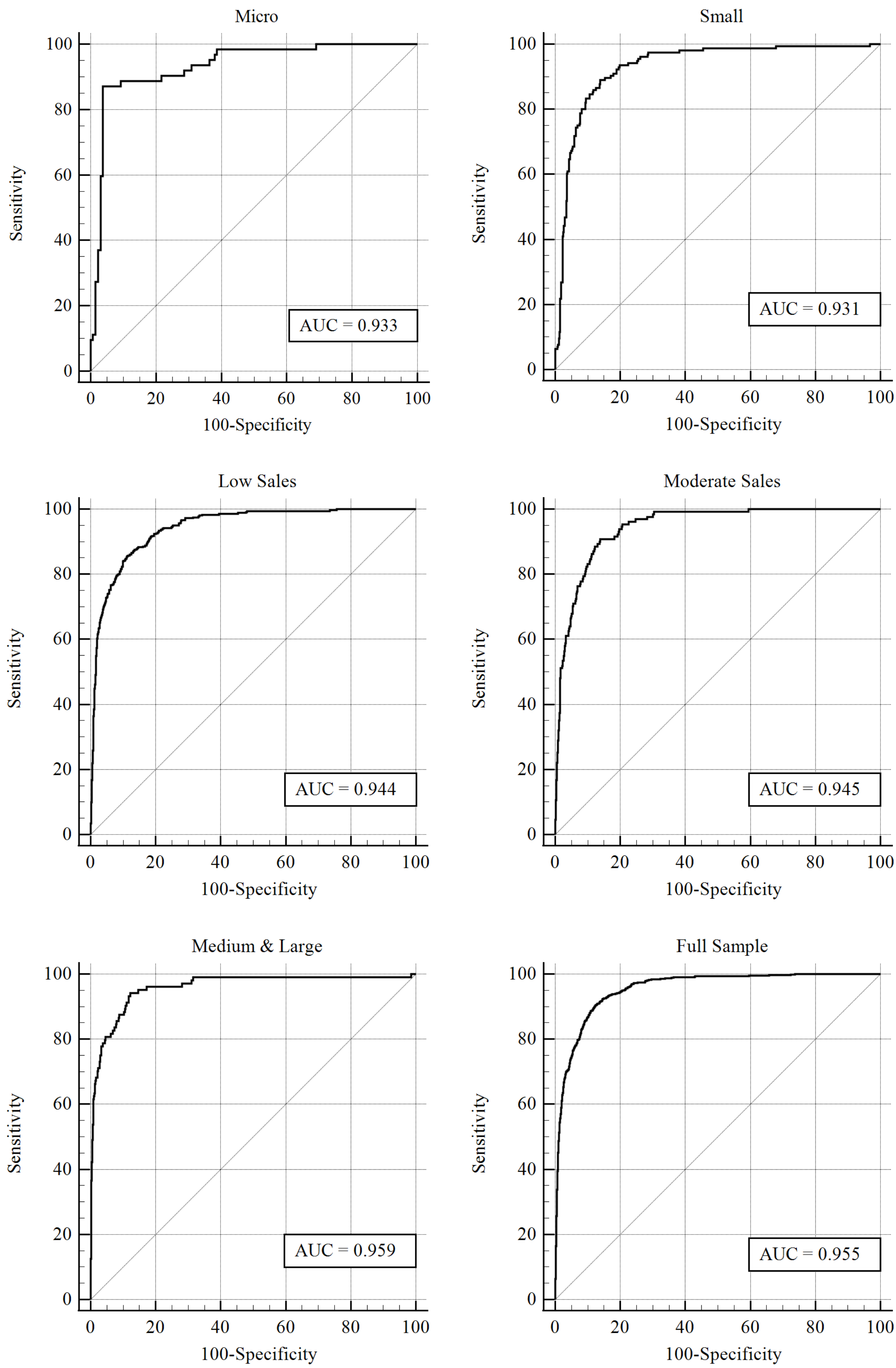

Figure 5.3: ROC curves. Source: Own elaboration

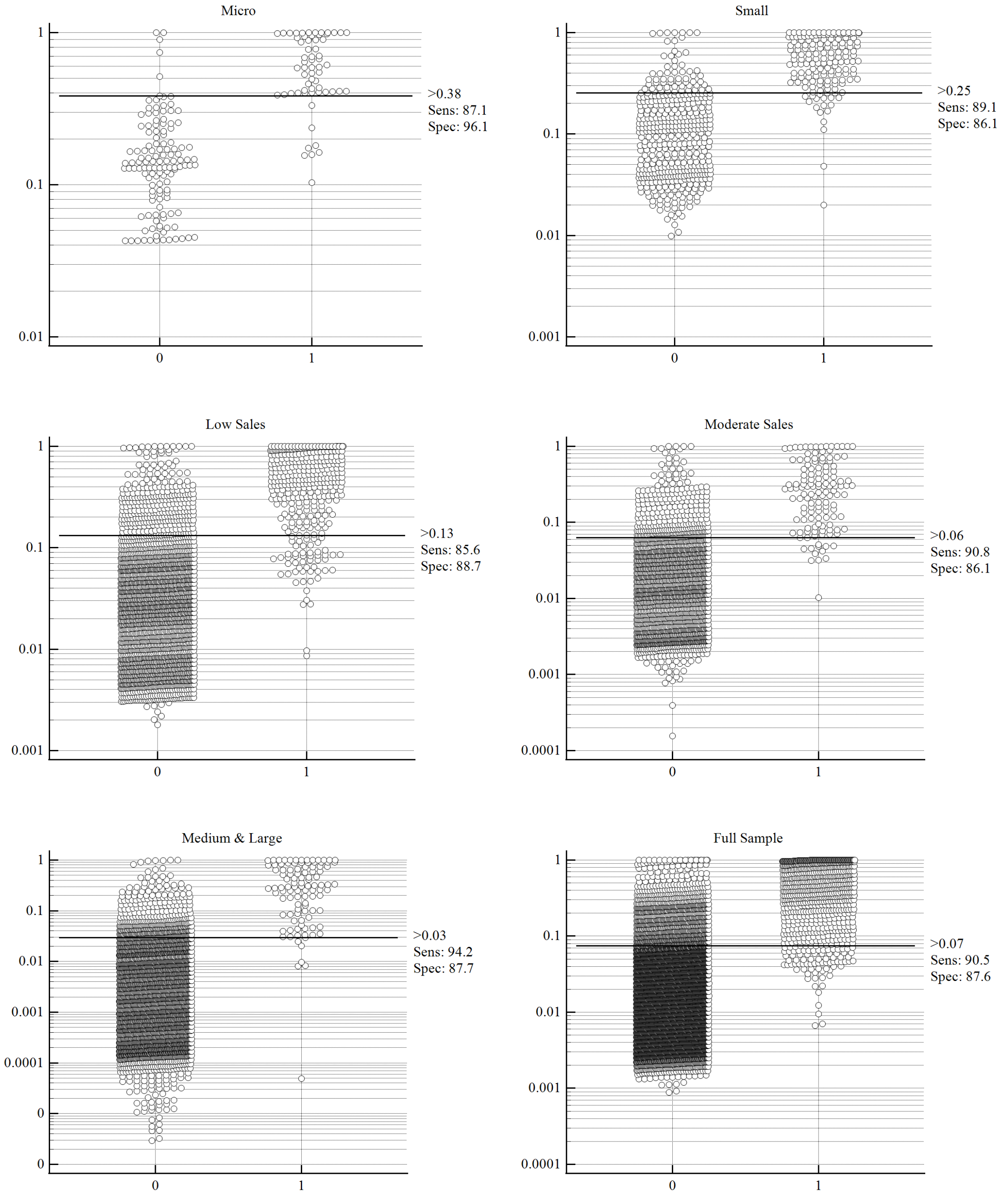

Figure 5.4: Dot diagrams - logarithmic scale. 0 - healthy firms, 1 - financial distressed firms. Source: Own elaboration.

Table 5.8: Estimation of the logit model

	Micro	Small	Low Sales	Moderate Sales	Medium & Large	Full Sample
Constant	-3.105	-3.151	-5.392	-5.944	-8.653	-4.285
p-Value	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
R04 WCTA		-0.742				-0.257
p-Value		(0.005)				(<0.034)
R07 TLTA	1.478	2.066	3.134	3.577	6.110	3.001
p-Value	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
R08 ROA			-0.633			
p-Value			(0.044)			
R09 EBITTA		-1.470		-2.476		-0.763
p-Value		(0.003)		(<0.001)		(0.004)
R10 EBITDAM					-4.995	
p-Value					(<0.001)	
R11 LR	1.189		1.675	1.275	1.166	1.715
p-Value	0.011		(<0.001)	(<0.001)	(<0.001)	(<0.001)
R12 NIC			-0.379			-0.336
p-Value			(0.002)			(<0.001)
R18 SIZE						-0.477
p-Value						(<0.001)
χ^2 Model	83.59	245.61	980.35	358.85	467.41	2 542.77
Model *p*-Value	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Nagelkerke R^2	0.495	0.495	0.527	0.420	0.523	0.520
-2 Log likelihood	157.18	439.03	1 267.91	634.29	484.17	3 115.82
N	191	595	3 058	2 283	3764	9 891

Source: Own elaboration

model, tested on all data, exhibited an AUC of 0.955 and an accuracy of 87.8

The confusion matrix results revealed low rates of Type I and Type II errors across the models, indicating that they effectively minimised false positives and false negatives. Notably, the "Microfarms" model had an exceptionally low rate of Type II errors, at only 3.9%. The "Medium & Large Farms" model had the best Type I error rate, with only 5.8%.

5.5 Conclusions and Limitations

Modelling risk forecasting in small-scale agriculture is a significant challenge due to the unique structure of these farms. Small-scale farms are often based on family structures or are considered additional sources of income for farmers. This heterogeneity in man-

Table 5.9: Accuracy of predictive models

Model	AUC	Cutoff	Confusion Matrix Parameters					Hypothesis (Area=0.5)	
			Accuracy	Sensitivity	Specificity	Type I Error	Type II Error	AUC ± 1.96 SE	p-Value
Micro	0.933	0.383	93.2%	87.1%	96.1%	12.9%	3.9%	0.895-0.972	<0.001
Small	0.931	0.253	86.9%	89.1%	86.1%	10.9%	13.9%	0.908-0.954	<0.001
Low Sales	0.944	0.132	88.3%	85.6%	88.7%	14.4%	11.3%	0.933-0.955	<0.001
Moderate Sales	0.945	0.063	86.3%	90.8%	86.1%	9.2%	13.9%	0.930-0.960	<0.001
Medium & Large	0.959	0.030	87.9%	94.2%	87.7%	5.8%	12.3%	0.938-0.980	<0.001
Full Sample	0.955	0.074	87.8%	90.5%	87.6%	9.5%	12.4%	0.949-0.961	<0.001

AUC - Area under ROC curve. SE - Standard error
Source: Own elaboration

agement makes it challenging to collect quantitative data as these farmers do not follow standard procedures. However, these small-scale agricultural units represent the majority of the agricultural industry. Although this presents a challenge in identifying specific variables of this small size, it is also a limitation. Additionally, smallholders are not encouraged to organize themselves legally following international accounting standards. Many continue their business as sole proprietors without even forming a formal business entity.

This study aims to predict financial distress in agricultural firms, considering different size classes based on varying concepts. The study focuses primarily on small-scale agriculture, which dominates the agricultural sector and is categorized into four classes, while the remaining firms are grouped into a residual class called Medium & Large Farms.

Out of 9,070 agricultural firms analyzed, 821 were identified to be in financial distress based on their *Insolvency Ratio* and *Interest Coverage Ratio* behaviour in 2020 and 2021. The study presents six prediction models, five for different size classes and one for the full sample, developed from an initial set of 19 variables calculated from the 2020 financial statements.

Through binary logistic regression, the study concludes that financial distress prediction can be determined effectively using a maximum of eight variables related to liquidity, leverage, profitability, activity, and others.

The primary findings of this study are outlined as follows. Firstly, the results indicate a significant association between financial distress and firm size. Specifically, a higher proportion of firms experience financial distress in smaller size classes, while a lower proportion faces financial difficulties in larger firm classes. Secondly, the study found that the size of firms, as measured by their assets, is only statistically significant when analysing the full sample of firms. However, when categorizing firms into size classes according to their revenues, the variable of size measured by assets ceases to be significant in predicting financial distress. These findings demonstrate the importance of considering firm size when predicting financial distress and the need to utilize an appropriate classification method for accurate modelling.

It is worth noting that despite their size differences, microfarms and large farms share some common variables. Specifically, the leverage of debt over assets is the only variable in all models. Additionally, the recurrence of losses is a strongly significant variable for larger classes of farms but loses significance in smaller properties, although it remains present in the microfarms model.

The main highlight of this study is the high accuracy of the estimated prediction models. All models have an accuracy of over 86%, and none have an AUC lower than 0.93. These results suggest that the models can accurately predict financial distress based on the given parameters.

However, some limitations of this study should be acknowledged. Smaller firms/farms may have lower-quality management information due to limited resources and expertise. As a result, farmers considering agriculture a supplementary activity may not adopt a management posture comparable to those with professional training and work full-time in agriculture.

Chapter 6

Conclusions and Contributions

The articles outlined in this thesis provide a comprehensive understanding of credit risk within the agricultural sector. Each paper delves into distinct facets of the industry, contributing valuable insights and implications for theory, practice, and policymakers.

All four studies underscore the importance of tailoring bankruptcy and financial distress prediction models to the specific characteristics of agricultural activities. Traditional financial ratios, while informative, exhibit varying degrees of effectiveness depending on factors such as vegetative cycles, crop types, and farm sizes. The studies collectively emphasise the need for nuanced approaches, considering the diverse nature of agricultural operations.

In the first paper, which investigates predictors for differentiating financial health in agricultural firms, the research identifies specific financial ratios that effectively distinguish between perennial and non-perennial crop firms. Furthermore, the study underscores the interconnected impact of economic policies and climate change on farmers' decision-making processes, the option for crops with more resilient vegetative cycles to positively impact financial returns.

The second paper focuses on region-specific predictive models for credit risk in agriculture. It meticulously demonstrates the significance of tailoring predictive models to specific regions, particularly in vineyards and olive groves. The study highlights the necessity for customized policies in Portugal, Spain, and Italy, considering the distinctive characteristics of different crops.

Moving to the third paper, which delves into risk forecasting in small-scale agriculture, the research acknowledges the inherent challenges in modelling risk for these diverse farms. Despite the heterogeneity, the study successfully establishes prediction models using a limited set of variables. Notably, it emphasises the critical role of firm size in forecasting financial distress within small-scale agricultural operations.

The fourth paper delves into climate risk management in agricultural lending, emphasizing the significant influence of climate change on loan recovery. It underscores the necessity of incorporating climate-informed risk assessments within the agricultural lending sector. Furthermore, the paper advocates for implementing green credit policies and addresses the vulnerabilities of developing countries, particularly concerning insufficient access to credit.

Implications and Recommendations

The integrated findings from these studies bear substantial implications for diverse stakeholders deeply entrenched within the agricultural landscape. **Policymakers** stand at a pivotal juncture, with the imperative to contemplate the intertwined impact of economic policies, climate change dynamics, and the distinctive characteristics of various crops. This multifaceted consideration becomes paramount in the meticulous formulation of agricultural policies, requiring a holistic approach that accommodates the sector's complexities.

For **financial institutions**, the call to action is clear: assimilating climate risk considerations into their lending practices is paramount. Moreover, adopting region-specific predictive models emerges as a strategic necessity, facilitating more precise risk assessments tailored to different geographical contexts' unique challenges and opportunities. The convergence of these measures ensures a more resilient financial ecosystem capable of navigating the intricacies of agricultural finance.

Amidst these transformative shifts, **farmers and business leaders** find themselves at the forefront, tasked with recognising the myriad factors influencing their financial health. This recognition is not merely an intellectual exercise but a pragmatic call to adapt strategies in response to the dynamic interplay of economic variables and climatic conditions. The ability to discern and navigate through these diverse influences becomes indispensable for fostering financial sustainability and resilience in the ever-evolving agricultural landscape. It beckons a paradigm shift in decision-making processes, urging stakeholders to embrace a proactive stance informed by a nuanced understanding of the factors shaping their financial destinies.

Limitations and Future Directions

While the studies contribute significantly to the understanding of financial distress in agriculture, limitations include focusing on specific variables and restricting certain geographical regions. Future research should explore additional covariates, consider a transnational context, and delve into the impacts of the latest agricultural policies.

For continued advancement, a classification into risk classes would be invaluable. Financial institutions, in particular, could benefit from a segmented approach to credit risk that tailors criteria, lending conditions and mitigation strategies to the distinct characteristics of specific regions, crop types and agricultural practices. Such a detailed classification can also guide policymakers in designing sensitive policies, improving support for the diverse needs of the agricultural sector.

Additionally, emerging methodologies like machine learning present promising avenues for future research in agricultural credit risk assessment. These techniques could improve predictive accuracy by uncovering complex, non-linear patterns within large datasets and across diverse variables, enabling more dynamic and adaptive risk assessments than traditional statistical methods.

While this thesis delves into the intricacies of agricultural credit risk, emphasising the necessity for nuanced models and tailored policies that contribute to academic discourse and informed decision-making, it is essential to acknowledge the formidable challenges looming over this ancient industry. As we venture into the coming decades, there will be a heightened impetus for researchers, myself included, to delve deeper into comprehending the sector's metamorphosis in response to escalating climate risks and the implicit imperative of ensuring food security.

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