LUISS

Department of Business and Management

Master's Degree in Corporate Finance

Chair of Business Valuation

Bankruptcy Risk under Different Monetary Regimes: An Empirical Analysis of European Listed Real Estate Firms

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Academic Year 2024/2025

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Introduction

In less than five years a global pandemic shock, stubborn inflation, monetary pressures and geopolitical uncertainties have affected the world economies in not yet completely understood ways. In particular, corporations had to change their long-term strategies and survive in an ever-more challenging environment.

Bankruptcy prediction is a topic within distress valuation that has attracted constant interest and thousands of contributions by researchers for decades. Those have developed models that are able to predict the likelihood of failure from financial information with years of advance.

The logic is that current financial statements carry data that enable to understand whether firms are facing increased pressures which eventually could lead to bankruptcy.

This thesis aims to examine whether the abrupt change in monetary policy after 2022 increased bankruptcy risk in the European real estate industry, testing three notorious prediction models.

Moreover, the analysis allows to understand which model is better able to explain the higher risk and to suggest the model best suited to the industry for future applications.

To the best of my knowledge, it does not exist a study that tests bankruptcy models in the large-cap European real estate industry, nor one that compares the results across different monetary regimes.

Thus, this thesis explores a specific methodology in a poorly studied field, with the goal of pushing the current academic literature beyond its current state.

The experiment is conducted on 63 large capitalization European real estate companies, with a total of 420 observations divided into a low and high-interest rate regime. The data is used to elaborate Altman's Z-Score, Ohlson's O-Score, Zmijewski's score and an industry-tailored, Ohlson modified specification.

Most of the models agree that a significant increase in bankruptcy risk is shown by the firms' financial statements. Moreover, the most significant model appears to be Zmijewski's, while Ohlson's modified seems to be the most comprehensive offering the most interpretations. On the other hand, the notorious Altman's model exhibits poorly meaningful and statistically insignificant results.

The findings are in line with the prevailing literature, which sees Zmijewski and tailor-made models as the best suited to the general real estate industry.

Additionally, the most influencing and predictive variables are individuated through models' decomposition. Those are size, leverage and cash flow generation.

The overall results shed light on bankruptcy prediction in the European real estate industry. Managers, policy makers and investors may use the findings of this research to adapt their models and shape their strategies, particularly when similar inflationary events happen again.

The thesis is structured as follows: chapter 1 addresses current bankruptcy trends and explains why the real estate industry is chosen for the experiment; chapter 2 reviews the literature about distress valuation and bankruptcy prediction; chapter 3 explains the data and the methodology utilized; chapter 4 displays the results of the experiment.

Finally, the conclusion section draws the final considerations and addresses the contribution and limitation of the thesis.

Chapter 1

1.1 Bankruptcy

One of the most feared and taunting aspects of Corporate Finance and Business Valuation is the abrupt termination of operations, formally known as corporate failure or bankruptcy. Once a corporation fails it is not only the founders who greatly suffer, but all the shareholders, employees, creditors and society are made worse off.

It is thus natural that corporate failure generates much attention both legally and economically. The former has shaped many articulated codes that discipline the matter of failure to protect at best all the characters involved, disciplined in Italy by the "Codice della crisi d'impresa e dell'insolvenza" and in the United States under Title 11 of the US Bankruptcy Code, especially Chapters 7 (Liquidation), 11 (Reorganization), and 13 (Individual Debt Adjustment).

On the other hand, economists have been focusing on estimating causes and effects and trying to predict bankruptcy, since they argue that such a definitive event - failure - may show some signs that, if correctly intercepted, can prompt life-saving changes.

When analyzing causes and effects, it is foremost necessary to define the distress process that eventually leads to bankruptcy.

Financial distress is defined solely by financial features, especially related to debt. This becomes more and more unsustainable and forces the management to take drastic decisions that sacrifice the long-term viability of the firm, like selling assets or rejecting profitable projects.

Additionally, financial distress has different degrees and definitions. Altman considered financial distress, failure, default and bankruptcy as the same condition, while other authors have argued that financial distress and bankruptcy are distinct events. They argue that mild financial distress could appear as a cash flow temporary slowdown, while failure leads to the discontinuity of the firm's operation.

On the other hand, operational distress happens following non-recurring events such as economic downturn or may be an effect of financial distress.

The observation of historical data regarding bankruptcy is a good indicator of current visible trends that influence the current well-being of the economy.

The first interesting variable to analyze is the total number of bankruptcy filings in the US. The data (Exhibit 1.1) are sourced by the United States Courts, the maximum jurisdiction for official filings in the US.

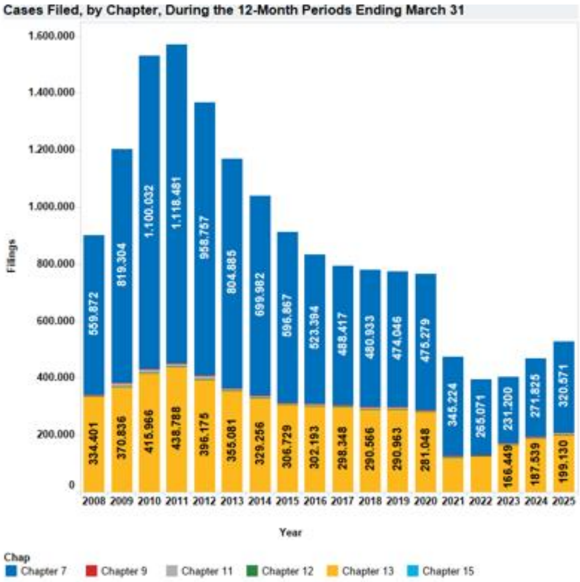
While the 2025 data is below the decade average, it is considerable higher than the previous 4 years, and a positive trend starting in 2022 can be seen.

The total number of bankruptcy filings in the US has had an annual historic average around 800.000-900.000 - excluding the Global Financial Crisis years - while on the wake of the post-Covid economic rebound the average figure decreased to 500000 circa. Now the total filings are increasing once again, moving towards the decade average, at a rate not seen since 2011.

Moreover, it is interesting to see the division by chapter code. Chapter 7 has remained the most filed-for type of bankruptcy, with an average of 60% of the total filings. Chapter 13 follows, with an average of 30% of the filings. Chapter 11 filings constitute a smaller proportion but have seen the highest increase in the last years, particularly +49.6% YOY in 2024 and +10.1% YOY in 2025.

This highlights the increased restructuring needs of corporations, which face unsustainable yet arguably resolvable financial difficulties, often caused by external and unpredictable shocks.

Exhibit 1.1 – Total Bankruptcy Filings in the US



Source: uscourts.gov, Bankruptcy Statistics Data Visualization, Bankruptcy Cases Filed, June 2025

A specific focus on Chapter 11 filings (Exhibit 1.2) shows that high borrowing costs and decreasing consumer spending contributed to pushing Chapter 11 bankruptcy filings to their highest level in eight years in 2024. Moreover, an accelerating rate in Q4 2024, suggests that this increasing trend of Chapter 11 filings will continue in all of 2025. Data are still incoming over the subject.

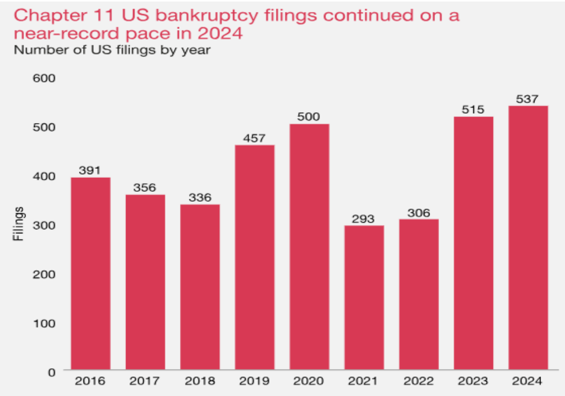
It can be seen how Chapter 11 filings in 2021 and 2022 were considerably low. This can be explained by the fact that weaker and smaller businesses were able to avoid restructuring thanks to extraordinary levels of government subsidies, a low-interest rate environment and an economic rebound that stimulated capital circulation and fueled M&A activity, ultimately enabling companies to borrow their way out of troubles.

As can be seen in Exhibit 1.3, bankruptcy filings in 2024 were not equal between sectors, and four industries dominated Ch 11 filings: consumer goods and services, real estate, healthcare and energy and industrials.

About the first, particularly restaurants were hit, showing mutated consumer spending patterns following increase in food prices. In the healthcare sector, inflation and decreasing reimbursement rates led to 75% higher filings than in the previous years. In particular, middle-sized healthcare businesses suffered the most because of their sub-scale, lack of negotiation leverage and limited geographical reach (high dispersion or lower income regions).

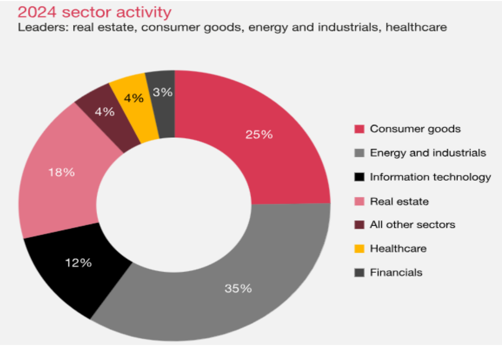
Finally, commercial real estates were among the most affected, displaying 35% of total filings. This can be explained by high vacancies in office properties combined with the impact of high interest rates. It is worth noting that most of the filings reported liabilities of less than $10 million.

Exhibit 1.2 – Total number of Chapter 11 filings



Source: 2025 Octus Intelligence, Restructuring 2025 Outlook, PwC

Exhibit 1.3 – Chapter 11 filings by sector



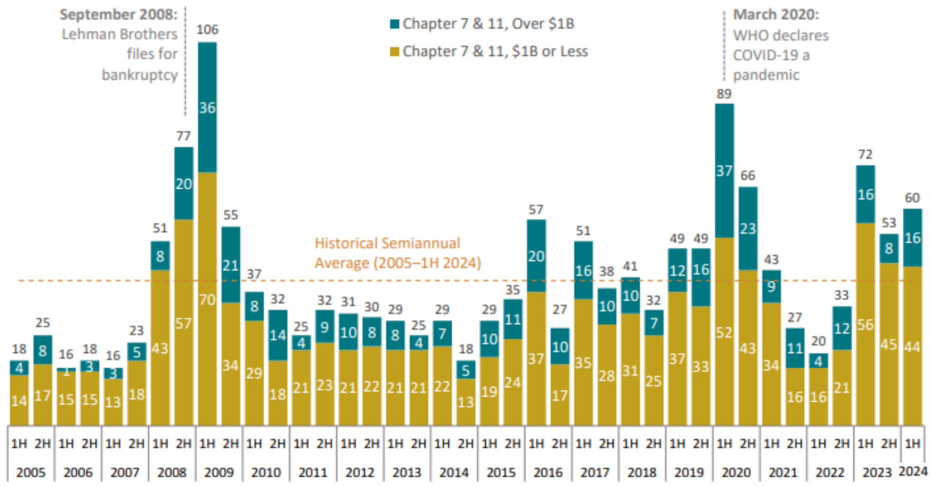
Source: 2025 Octus Intelligence, Restructuring 2025 Outlook, PwC

Another relevant trend involves large corporate bankruptcy (Exhibit 1.4). As a matter of fact, 113 large corporations filed for bankruptcy in 2024, an 8% increase YOY and 43% above the 2005-2023 average. In Q1 2025, Chapter 11 filings increased by 22%, and Chapter 13 filings by 8.3% YOY.

At the time of bankruptcy, average assets were $673 million, about half of the 2005-2023 average. On the other hand, there were 24 'mega' bankruptcies (> $1 billion assets) in 2024, above historical average. By late 2024, rated U.S. non-financial corporations carried a record $8.45 trillion in total debt, while interest coverage ratios are seen in constant deterioration.

Most of the files attributed the declaration to high inflation, interest rates and persistent effects of Covid-19 struggles, in addition to increased competition, unsuccessful strategy and logistical and supply chain issues.

Exhibit 1.4 – Monthly filing of bankruptcy by large corporate



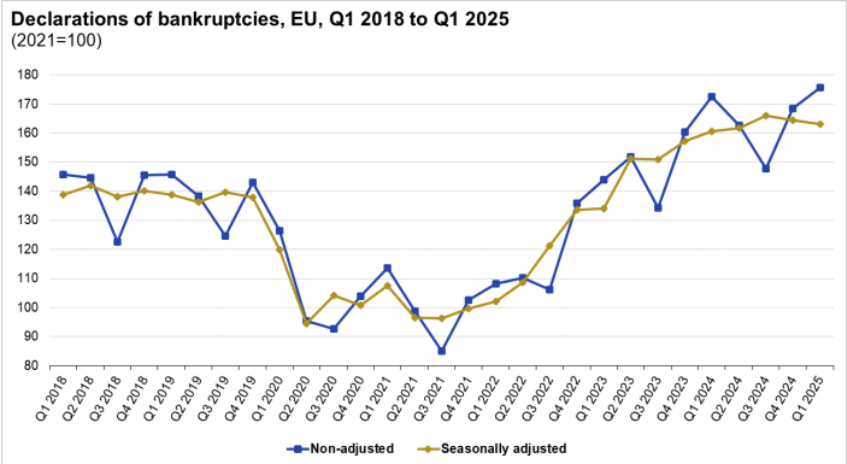
Source: BankruptcyData, Cornerstone Research 2024

A similar analysis can be conducted for European bankruptcy filings (Exhibit 1.5). The data are sourced from Eurostat for a 7-year period and show a positive trend particularly between Q1 2022 and Q1 2024.

In Q1 2025 bankruptcy filings decreased by 0.9% compared with Q4 2024, while still being at a higher level than during the period from Q1 2018 until Q2 2024. This may signal economic relief for many companies across Europe, but further data is needed to confirm.

Interestingly, the highest increase in filings in Q1 2025 QoQ were observed in Greece and Sweden, and in the accommodation, education and communication industries.

Exhibit 1.5 – Bankruptcy Filings in the EU



Source: Quarterly registrations of new businesses and declarations of bankruptcies – Statistics, Eurostat May 2025

Not only Europe and the United States are experiencing these trends. Allianz estimated a rise by +11% YOY of its Global Insolvency Index for the year 2024, and it expects even tighter environment for the full year 2025 given slowing growth, geopolitical frictions and the unprecedented slow easing of financing conditions. No region seems to be excluded from the trend which will likely reach its peak in 2026. The number of jobs directly at risk in Europe and North America will exceed 1.6 million in 2025 (Allianz, 2024).

In addition, recent political and economic disputes, which could not have been foreshadowed at the end of 2024, threaten global growth prospects even more. Moreover, while it is true that high rates forced companies to reevaluate and adapt their capital structures, the long-waited monetary easing cycle will certainly support struggling firms, but it will not entirely eliminate intrinsic failure risks.

In conclusion, bankruptcy is a more-than-ever relevant topic that interconnects macroeconomics and corporations worldwide. The numerous reports here analyzed and the future prospects indicate rising pressures for firms, which are showing increased weaknesses.

Many companies were already stranded by a series of unpredictable external shocks, to which an all-time high volatility was added. In addition, monetary and political environments have abruptly changed worldwide. As consequence, many firms are forced to review their projects or even restructure. The effects over employment and growth are only imaginable.

It is critical to study the phenomenon of business failure to understand future trends and act before severe consequences affect the global economy.

1.2 The Real Estate Industry

It was previously shown how the real estate industry suffered heavily in the last years. Because of a combination of macroeconomic factors and intrinsic characteristics, the sector is particularly relevant to study the effects of different monetary regimes over bankruptcy risks.

This chapter presents the industry, shows some trends and explains the logic behind this study.

1.2.1 Industry introduction

The Real Estate industry represents one of the pillars of the global economy. It encompasses a wide range of properties and facilities that meet different but fundamental human and society's needs. Properties are generally classified by usage type, namely residential, office, industrial, retail, and hospitality.

Real estate strategies are well represented in investors' portfolios because they offer diversification across return sources, degrees of sensitivity to economic cycles, and a combination of income and long-term growth. Core real estate has historically served as an attractive and sound source of income, with yields that outpaced inflation over the past 30 years.

Real Estate is deeply interconnected with global demographics and secular megatrends. Many macroeconomic variables have a strong effect on the industry, such as demographics, prices level, employment, political and legislative environment. All of these contribute to determining the value and prices of real estate properties.

Moreover, the real estate sector is composed of many different actors: there are asset management companies, investment vehicles - such as REITs – developers, construction companies, and service providers (advisory and brokerage companies). Each class operates under different business models, risk profiles and capital structures, leading to difficulties in comparing and evaluating the industry as a whole.

Particularly, REITs and asset-heavy property firms have close affinity with financial firms, having a high-leveraged balance sheet, long-term investment horizons and being intrinsically illiquid. They suffer the so-called maturity mismatch, like banks do – namely when a company uses short-term fundings to finance long-term assets.

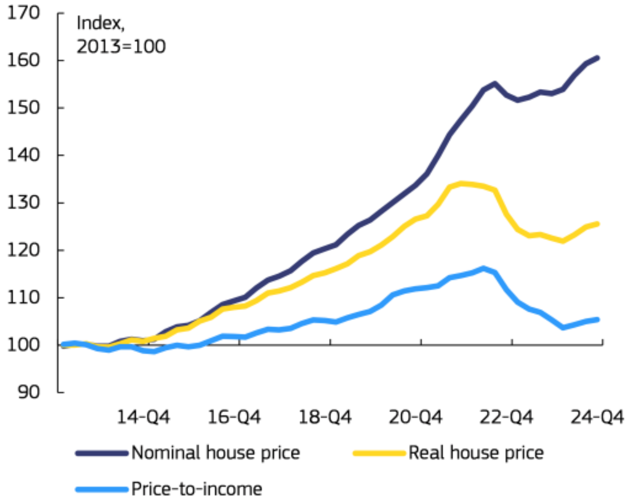
The global real estate market size amounted to $4.12 trillion in 2024 and is expected to grow by 5.5% CAGR in the next decade (Research, 2024).

In Europe the real estate industry generated €275.1 billion value added in 2022 and employed 2.7 million people (Eurostat, 2025). Following a declining period, the European Real Estate industry is growing again. The MSCI European Real Estate returns increased by 4.8% in 2024. Investment volumes increased by 46% in Q4 2024 YOY (Investments, 2025).

The Netherlands, Portugal, Sweden, Spain and Denmark led the rise, as did the industrial, hotel and residential sectors. The reason for increased returns was a notable improvement in liquidity and capital markets.

In general, a broader positive trend in house prices has been observed since 2013 (Exhibit 1.6), apart from a decrease in 2023 which was largely driven by weakening borrowing capacity. Regardless, in 2024 there was a recovery, as showed by 5% higher prices in Q4 2024.

Exhibit 1.6 – Housing prices and price-to-income ratio in the EU



Source: European Commission, Economy and Finance, Signals of a turnaround in the housing market, 2025

It was noted the importance of borrowing capacity, a variable driven by household incomes, mortgage rates and less notably tax rates and others.

Given the fact that the majority of transactions are financed via long-term mortgages or loan structures in both residential and commercial segments, it is clear the importance of mortgage rates on housing prices and the general real estate industry.

Mortgage rates are typically benchmarked to the sovereign 10-year bond yield, which is often considered the risk-free rate (if the country is believed to be sound), to which is added a spread. The yield of the 10-year bond is determined by expectations for short-term interest rates in addition to a 'term' premium to remunerate for duration risk. In turn, short-term rates are dictated by central banks and reflect expectations for economic growth, inflation, employment and fiscal policy.

As a result, changes in short-term rates propagate through the yield curve and affect mortgage costs. It is thus derived a very strong link between the real estate industry and short-term rates, even though it may sound counterintuitive given the very different horizons. When short-term rates go up, mortgage financing becomes more expensive, and demand for real estate diminishes. On the contrary, when short-term rates go down more buyers will push the prices higher.

It is very well known that interest rates and monetary policy have a great effect on the real estate sector, which is highly sensitive to near-term rate changes. Together with economic growth and employment, interest rates dictate the cycles of the industry, which range from recovery to recession, passing by expansion and oversupply.

The study of the relationship between the real estate market and its key variables is crucial to understanding the dynamics of the industry and enables to have a glimpse of the unfolding of future trends.

1.2.2 Valuation in the Real Estate industry

To understand what affects real estates, it is important to assess the various ways through which analysts perform valuations in the real estate industry.

1.2.2.1 Asset-level valuation methods

Firstly, there are several ways to value a single property. Those are market, income and cost approach.

The former estimates the value of an asset by comparing similar assets for which information is available on the market. That is the same ratio behind precedent transaction valuation, used to calculate the value of a company. This approach is recommended for standard and homogeneous assets but has several pitfalls. Market information is often incomplete and most of the assets/firms do not disclose such data (either they are not public or are traded in private transactions), in addition to difficulties in finding the right comparables.

The cost approach derives the asset value by calculating the replacement or reconstruction costs. The reconstruction method is more suitable for new buildings or unique properties, while the residual application is more relevant for properties undergoing development or transformation. The approach is used when other methods are not applicable.

Finally, the income approach estimates the value of the asset by discounting future cash flows to determine its present value. The direct application is the discount cash flow method, extremely popular for any kind of valuation. This approach is the most preferred and is used whenever possible.

The application of the Discount Cash Flow method to a real estate asset has some peculiarities: nominally there are not sales, EBIT and Net Working Capital as they are conceived for other assets, but rental income and Net Operating Income (gross income minus operating expenses, equivalent to EBIT). Net working capital variations are typically absent because real estate operations involve minimal asset turnover compared to other industries.

The capitalization rate used in the discounting process reflects expectations for risk and growth and is usually picked through a market analysis of similar assets.

1.2.2.2 Company-level valuation

The valuation of the different companies that are part of the real estate industry is challenging given their different businesses, capital structure and development projects. Most of the valuation falls in between the lines of intrinsic valuation and relative valuation, which correspond to the income and market approaches.

The Discounted Cash Flow is the most used method, given its popularity and relative simplicity.

Particularly relevant for asset-heavy firms is the Net Asset Value method, which estimates the market value of a company's assets by applying market-derived capitalization rates to forecasted Net Operating Incomes (NOI).

To get a full picture, the results of the intrinsic valuations are cross-checked with market methods, particularly using trading multiples. The relative approach is useful because it captures market sentiment and sector-specific risk premia, but can be biased by cyclical pricing, market bubbles and liquidity conditions.

Given that depreciation significantly distorts accounting earnings in real estate, analysts often use industry-specific multiples. In addition, given the tax and dividends' payment peculiarities, usually Cash Flow multiples are implemented. The most used are Price/AFFO, Price/FFO and EV/EBITDA.

1.2.2.3 REIT specific methods

To determine the value of REITs, analysts generally utilize a set of intrinsic and relative valuation methods. REITs have a peculiar nature: they are asset-heavy and hold illiquid real estate, in addition they tend to increase asset value over time and aren't taxed at the corporate level, but only when dividends are distributed.

For these reasons, the Net Asset Value (NAV) method is the best applicable. This involves estimating the market value of a REIT's real estate assets by applying capitalization rates to the estimated operating income (NOI) of properties – any type of property (wholly owned and joint ventures). In addition, specific income fees typical of the industry are usually capitalized at a higher cap rate to reflect their riskier nature.

Subsequently, the market value of all the other assets (developments, unused lands) present on the balance sheet is added in a conservative way to reflect their higher embedded risk. Finally, liabilities and other claims at book value are subtracted to derive the net value.

There are some peculiar metrics and ratios that are considered exclusively for REITs such as Price to Adjusted Funds from Operations (AFFO) or Price to Funds from Operations (FFO). AFFO is considered a more accurate measure than EPS for REITs, because it better reflects the REIT's ability to pay out cash flows to its shareholders.

In summary, real estate valuation occurs at two distinct but intertwined levels: the appraisal of individual assets and the valuation of the companies that own them. Asset-level approaches - market, income, and cost methods - provide the inputs to firm-level valuations, which blend intrinsic and relative methods depending on the company's structure and strategy. REITs, with their asset-heavy balance sheets, income distribution requirements, and tax advantages, are typically valued based on NAV-driven models and cash-flow multiples such as P/FFO or P/AFFO.

It is necessary to learn about these valuation models in order to make sense of financial ratios, changing environment and market turbulences.

1.3 Bankruptcy prediction in the Real Estate industry: the Research Question

The precedent sections showed the significance and gravity of business failure, as well as the structural characteristics that make the real estate industry economically important and financially vulnerable. Given the sector's size and interconnection with other industries, the consequences of eventual distress or default would affect a large size of the global economy.

As introduced before, the real estate industry is notoriously among the most sensitive to interest rates changes. The combination of high leverage, asset-heavy nature, market illiquidity and reliance on debt financing - key characteristics of the industry - imply that shifts in monetary policy highly affect volumes, prices and valuation.

Theoretically, even just a tiny basis-points increase in benchmark policy rates can influence borrowers' decisions, elevate debt service costs and reduce market value of assets, thus affecting the economy by billions of euros.

Monetary trends are indeed closely observed by analysts and investors. Between 2009 and 2022 developed countries experienced unprecedented monetary conditions. Following the 2007-2008 Global Financial Crisis, there was a long period of recovery marked by low inflation and economic growth. To stimulate the local economies, central banks lowered policy rates to the lowest-ever levels, even below zero, to push investments and stimulate growth. This had massive implications for financing decision: borrowing money became extremely cheap and very convenient.

Obviously, most corporates and governments decided to finance more and more of their projects via debt financing, since it was affordable.

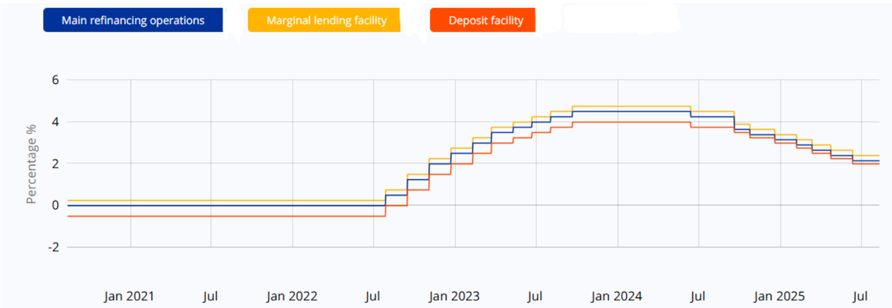
In 2022 the situation abruptly changed. Post-pandemic demand recovery, supply chain constraints, and the energy price shock triggered by the Russia–Ukraine conflict drove inflation well above target.

In response to this and accordingly to their mandate of keeping inflation below 2%, central banks around the world implemented one of the fastest tightening cycles in recent history, increasing their benchmark policy rates. That is considered the standard and most effective way for central banks to influence monetary policy and keep prices stable.

As a result, beginning in 2022, interest rates across developed countries were increased by as much as 550 basis points. Policymakers continued to maintain those high rates until they considered necessary, and in 2024 it began a gradual easing phase. Exhibit 1.7 shows the behavior of key European interest rates over the last years, a very similar trend took place in England, the United States and others.

As of September 2025, interest rates remain at an average 2% in the European Union, 4.25% in the US and 4% in the United Kingdom.

Exhibit 1.7 – Key ECB interest rates



Source: European Central Bank, ECB Data Portal, July 2025

These considerable shifts heavily affected corporations in all industries, at first hindering financing costs and reducing liquidity, later contributing to corrections in asset allocation and project decisions.

The resulting environment is an ideal natural experiment to assess how shifts in the interest rate regimes affect financial stability indicators within key industries.

Given its structural dependence on external financing, the real estate sector is particularly exposed to similar shocks, making it an ideal setting for studying the impact of interest rate regimes on corporate financial stability.

It is of great importance for the economic literature to focus the attention on the weaknesses of this industry and deepen the knowledge about poorly studied effects and remedies of possible bankruptcies.

A good way to assess the failure risks of a certain industry is to run bankruptcy prediction models. Those provide a framework for quantifying the likelihood of corporate failure.

The hope of developing a model that correctly predicts financial difficulties of a corporation with years of advantage is something that inspired generations of economists' work.

They correctly argue that such a model would be of great benefit to several actors. In the first instance to the management, who could promptly steer the current policies and avoid serious harm to the company.

Secondly, to policymakers and legislators who could easily spot weak firms that need help and develop a framework to act before it becomes too late.

Subsequently, to shareholders and creditors who could better allocate their capital or negotiate with the struggling company – as a matter of fact, give some ground is better than losing everything.

Finally, to all stakeholders, since a failure affects employees and their families and many more, thus harming the whole of society.

Given that the Real Estate industry employs 2.7 million people in the European Union, it is of great relevance to analyze the possible scenarios and try to prevent future failures.

In addition, the industry was certainly impacted by the recent market turbulence - the Dow Jones US Real Estate Index had a max drawdown of 37% in October 2023 from its peak in December 2021 (S&P Global, 2025) -, but with which effects over bankruptcy rates and what can be learnt?

While many bankruptcy prediction models such as Altman's Score, Ohlson's Score, and Zmijewski's Score are widely known, sector-specific applications remain scarce. Even fewer studies focus on a large but significant geographic area such as Europe is and for specific industries like the real estate one. Existing research often treats this sector as part of the broader financial or construction ones, overlooking its unique combination of assets, leverage and sensitivity.

The existing studies have narrow applications in terms of temporal horizon or geographic reach. As an example, many studies from the last years have focused the research on Asian countries such as Indonesia. This confirms the comment by Dimitras, Zanakis and Zopoudinis (1996) (Dimitras A., 1996), according to which researchers and scholars tend to study only the peculiar aspects or stages of corporate failure based on their interest or geographical residency, with little to none reference to the theoretical framework.

The past and current state of the literature regarding bankruptcy prediction models will be reviewed later.

A significant gap in the literature is in the study of bankruptcy prediction models across different monetary regimes. This is the logic behind and the Research Question of this thesis. This comparative analysis can help in understanding which model best accounts for monetary shifts and can highlight how much the companies in the industry were affected and how good they coped to external shocks.

This thesis addresses that gap by applying three established bankruptcy prediction models to a panel of European listed real estate firms across two distinct monetary environments: a low-rate period (2016–2019) and a high-rate period (2022–2025). The study seeks to answer the following questions, here in the form of hypothesis:

H1: How do different monetary regimes affect bankruptcy prediction model output in the real estate industry?

H2: Which bankruptcy prediction model best suits the real estate industry?

The experiments will be performed using existing and notorious bankruptcy prediction models, such as Altman's, Ohlson's and Zmijewski's. The goal is to understand which works better and why, analyzing the key variables.

The sample test is composed of 63 real estate firms, most of which listed on the Euro600 – the stock exchange that includes the most valuable European listed companies. All the selected firms operate in the European real estate sector, as constructors, REITs or service firms. The financial data will be extrapolated by the respective financial statements using the software LSEG, formally known as Refinitiv.

The results will be analyzed in Chapter 4, where they shed light on the European real estate market and the risk of bankruptcy. The findings will be useful for future researchers, policymakers and practitioners.

Chapter 2 - Literature Review

2.1 Distress Valuation

The valuation of distressed firms is a detailed branch of corporate finance and has thoroughly been expanded in the last decades. It is a fundamental topic that anticipates and includes bankruptcy prediction, thus has to be reviewed first.

Firstly, it is necessary to define distress. Many authors have given different views and definitions about distress and related words. The former adjective can be assigned to a firm that is facing some sort of challenges and whose fate is uncertain.

Analysts usually distinguish between financial distress and operational distress. The former is a condition given by financial uncertainty and burden. In fact, it usually stems from high interest charges, which affect the ability to access capital markets.

Moreover, it ripples effects over equity and debt values, displaying the potential or likelihood of default or liquidation. This form of distress causes a deadly spiral as the firm focuses most of its attention on short-term liquidity and rejects profitable projects.

On the other hand, operational distress may happen more sporadically and be more random. It is attributable to non-recurring and non-foreseeable events, such as periods of economic downturn, under-capacity utilization or high employees' turnover.

The starting point to compute the valuation of a distress corporation is understanding the distress, the causes and the recoverability.

Following this assessment, analysts can begin the valuation through modelling practices.

2.1.1 Adjusted DCF

While the Discounted Cash Flow is the most complete and used valuation approach, it is not the best choice to value a distress corporation.

As Damodaran (2012) stresses out, despite the flexibility of the DCF approach it implies that a firm is a going concern with an infinite life – assumption particularly needed for the calculation of the Terminal Value, that usually accounts for 50% to 80% of the final Enterprise Value.

The Terminal Value is either estimated by assuming the perpetual growth of Cash Flows and Earnings or using exit multiples, derived by looking at publicly traded peers – usually healthy ones.

Moreover, distress firms face refinancing risk, margin compression, assets sales and leverage changes. Those imply that a single and constant cost of capital is inconsistent and can not be used.

Because of all the above issues, a standard DCF cannot be used to value distress firms. To solve those issues, practitioners replace a single Terminal Value with scenario or survival-weighted valuations. Those allow to influence the valuation according to the likelihood of low growth, mild distress or liquidation.

A more structured approach is the Changing Capital Structure, where the valuation is done assuming a specific cost of capital for each year.

This proposes to solve the circularity problem (to calculate the cost of capital the value of equity is needed, to calculate the value of equity the cost of capital is needed) through an iterative approach in a simplified or detailed way. The former instruct to calculate leverage for every year based on simplified assumptions (leverage aligned with the market average), the latter dictates to calculate the Enterprise Value and capital structure for each year starting from the last one.

These approaches allow the use of the Discounted Cash Flow method in the valuation of distress corporations. Because of this, they are useful approaches, even if sometimes computational heavy.

2.1.2 APV

The Adjusted Present Value is a notorious valuation approach used in corporate finance. Unlike the traditional DCF, which discounts cash flows using an average cost of capital, the APV method separates the enterprise value into two different components.

$$EV = V_{unlevered} + PV(\text{tax shield})$$

Where the value unlevered is the enterprise value calculated by discounting Cash Flows using unlevered cost of equity and the present value of tax shield is discounted at an appropriate rate - following Ehrhardt and Daves (1999) usually unlevered cost of equity.

This method was first formalized by Myers (1974), refined by Kaplan and Ruback (1995) and Luehrman (1997), and is based on the notorious corporate finance notions stated in the first instance by Modigliani and Miller (1958).

The APV approach is perfectly suitable for distress valuation because it intrinsically handles unstable capital structures, since it values the business as unlevered and adds afterwards financing side elements. Moreover, APV avoids the circularity problem that arises with adjusted DCFs and is flexible in scenario analysis.

In fact, APV can be easily adjusted for distress valuation:

$$EV = V_{unlevered} + PV(\text{tax shield}) – PV(\text{expected distress costs})$$

In this way the enterprise value is computed as the sum of unlevered firm value and tax benefit minus the expected distress costs. Interestingly, Altman (1984) pointed out how those distress costs can be on average approximately 10-20% of the firm's value.

In conclusion, the APV method is a valid and flexible alternative to the DCF. Kaplan and Ruback (1995) demonstrated that the two approaches usually grant similar results, but APV is more robust in certain situations (like distress).

Since Luehrman (1997) popularized it and Damodaran (2012, 2018) recommended it, the APV has become a standard approach in corporate finance and particularly for the valuation of distress corporations.

2.1.3 Asset-based and mixed approaches

An asset-based approach values the firm by estimating the market value of all assets minus the value of outstanding liabilities. This is a niche method only used in certain scenarios.

The asset-based method is particularly relevant for companies in severe distress, because it allows to compute the value of liquidation. Hence, this approach implies an orderly or forced sale of assets, with significant discounts that account for illiquidity and urgency. Some empirical studies – Altman and Hotchkiss (2006) – suggest that such discounts can be approximated at 20-40% of book value.

Liquidation costs should be accounted for and subtracted from the calculated Enterprise Value.

Given the restrictive scope of application of the asset-based approach and the fact that it usually do not consider the going-concern value, many analysts use mixed or hybrid approaches.

Those should be applied when the firm is going through a temporary distress period, followed by a reversion to a normal going-concern condition.

Among the mixed methods there is the possibility to account for the average equity-income value, the autonomous estimation of goodwill or to make income adjustments to NAV.

Overall, asset-based and mixed methods offer a conservative "floor value" but it is important to combine them with other variables to capture the full shades of distress valuation.

2.1.4 Option method

A more complex but market-based approach to evaluate distress firms is related to options.

Built upon the option pricing model developed by Black and Scholes in 1973, Merton (1974) built a model that interprets firm's equity as European call option on the firm's assets.

Merton makes some assumptions and modifications to the standard option pricing model. In his version the value of the underlying asset corresponds to the value of the firm, the strike price to face value of debt, the life of the option to the life of zero-coupon debt and the risk-free rate is assumed to be the T-bill corresponding to the option's life.

In the model's simplest form, the capital structure of any company is comprised by equity and by a zero-coupon bond with maturity T and face value of D. If the company's asset value (V) is not enough to pay back the book value of debt (D) at maturity, the firm defaults, the bondholders take control and shareholders receive nothing. Otherwise, it does not default and the shareholders receive (V-D).

The equity payoff is then:

$$E_T = \max (Vt - D, 0)$$

The above formula is equal to the payoff of a European call option, thus the model proceeds applying the Black and Scholes formula for the equity value, the probability of default and the value of debt.

$$E = V\, N(d_1) - D\, e^{-rT} N(d_2)$$

Where:

$$d_1 = \frac{ln\left(\frac{v}{D}\right)+\left(r+\frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

$$d_2 = d_1 - \sigma\sqrt{T}$$

While the option method provides a fascinating and thorough theoretical framework to evaluate distress firms, it is scarcely applied by practitioners. The model assumes a single class of zero-coupon debt, efficient markets and known volatility.

Because of these heavy assumptions, the option method is not widely used for direct valuation, while it has different applications in bankruptcy prediction and credit risk models.

2.1.5 Relative Valuation

Relative valuation implies the estimation of either Enterprise Value or Equity Value by comparing it to similar companies. In fact, it is believed that a company should have certain ratios in line with its closest peers. In sum, relative valuation reflects how the market prices similar assets.

Despite being a useful complementary valuation method, relative valuation is not suited for distress firms. The application of multiples can lead to serious errors due to lack of consistency with the comparables. Those are generally healthy firms and a distress corporation typically trades at a serious discount that reflects higher risk, uncertainty and illiquidity.

In conclusion it is a serious mistake to use relative methods for the valuation of distress firms.

2.1.6 Cost of capital for distress firms

A distress corporation is obviously seen as riskier by investors. This is reflected in the cost of capital. A distress firm will have a higher cost of capital which mathematically lowers the Enterprise Value.

The cost of debt is considerably higher for distress firms given their greater risk of default that investors have to price in and the reduction of tax benefits. Altman and Hotchkiss (2006) showed that distress firms face considerably higher bond yields.

For the matter of cost of equity, there are some adjustments that can be made to account for the increased idiosyncratic risk that characterizes distress entities.

As reviewed by Pratt (2010) there is the possibility to add specific risk premia, to estimate the operating risk and matching it with observed market returns, to use the Fama-French three factor model or to use volatility-based risk measures.

The former and most used application was proposed by Duff and Phelps (2013). This method involves the addition of specifically computed premia to the standard CAPM.

Those premia are consistent with and related to Altman's Z-score. For each range of Z, corresponding to a discrimination zone, there is a corresponding premium over CAPM which shall be applied, for both manufacturing and service firms. Thus, companies in the distress zone will collect higher premia.

This approach is very useful and provides a ready-to-use framework. Unfortunately, Duff and Phelps' data are not publicly available since their rights were acquired by Kroll.

In conclusion, the above approaches are summarized in the following table (Table 2.1). Those are the methods that analysts use in the evaluation of distress companies.

Those may be imperfect, but most authors agree that they summarize the best practices and should be used as complementary. Moreover, a series of best practices guides senior analysts in the implementation of each approach.

Unfortunately, valuation alone does not provide an explicit bankruptcy model. This motivates the study and application of prediction models. Section 2.2 explores the prediction-oriented literature.

Table 2.1 – Summary of valuation approaches

Model	Suited distress phase	Practical application
Standard DCF	No distress	Very used
Adjusted DCF	Recoverable	Often used
APV	None to recoverable	Very used
Asset approach	Not recoverable	Scarcely used
Mixed approach	None to recoverable	Often used
Option method	Not recoverable	Scarcely used
Relative valuation	No distress	Very used

2.2 Bankruptcy prediction

2.2.1 Accounting Based Models

The first models ever produced and the most used since are those based upon key financial ratios easily available for public listed companies.

The idea of using those critical ratios and accounting information to detect corporate financial difficulties is given by the rational that financial statements should depict the financial situation of the firm in the given year.

Accounting-based models can be divided into subcategories according to Mousavi et alia (2015): Univariate ratio models, Multiple Discriminant Analysis, Probabilistic regression models and others. This proposed division follows a logical and chronological order, since the first models were the 'simplest' and the literature grew to produce more complete models in the following years.

2.2.1.1 Univariate Ratio Models

The study of business failure started in the 1930's, with many different papers concluding that failing firms exhibit significantly different ratio measurements than sound ones.

The modern literature on bankruptcy prediction generally begins with the seminal paper by Beaver (1966), which formally investigated the ability of single financial ratios to discriminate between failing and non-failing firms.

Using a matched sample of 79 failed and 79 non-failed U.S. companies between 1954 and 1964, Beaver tested 30 accounting ratios over a five-year time horizon prior to bankruptcy. Those ratios were chosen based on popularity, performance and liquidity, and are presented below in Table 2.2

Table 2.2

FAMILY	**RATIOS**	
Cash-Flow Ratios	Cash Flow/Sales Cash Flow/Total Assets	Cash Flow/Net Worth Cash Flow/Total Debt
Net-Income Ratios	Net Income / Sales Net Income / Total Assets	Net Income/Net Worth Net Income/Total Debt
Debt-To-Assets Ratios	Current Liabilities/Total Assets LT Liabilities/Total Assets	Total Liabilities/Total Assets (Liabilities + Preferred Stock)/Total Assets
Liquid-Assets To Ta	Cash/Total Assets Quick Assets/Total Assets	Current Assets/Total Assets Working Capital/Total Assets
Liquidity Ratios	Cash/Current Liabilities Quick Assets/Current Liabilities	Current Assets/Current Liabilities
Turnover Ratios	Cash/Sales Accounts Receivable/Sales Inventory/Sales Quick Assets/Sales	Current Assets/Sales Working Capital/Sales Net Worth/Sales Total Assets/Sales Cash Interval Defensive Interval No-credit Interval

Beaver’s approach, known as univariate analysis, assessed one ratio at a time.

He considered the firm as a “reservoir” of liquid assets, fueled by inflows and depleted by outflows. Failure occurs when the reservoir empties, and the firm is unable to meet its obligations.

The most significant predictor among the 30 ratios was Cash Flow to Total Debt, followed by Net Income to Total Assets, Total Debt to Total Assets, and liquidity ratios. Interestingly, differences between failed and non-failed firms were already visible and evident up to five years prior to bankruptcy, reflecting the early-warning potential of financial statements.

To validate the accuracy of his findings, Beaver conducted a dichotomous classification test by comparing company ratios to critical cut-off values. Firms below the individuated threshold were classified as bankrupt, while the companies above were considered safe.

This framework also helped in the formulation of the concepts of Type I errors (failing companies misclassified as healthy) and Type II errors (healthy firms misclassified as failing), which remains essential in today's statistical analysis and has become standard in evaluating predictive models.

Although Beaver's results indicated that accounting ratios contain useful predictive information, his univariate methodology was affected by important limitations: ratios were tested individually ignoring their interdependence and there was risk of misclassification.

A firm experiencing profitability or solvency problems with ratios below the cutoff point could have been easily classified as bankrupt, despite actually having sufficient level of liquidity that could have been used toS avoid failure.

These shortcomings led to the shift towards multivariate techniques, most notably Altman's Z-Score (1968), which combined several ratios into a single predictive function.

2.2.1.2 Multiple Discriminant Analysis

While Beaver (1966) demonstrated that individual financial ratios can be interpreted as predictive power, Altman (1968) proposed to integrate several indicators into a single discriminant function.

This marked a methodological shift: instead of examining ratios separately, Multiple Discriminant Analysis (MDA) builds a linear combination of financial metrics that maximizes the separation between distressed and healthy firms.

Altman's original and notorious study considered 66 U.S. manufacturing companies (33 bankrupt and 33 non-bankrupt) between 1946 and 1965, excluding very small and very large firms to ensure comparability.

From an initial set of 22 ratios across the categories of leverage, liquidity, solvency, profitability, and activity, five were ultimately retained for their statistical and economic relevance.

The discriminant function takes the form:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$$

where:

- X_1 = Working capital / Total assets (liquidity measure)
- X_2 = Retained earnings / Total assets (measure of profitability and leverage)
- X_3 = EBIT / Total assets (operating performance measure)
- X_4 = Market value of equity / Total debt (solvency ratio)
- X_5 = Sales / Total assets (asset turnover)

Through a statistical analysis, Altman derived that the resulting Z-score categories were as follows:

- $Z < 1.81$ → Distress zone
- $1.81 < Z < 2.99$ → Grey zone
- $Z > 2.99$ → Safe zone

The model achieved an initial in-sample accuracy of 95%, with predictive ability up to two years before failure. Importantly, Altman as well recognized the importance of type I vs. type II errors (misclassification of failed or healthy firms), which still is a central trade-off in prediction research.

Recognizing the main limitations of the model, Altman revised and updated the coefficients to adapt the model for private companies (Z′, 1977) and non-manufacturing or emerging market contexts (Z″, 1983).

The former adaptation was done with the substitution of one variable (market value of equity) another one addressing the absence of market data in private firms (book equity):

$$Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5$$

where X4 = Book equity / Total liabilities.

In this formulation, the cut-off thresholds changed to:

- $Z' < 1.23$ → Distress zone
- $1.23 < Z' < 2.90$ → Grey zone
- $Z' > 2.90$ → Safe zone

The final adaptation was intended to apply the Z-Score to all those firms that are non-manufacturing. In this version the asset-turnover variable was removed in order to reduce the industry effects.

$$Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

In this formulation, the cut-off thresholds are:

- $Z'' < 1.1$ → Distress zone

- $1.1 < Z'' < 2.60$ → Grey zone
- $Z'' > 2.60$ → Safe zone

The Z-score has set the industry standard and remains the most highly cited and influential bankruptcy prediction model both in practice - auditors, banks, and credit rating agencies still employ it in creditworthiness assessment - and theoretical work. This is because of its simplicity, interpretability and timely warning.

On the other hand, the employment of linearity, historical observations and the need for calibration means that its application to specific sectors should be executed with carefulness and circumspection.

Whereas Altman's (1968) Z-Score emerged as the standard, several researchers in the following decades developed alternative MDA models tailored for different samples and contexts.

Deakin (1972) used 14 ratios on a sample of insolvent firms and demonstrated discriminant analysis to be able to distinguish between firms with a substantial degree of validity. Edmister (1972) studied the small-business model, showing that industry and company size could adjust the predictive power of ratios. In Europe, a four-factor model for UK firms was developed by Taffler (1977) and was extremely influential in non-US settings. Springate (1978) also constructed a Canadian version of Altman's model, utilizing four ratios, which was similar in accuracy to its original counterpart.

These research studies revealed that MDA could be replicated and calibrated for specific markets but also revealed the need for context-specific calibration and the fact that there is not a single universal model.

Despite its success, MDA has some known and important limitations. It assumes that the predictor variables follow a multivariate normal distribution and that the covariance structures of the failed and non-failed groups are identical. These assumptions rarely hold in financial statement data. Moreover, the linear form of the discriminant function may not capture more complex, nonlinear relationships between ratios and bankruptcy risks.

These weaknesses encouraged a shift in the literature toward alternative statistical techniques, particularly probabilistic models such as logit and probit regressions, as well as survival analysis. Such approaches relax distributional assumptions and allow a more flexible estimation of failure probabilities.

2.2.1.3 Probabilistic Models

Probabilistic models emerged as a response to the restrictive assumptions of Multiple Discriminant Analysis. Unlike MDA, which generates a linear score with arbitrary cut-offs, probabilistic approaches directly estimate the probability of failure in a bounded interval. This allows more thorough interpretation, formal hypothesis testing, and flexibility in estimation.

Ohlson (1980) was the author to move forward and to propose logistic regression to bankruptcy prediction. He criticized MDA for three main limitations:

1. Assumption of multivariate normality of predictors.
2. Assumption of equal covariance matrices for bankrupt and non-bankrupt firms.
3. Biases given by the use of matched samples (by size and industry)

To overcome those, Ohlson proposed the logit model, where the log-odds of bankruptcy is a linear function of financial ratios:

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

where:

- P= probability of bankruptcy
- X_i = predictor ratios
- β_i = estimated coefficients

Ohlson's sample included 105 bankrupt firms and 2058 non-bankrupt listed companies from the NYSE and AMEX from 1970 to 1976. Three prediction horizons were tested: 1 year, 2 years, and 1–2 years combined.

Ohlson's final model, also known as O-score, includes 9 variables grouped into size, leverage, liquidity, and performance:

- X1 = log (TA/GNP deflator)
- X2 = TL / TA
- X3 = WC / TA
- X4 = CL / CA
- X5 = 1 if TL > TA; 0 otherwise
- X6 = NI / TA
- X7 = Operating Income / TL
- X8 = 1 if NI < 0 for 2 consecutive years; 0 otherwise
- X9 = $(NI_t - NI_{t-1}) / (|NI_t| + |NI_{t-1}|)$

In practice, many researchers substitute the first ratio with log(TA) out of simplicity.

X7 uses an operating metric as numerator. Many following authors interpreted it as EBIT, while others used Operating Cash Flows.

The final logit function form is:

$$P(\text{Bankruptcy}) = \frac{1}{1+e^{-z}} \quad \text{where } Z = \beta_0 + \sum_{i=1}^{9} \beta i X i$$

Ohlson noted that a cutoff of P = 0.038 minimized Type I and II errors.

From Ohlson's logit model was created the probit approach. Zmijewski (1984) was the one that extended probabilistic approaches by introducing the probit model.

Similarly to the logit analysis, the model of Zmijewski estimates the probability that the firm will go bankrupt. The relevant difference with the logit model is the admission of non-linear estimation.

Zmijewski's sample consisted of 40 bankrupt against 800 non-bankrupt firms from 1972 to 1978 listed on the NYSE, with the exclusion of financials, services and public administration industries.

The model displayed an accuracy of 99% and has out-of-sample applications (Mehrani et al., 2005; Grice & Dugan, 2001), with accuracy around 80%. The final estimated probit function is:

$$\text{Zmijewski's Score} = -4.3 - 4.5X_1 + 5.7X_2 + 0.004X_3$$

The predictive ratios are the following:

- X1 = NI / TA
- X2 = TL / TA
- X3 = CA / CL

Importantly, Zmijewski highlighted how other models suffer from choice-based sampling bias and sample selection bias. The former is the result of "over-sampling" distressed firms (Zmijewski, 1984, p. 59), which leads to biased probabilities in the models. The latter occurs when the distress probability of the complete data is significantly different from the distress probability of incomplete data (Zmijewski, 1984, p. 74).

Zmijewski's model often outperforms logit in robustness but is computationally heavier.

In the following decades many were the applications of probabilistic models: Grice & Dugan (2003) and Hensher & Jones (2007) applied and expanded the logit approach. Shumway (2001) introduced a discrete-time hazard model, arguing that static logit/probit ignores the time dimension of bankruptcy and including both accounting ratios and market variables.

Campbell, Hilscher & Szilagyi (2008) applied hazard models with market data on a sample of 1963–2003 US firms, demonstrating better accuracy than Ohlson or Altman. In the last years Mixed Logit Models have been developed which account for heterogeneity across firms and Machine Learning extensions.

2.2.1.4 Beyond the classic models

As seen, the classic accounting-based models were formulated by Beaver (1966), Altman (1968), Ohlson (1980) and Zmijewski (1984). Those have remained the most cited and applied, but in the following decades there were many refinements and extensions to overcome their limitations and make their applicability broader.

Altman himself revised multiple times his model. As the first version was limited to publicly traded manufacturing firms, the Z'-score (1977) was intended to private manufacturing firms. The following version (Z''-score, 1995) was designed for non-manufacturing and emerging markets. Finally, Altman et alia (2000, 2002) tested the application of the model in emerging economies and specific industries.

Alongside Altman, other authors published refined papers in the 1970s and 1980s. Deakin (1972) confirmed the predictive accuracy of liquidity and leverage ratios. Edmister (1972) focused on small US companies, while Taffler (1977) focused on UK companies and became the European reference.

Hensher and Jones (2007) developed mixed logit models acknowledging heterogeneity in the causes of distress, while Grice and Dugan mostly showed the limitations of logit and probit models, highlighting the need for dynamic models.

It is clear that accounting-based models are useful, intuitive and easy to compute, but they have several limitations. Particularly it is difficult to accept the static nature of ratio-based data.

An abrupt development to solve this problem and to move beyond the classics saw the adoption of survival analysis and hazard models. Those are based on accounting ratios but are dynamic and forward-looking, thus presenting an innovative and modern approach.

Shumway (2001) integrated accounting ratios and market-based indicators in a discrete-time hazard model, thus treating bankruptcy as a time-dependent event. The results indicated that his hazard model outperformed MDA and logit models in accuracy.

Chava & Jarrow (2004) extended Shumway's model including macroeconomic and firm specific variables. Campbell, Hilscher and Szilagyi (2008) combined accounting, market and macroeconomic variables to find that forward-looking variables significantly improve predictive performance.

Despite these contributions, accounting-based models keep on having several limitations, like sample bias and reliance on financial statements, which inevitably contributed to a shift toward the implementation of market-based variables and the study of machine learning approaches.

2.2.2 Market-based models

Market based models use information and variables taken from the market, such as share price or volatility. This allows to assess the sentiment and expectations of market agents who usually price in financial struggles.

In addition, market prices are constantly moving, thus updates are available on a daily basis, whereas financial statements only update data once a year.

2.2.2.1 Structural models

The most relevant market-based models are built upon the option pricing model developed by Black and Scholes in 1973, and apply it to the valuation of a firm's capital structure. Merton (1974) was the first to apply the model to market-based approaches, showing that firm equity can be interpreted as a European call option on the firm's assets. The extended model was already introduced in the first part of this chapter (2.1.4).

Given the Black and Scholes formula for the equity value, the probability of default and the value of debt:

$$E = V\,N(d_1) - D\,e^{-rT}\,N(d_2)$$

$$d_1 = \frac{ln\left(\frac{v}{D}\right)+\left(r+\frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

$$d_2 = d_1 - \sigma\sqrt{T}$$

The probability of default is computed as:

$$P = N(-d_2)$$

In order to implement the model, the volatility and asset value of the firm are necessary, since they are not directly observable.

To estimate those some authors propose the use of Itò's Lemma to obtain a system of two equations. Duan (1994) proposes another method for the estimation of Vt and volatility, based on Maximum Likelihood estimation using equity prices. Finally, Jones et al. (1984) proposed to simply estimate the asset value as the sum of the equity market value, the market value of traded debt and the estimated value of non-traded debt.

Merton's model is particularly useful is credit risk assessments and is widely spread for commercial applications– Moody's KMV Expected Default Frequency model, one of the most used credit risk tools, uses it.

While Merton's model allows the direct application of option pricing theory developed by Black and Scholes, there are substantial difficulties in the application and in the meeting of the assumptions. In particular, the default time cannot be restricted to maturity and the capital structure of a company cannot be approximated by a coupon bond.

Many following extensions to the model introduced more realistic and relaxed assumptions. Merton himself presented some extensions to account for callable bonds and stochastic interest rates. Black and Cox (1976) posed that default can occur before maturity, Geske (1977) introduced multiple debt maturities, Leland (1994) derived endogenous default models.

2.2.2.2 Reduced form models

Opposed to structural models that derive default endogenously, reduced form models consider default as an exogenous random event dictated by a hazard rate. With this approach, default can occur randomly and depends on observable variables, while asset values of capital structure are not computed.

The key variable is the default intensity, or hazard rate λ. This is the probability that a firm instantaneously and exogenously defaults conditional on survival up to time t.

$$P\ (\text{default in } [t,t+dt] \mid \text{survival until } t) = \lambda_t\ dt$$

Survival probability up to time T:

$$S\ (T) = \exp\ (\ -\int \lambda_s\ ds)$$

Probability of default by time T:

$$P\ (\tau \leq T) = 1 - S(T)$$

where τ is the random default time.

λt can be a function of many different variables, such as leverage, profitability, stock returns or macroeconomic factors, which allows for flexibility and dynamism in modelling.

Jarrow and Turnbull (1995) were the first to use reduced form models, applying it to derive a pricing framework in credit risk. Later, Duffie and Singleton (1999) extended the model and included recovery rates and credit spreads.

Notably, Duffie, Saita and Wang (2007) applied reduced form models to bankruptcy prediction, estimating multi-period hazard models with stochastic covariates using large data volumes. In the end, their findings displayed better results than static structural approaches.

Shumway (2001) combined accounting ratios with market variables, such as market size and volatility, to improve accuracy compared to only accounting-based models. Surprisingly, he outperformed both Altman and Ohlson in predicting bankruptcy.

Similar findings were obtained by Chava (2008) for US samples and Bauer (2014) for the UK setting.

In general, reduced form models only use observable variables - thus excluding the problems of computing asset values or volatility like in option models - are very flexible and provide constant updates of default probabilities.

On the other hand, reduced form models only conceive default as exogenous, with no link to financial statements or even economic fundamentals. It is clear how the results may lack accuracy and interpretation and sometimes be skewed or random.

2.2.3 Modern and Hybrid models

2.2.3.1 Machine Learning models

After the seminal papers of Beaver (1966) and Altman (1968) that formally introduced bankruptcy prediction models, many scholars started to apply bankruptcy prediction models to the newly influential computer sciences. This branch of research introduced machine learning in this field.

That approach remained a niche until the 1990s, after which the interest in machine learning skyrocketed. The attention increased once again with the AI boom of the last years. Because of those, the application of machine learning to bankruptcy prediction has become extent and complete.

According to this approach, bankruptcy prediction is seen as a supervised classification problem: given a firm's inputs (the ratios), the model evaluates the probability of default and then evaluates out-of-sample data.

In sum, bankruptcy prediction can be considered a classification problem where a model is firstly trained using a dataset, then the model is asked to classify new data to measure its accuracy. If a sufficient level is reached, the model is considered effective at distinguishing real-world scenarios.

Many different ML techniques were employed to forecast bankruptcy: support vector machines, decision trees, neural networks, Bayesian networks and genetic algorithms.

Kumar and Ravi (2007) and Alaka et al. (2018) offer comprehensive surveys that highlight the growing importance of machine learning techniques.

The first wave of ML application showed that artificial neural networks could perform better than MDA or logit approaches. Odom and Sharda (1990) were the first to apply neural networks to bankruptcy prediction, while Tam and Kiang (1992) first demonstrated the high accuracy results of neural network models for predicting US bank failures.

The second wave explored support vector machines - SMV – and was introduced by Cortes & Vapnik in 1995. This approach maximized margins and kernel flexibility and ultimately showed to be a powerful and flexible tool when dealing with complex data structures and variables interrelationships. Min and Lee (2005) demonstrated how SVMs can outperform traditional models, in particular when dealing with complex dataset.

In the late 2000s ensemble learners were introduced by Nanni and Lumini (2009). Bagging, boosting and random subspaces were found to outperform single classifiers and are since used as default baseline for tabular financial data. Those models are able to reduce variance and account for complex decision boundaries.

Barboza et al. (2017) found that using machine learning models - particularly random forests - drastically improves the accuracy of bankruptcy prediction. The study integrated Altman's original Z-score with six additional variables and applied it to 10000 North American firm-years. The results highlighted that random forest could predict bankruptcy with 87% of accuracy, and the overall result increased when adding additional variables. The test outperformed both MDA and logit regression. Since this seminal paper, random forests and boosting are considered the reference framework in large scale bankruptcy predictions.

Neural network is another approach that was developed from random forests. Those networks are inspired by human brains, where data are spread between nodes (neurons). Each neuron receives, processes and produces an outcome. The same approach can be used for bankruptcy prediction, where each node will receive the financial data, process it and produce the probability of bankruptcy. As long as this approach is fascinating, it makes it difficult to derive an explanatory factor and is generally too much calculation heavy.

More recently deep learning has been explored. Hosaka (2019) converted a series of financial ratios into images and trained a convolutional neural network. The accuracy was stronger than compared to tabular baseline, showing that deep learning can capture patterns in financial statements that are otherwise difficult to spot and generally be competitive on accounting data, but future research is needed.

To conclude, machine learning models usually deliver excellent accuracy, even achieve results above those of classic models. They represent the frontier of academic research and will certainly get better in the future years, but they have some serious pitfalls.

Firstly, datasets are usually biased and imbalanced, thus researchers are forced to use evaluation metrics and remedies (i.e. PR-AUC, Matthews correlation coefficient, class weights, SMOTE).

Secondly, the output has limited interpretability and the models are often criticized as "black boxes", given the difficulty in understanding the reasoning behind the predictions.

Finally, ML models are data-heavy and require huge calculation power, directly correlated to electric consumption.

All of the above make the approach less competitive and accessible to researchers.

2.2.3.2 Hybrid approaches

Hybrid models incorporate aspects of different approaches or data sources and are found to produce in most cases better results than the individual models.

The first hybrid models combined accounting and market approaches. A seminal study was conducted by Shumway (2001), who combined accounting ratios and market variables in an expanded hazard model. In particular, two were the accounting ratios from Altman (NI/TA and TL/TA) and three were the market ratios implemented (market size, stock returns and standard deviation). The results showed considerably higher accuracy than Altman or Ohlson.

Chava and Jarrow (2004) expanded Shumway's study with a market-based intensity framework. Campbell, Hilscher and Szilagyi (2008) used a dynamic logit approach combining firm-level ratios with market covariates.

Other contributions by Miller (1998), Loffler (2007) and Mitchell and Roy (2008) all point to the fact that the combination of different prediction approaches delivers high levels in accuracy of results and prediction power.

Among the models that combine accounting-based and machine learning approaches there are Grice and Dugan (2003) and Barboza et alia (2017). More recently, some publications combine firm data with macroeconomics variables to improve robustness across cycles.

Overall, hybrid models represent a good approach, as they can integrate information and pros of accounting ratios, market indicators and macroeconomic variables to deliver superior results. However, their effectiveness heavily depends on the choice of the right variables.

A common mistake is to pursuit marginal accuracy improvement including more and more variables without considering robustness, interpretability or out-of-sample application.

Once this is kept in mind and avoided, hybrid models not only generate higher accuracy but also produce meaningful interpretation insights.

2.2.4 Bankruptcy prediction in real estate

As briefly discussed before, standard bankruptcy models do not show the same results across different industries and samples. One may argue that each sector requires a specific model or at least expansions or adjustments to make conventional models fit.

The real estate industry has some peculiar characteristics that make it a unicum: high leverage - which results in high interest expenses - mostly stable earnings and peculiarities about EBIT and taxes.

To grant the highest accuracy in bankruptcy prediction it may be useful to adjust classic models accounting for these peculiarities.

Lussier (2005) adapted his original non-financial model (1995) to predict the success of ventures to the real estate industry. He found out that five key non-financial factors (capital, industry experience, strategic planning, consultation and owner's age) display a vital part in determining the failure or success of real estate young firms. However, the model only reached 74% of accuracy, lower than the original model, and uses non-financial data which are difficult to retrieve. Overall, the model offers poor replicability and adaptability.

Andriani and Sihombing (2021) applied three different bankruptcy prediction models - including Altman and Zmijewski's Score - to listed Indonesian real estate firms. The results showed that Altman's Z-score had the lowest accuracy with a mere 25%.

The study concluded that Altman's model is not the one that fits better the real estate industry, but other variables could have been involved (i.e. the country specific public market). On the other hand, the paper demonstrated that Zmijewski's model may be the best suited for the industry: it achieved 90% of accuracy and outperformed all the others. Overall, the study offers many insights but it may suffers from emerging market and small sample bias.

Toudas et alia (2024) applied Altman, Ohlson and Zmijewski's models to the Greek construction industry, showing once again that Altman's Z-score is the less accurate and underperforms the others. This study is a good example of adaptation to a specific country and sub-industry, but has limited transferability.

Purwanti (2024), Jariah (2024) and Yendrawati (2020) applied different bankruptcy models to the Indonesian real estate industry, signaling the growing interest for this developing country. The results achieved exhibit controversy: while Purwanti showed that Zmijewski's score vastly outperformed Altman's score (86% vs 28% of accuracy), Yendrawati found the Z-score as the most accurate.

This highlights how the literature does not agree over which model better fits the real estate industry, and a combination of variables, sample characteristics, selection, robustness and contextual sensitivity affects the findings of the studies.

Fernandez (2007) and Manda (2021) studied different cash flows in the REITs industry. Their work is used by Manda (2024), who studied bankruptcy prediction in the South African REIT sector. Importantly, this paper does not consider firms that filed for bankruptcy like others do (since there were none) and each REIT is analyzed as a standalone.

The analysis was done modelling a VAR model based on Altman, with the addition of FFO variable (a specific REIT performance measure). The results highlight Altman's variables interconnection, with significant predictive capabilities of the variables RE/TA (retained earnings over total assets) and FFO, the former having negative effect and the latter with positive effect on risk.

Overall, the study is rich in insights but may suffer from country bias. However, Manda's findings are crucial for the future development of the literature since they showed a specific variable suitable for a real estate sub-industry. This was the first finding of this type.

Aarbo (2024) studied bankruptcy prediction in the Norwegian commercial real estate sector following the increase in interest rates of 2022. The results showed that 66% of the 5872 companies analyzed were at risk of bankruptcy in that year and the probability of bankruptcy would rise considerably if real interest rates were to exceed a threshold of about 6.7%. The conclusions speculate about the fact that bankruptcies in the Norwegian real estate industry would have risen in the following years (post 2022).

Despite these insightful contributions, no study - to the best of my knowledge - has applied Altman's Z-score, Ohslon's O-score and Zmijewski's Scores for the broad European real estate industry, nor has anyone compared the models' performance across different monetary policy regimes.

This gap is filled by this thesis, which goal is to answer the research question and hypothesis posed in the first chapter.

As a gap-filler, this thesis tries to expand the current literature and push further the academic knowledge. Even if the findings may result in biases or misinterpretations, this work will hopefully be insightful and beneficial to the academic world. The next chapter explains the data retrieval and the methodology utilized for the derivation of results.

Chapter 3 – Methodology

While the first chapter reported the current situation and the scrutiny that bankruptcy requires, the second chapter highlighted the valuation methods and the bankruptcy models theorized and used in practice by analysts.

Both chapters showed a compelling topic which lacks literature attention: failure probability of European real estate firms, particularly under different monetary regimes.

This gap is the research question of this thesis and will be analyzed in the current and following chapters. These chapters focus on the application of certain theoretical models to current real-world data.

3.1 Data

For the sake of the analysis some actual financial data were retrieved, and a database was constructed. In order to observe the effects that different monetary regimes had over real estate companies, the dataset was created with a decade of financial information, thus for each firm the data belong to the 2015-2025 period.

The dimension and composition of the sample were object of great scrutiny: the goal was to make a comprehensive dataset that best depicted the European environment.

A strong first assumption was to select only public listed companies, since they fully disclose financial data. The best option was to select companies that are part of the Stoxx Euro600, a stock index containing 600 large and mid-cap companies among 17 European countries. Those represent approximately 90% of the free-float by market capitalization of the broad European market – thus not limited to the Eurozone.

By doing so, the sample comprises firms from different countries, even the United Kingdom. Multinationalism is not a problem since the companies exist in similar markets, share similar financial conditions and even have relationships between themselves (either competitive or collaborative).

Moreover, while the different countries of the broad European continent may be subject to different monetary authorities, the shocks and policies adopted were extremely similar in the last years.

A second assumption regards the dimension of the selected firms. Obviously, the companies listed on the Stoxx Euro600 share large or mid-cap sizes. These firms are less likely to face failure risks compared to small or new businesses.

Regardless, large and mature companies are usually more leveraged and have more static cash flows. They are more likely to hold illiquid assets or undertake long-term projects, while obviously they drive most of the investments and employ more people. Considering that a relevant current trend regards the historic high level of large firms filing for bankruptcy, the conclusion is that it is important to analyze the effects of severe shocks over large corporates and the sample is thus justified.

The third assumption was to select firms from the macro real estate sector, regardless of their sub-industry or specific end-market. Because of this, the sample is composed of firms with very different characteristics: REITs (financial vehicles), operating companies and brokerages. While this may be a limitation, it shows the trends of the broad real estate industry, where actors with different characteristics - often strong relationships - coexist. On the other hand, the use of a specific filter would have drastically affected the sample size. Future research may focus on specific categories and address this limitation.

In conclusion, the firms listed on the Stoxx Euro600 belonging to the real estate industry were selected. The initial sample was composed of circa 40 firms. Given the small figure, other real estate listed firms were included. Those are European real estate companies above €100 million by market capitalization. The threshold was decided in order to exclude small-cap companies. The final sample is composed of 80 firms.

Some small adjustments were necessary to fine tune the sample. Some firms were not actually real estate, but IT companies employed in or complementary to the industry. Some other companies lacked several key financial data for several years and were thus excluded. Finally, a small number of firms were not listed for the whole period or were delisted during the timeframe, thus leading to exclusion. Example of this is Coima Res, an Italian REIT who was listed on the Milan Stock Exchange until July 2022 when the tender offer promoted by Evergreen - sponsored by Qatar’s Sovereign Wealth Fund - ended successfully.

The final sample is composed of 63 European real estate firms, described and decomposed in the following Table:

Table 3.1 – Decomposition of the sample

Country	Number of companies	%	Number of REITs
United Kingdom	14	22%	12
Sweden	11	19%	11
Germany	9	14%	0
Belgium	9	14%	6
France	7	11%	7
Switzerland	3	5%	0
Finland	3	5%	2
Spain	2	3%	0
Netherlands	2	3%	2
Italy	1	1,5%	1
Ireland	1	1,5%	1
Austria	1	1,5%	0

Northern European countries are the most represented in the sample. This makes sense given the fact that their economies are financially prompted and firms find it convenient to go public. Regardless, there are firms from South and Western Europe, thus the sample is fairly representative of the European environment.

REITs companies are the majority, making up 2/3 of the total firms. This is given by the fact that those investment vehicles are able to reach large dimensions. Since REITs are predominant, the use of REIT specific metrics is considerable.

The final sample is composed of 63 firms observed between 2015 and 2025, with an unbalanced structure due to missing years for some firms.

The sample size is in line with Altman's original study (66 total firms), while it appears to be modest in size compared to Beaver (150), Zmijewski (800) and modern machine learning models, which use thousands of data. Regardless, the sample is unique in its sectoral, geographic and size focus, which justify the dimension.

Financial data for the sample companies were obtained via LSEG (former Refinitiv). For each firm 11 financial variables were retrieved from their financial statements. Those, according to Altman, Ohlson and Zmijewski, were:

- Working Capital
- Total Assets

- Total Liabilities
- Retained Earnings
- EBIT
- Book Value of Equity
- Revenues
- Net Income
- FFO
- Current Assets
- Current Liabilities

For most of the companies Net Operating Income was used instead of EBIT. The latter is a measure poorly used by real estate companies, which only report NOI - the equivalent to EBIT for real estate companies. Moreover, this is in line with other studies in the literature, given that many authors used different Operating indicators compared to Ohlson's initial contribution.

The data were obtained for the years 2015-2025. In total the database is composed of 470 firm years. The currency chosen for the variable is euro, as LSEG allows to select a specific currency.

The data was downloaded and then a database was constituted on both Excel and Python.

3.2 Approach

The goal of this thesis is to compare European real estate bankruptcy risk across interest regimes.

To do so, the firm-year data were divided into two separate interest regime environments: low and high. The former corresponds to the years 2016-2019, the latter comprehends the years 2022-2025.

The first year of the sample (2015) was excluded because many crucial data were absent. The Covid-19 years (2020–2021) were excluded as an exceptional phase characterized by unpredictable and exogenous shocks useless for this analysis.

The final dataset contains 244 firm-year observations in the low-rate regime (2016–2019) and 182 firm-year observations in the high regime (2022–2025). While the regimes are asymmetric, the analysis is based on firm-year observations, thus the asymmetry is statistically irrelevant.

Once the database was finalized, the financial variables were used to derive 15 key financial ratios, which are fundamental for the following section of the analysis.

To measure the financial risk of bankruptcy of the sample, three bankruptcy prediction models which are considered relevant and comprehensive by the literature were employed. Those are Altman's Z-score, Ohlson O-score and Zmijewski's score.

These models were selected because they represent different methodological traditions (discriminant analysis, logit, probit) and because of their constant application in different industrial and geographical contexts.

Ohlson and Zmijewski's models are used by applying the published coefficients from Ohlson (1980) and Zmijewski (1984) to the financial ratios. No re-estimate of the logit or probit models was computed.

In addition, as suggested by other papers regarding the application of these models to the real estate industry, a fourth model is applied, in which a small modification to Ohlson's model is operated.

The first model implemented is Altman's Z-score for non-manufacturing firms (1995 version). The formula is:

$$Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

Where the variables are:

X_1 = Working Capital / Total Assets

X_2 = Retained Earnings / Total Assets

X_3 = EBIT / Total Assets

X_4 = Book Value of Equity / Total Liabilities

Higher Z'' values (>2.6) indicate greater financial soundness, while scores below 1.1 typically signal distress. Values in between fall in the grey zone.

The second model is Ohlson's O-score:

$$O = -1.32 - 0.407\ SIZE + 6.03\ TLTA - 1.43\ WCTA + 0.076\ CLCA - 2.37\ NITA \\ - 1.83\ OENEG + 0.285\ INTWO - 0.521\ CHIN$$

Where higher values indicate increased failure risk.

Given a discrepancy in the literature regarding the first variable, a decision was made to select ln(TA) out of simplicity and according to similar papers.

Some authors in fact argued that the variable should be controlled by some sorts of inflationary parameters, such as GDP deflator. Regardless, given the contradiction of several authors and because of the large number of different countries composing the sample, the simpler version is used for this dataset.

As argued by previous researchers who applied Ohlson's model to the real estate industry, EBIT is poorly informative as a key variable for REITs. Accordingly, the third model applied in the analysis is Ohlson's model adapted by replacing Operating Income / Total Liabilities with FFO / Total Liabilities. The goal is to try to have greater explanation power with this little change.

The last model is Zmijewski's score.

$$X = -4.336 - 4.513\ NITA + 5.679\ TLTA - 0.004\ CA/CL$$

Simarly to Ohlson's model, higher values correspond to a greater probability of financial distress.

Collectively, these four models allow for a robust comparison: Altman's application emphasizes balance sheet solvency, Ohlson's model a broader accounting-based approach, Zmijewski's one a model that stresses profitability, leverage and liquidity, and the modified Ohlson enables industry specific adjustments**.**

The models are applied to the panel dataset on a firm-year basis. The objective is to assess which specification captures the potential increase in distress risk between the low and high-interest rate regimes.

Although large companies are generally less likely to both face failure and to show serious financial troubles compared with small firms, it is reasonable to expect that changes in the macro environment may leave detectable signals in their financial statements.

To formally test whether risk levels differ across regimes two complementary approaches are used. Welch's unequal-variance compares the model scores with a model-free approach, complemented by p-values and effect size measures. Secondly, an OLS regression is estimated for each model.

Each model generates statistics that enable an analysis of the soundness of European listed real estate firms across different monetary regimes. Moreover, the hypothesis tests implemented via p-value and Welch analysis allow to understand which model better explains the supposed increase in failure risk and generally which bankruptcy model better suits listed European real estate companies.

In addition, the decomposition of the models' variables allows an assessment of the relative importance of individual financial ratios, highlighting which variables contribute most to distress predictions and thus drive overall risk assessments. The results and interpretations are shown in the following chapter.

While the classical application of bankruptcy models is to estimate the accuracy in predicting actual failure, this thesis uses a different approach. Following recent studies such as Aarbø (2024), the models are applied to non-bankrupt firms in order to interpret their current scores and to analyze the potential evolution of risk under different monetary regimes. This approach highlights whether rising interest rates are reflected in higher distress indicators even in the absence of observed bankruptcies.

This study has some limitations. Firstly, it suffers from survivorship bias since delisted firms and companies that lacked financial data were excluded. Secondly, the sample is limited to European large corporate, thus implies a sample bias. Finally, while the models used are widely cited, they were not originally designed for the European real estate sector, which may affect their predictive accuracy. Future research can extend the sample, use alternative models or validate predictions against actual bankruptcy events as more data become available.

3.3 Methods to evaluate results

The results of the selected models are evaluated with a combination of descriptive and inferential statistical techniques. Statistical tests were performed in python using pandas, statsmodels and scipy libraries.

Firstly, descriptive statistics such as means, medians, standard deviations and quintiles provide an overview of the distribution of scores generated by the models across different monetary regimes.

This allows for an overall risk analysis and serves to answer the question posed by the first hypothesis: was there an increase in bankruptcy risk for large European real estate firms following an increase in interest rates?

Secondly, a series of statistical techniques are implemented to test the statistical significance of the results. Welch's test is the first methodology selected, and is chosen over Student's t-test because it does not assume equal sample size or variances, which is particularly relevant for the asymmetry of the used dataset.

Additionally, p-values are calculated to indicate the probability of observing a difference at least as small as the one measured. According to classical analysis and conventional thresholds, p-values below 0.05 are considered statistically significant.

In addition, Hedges' g is used to estimate effect size. This gauges the magnitude of differences between regimes independently of sample size. In general, effect size allows for assessing whether the observed differences are not only statistically but also economically significant. Conventionally, values around 0.2 are considered small, 0.5 as medium and above 0.8 are interpreted as large effects.

Finally, in addition to statistical tests conducted via Welch's and p-value analysis that provide an assessment of differences between regimes without a specific model, the present research uses a panel regression as a complementary tool for robustness check.

For each bankruptcy model a simple regression is run, which highlights the outcomes under the high-rates regime. The regression is run twice, the second to control whether time-invariant firm specific characteristics such as size or country affect the scores, thus eliminating the influence of permanent differences between firms.

The dependent variable is the model score for each firm-year observation. The key explanatory variable is a dummy indicating the high regime (X).

The first simple OLS specification estimates:

$$Score_t = \alpha + \beta_1 X_t + \varepsilon_{it}$$

where Score is the bankruptcy score for each firm in year t; alpha is a single constant term that captures the average score across all firms in the low-rate regime; X is a dummy variable taking 1 in the 2022–2025 period and 0 otherwise. The coefficient β_1 measures the average change in the score between regimes.

The second OLS specification adds firm fixed effects:

$$Score_t = \alpha_i + \beta_1 X_t + \varepsilon_{it}$$

where αi is a different intercept for each firm that captures all firm-specific differences (country, size, leverage, ecc).

Standard errors are heteroskedasticity robust. The results display the coefficient β_1, its p-value and the R^2 to show how much of the variation in scores between regimes is explained and is statistically significant.

The use and comparison of the two regressions allows to assess whether idiosyncratic heterogeneity is biasing the estimated results and whether the regime effect is genuine among the data sample.

All together these methods enable to understand whether the differences are statistically reliable and economically meaningful and serve to answer the second hypothesis: which bankruptcy prediction model better suits the European real estate industry.

Chapter 4 – Results

Given the theoretical framework provided in Chapter 2 and the methodological framework presented in Chapter 3, the results of the analysis conducted are shown in this chapter.

4.1 Descriptive statistics

A general overview of the results is displayed in Table 4.1

Table 4.1 – General overview

	count	mean	std	min	25%	50%	75%	max
Altman_Z	608.0	6.271	5.242	1.847	4.665	5.282	6.533	68.732
Ohlson_classic	549.0	-1.926	1.174	-10.268	-2.530	-1.923	-1.295	3.338
Ohlson_Modified	549.0	-1.944	1.426	-14.809	-2.644	-1.878	-1.239	5.218
Zmijewski	608.0	-1.878	1.034	-11.808	-2.305	-1.758	-1.303	0.995

It can be inferred that the sample is fairly sound throughout the years. In particular, Altman's Z-score signals extremely sound scores, with significant max values. Those imply that – according to Altman's variables – there are some outliers with very sound financials.

The following table shows the variation in mean across the different monetary regimes. Table 4.3 shows the complete descriptive statistics.

Table 4.2 – Mean analysis

variable	n_low	n_high	mean_low	mean_high
Altman Z″	244	182	6.453014	6.046988
Ohlson Modified	244	182	-2.055639	-1.644706
Ohlson classic	244	182	-1.930649	-1.804646
Zmijewski	244	182	-2.005191	-1.654737

Based on a simple difference-in-means analysis, all models agree that there was increased bankruptcy risk in an environment characterized by higher interest rates.

It is important to remember that lower levels of Altman's Z-score indicate more risk, while the opposite is true for Ohlson and Zmijewski.

The Z-score shows a deterioration in risk, but no significant threshold is reached or exceeded. In fact, the Z value remains far above the distress (<1.1) and the grey-zone area (1.1<x<2.6) among both regimes. This implies that the firms in the sample are extremely safe according to Altman's model.

The change in risk is present but slightly visible. The Z value only decreased by 6.2%, which is the lowest variation in absolute terms. This suggests that Altman's framework may be the model with the least applicability to the European real estate sector.

Ohlson's models reveal stronger results, namely an increase in failure risk as displayed by mean. Surprisingly, while the classic Ohlson's model shows a modest variation between regimes (7%, very similar to Altman), the modified Ohlson's score shows the largest absolute-term variation (20.3%).

This means that a simple variation of one variable (EBIT/TL with FFO/TL) implies a triple increase of failure in the sample according to Ohlson's model. This is a strong result which may suggest that the introduction of a sector specific variable considerably changes the model's explanatory power.

Finally, according to Zmijewski the high interest rates environment carried a 17.5% higher distress risk. This is considerably higher than Altman and classic Ohlson, and similar to the value shown by the modified Ohlson's model.

Taken together, these results support the hypothesis that there was a higher bankruptcy risk in a tight monetary policy environment, with the modified Ohlson and Zmijewski models showing the clearest evidence.

Table 4.3 – Complete descriptive statistics

Stat Model	Regime	count	mean	std	min	25%	50%	75%	max
Altman_Z	High	182.00	6.05	3.88	3.12	4.72	5.33	6.31	41.06
	Low	244.00	6.45	6.31	1.85	4.60	5.28	6.62	68.73
Ohlson_Modified	High	182.00	-1.64	1.28	-4.85	-2.36	-1.74	-1.00	5.22
	Low	244.00	-2.06	1.55	-14.81	-2.67	-1.90	-1.31	2.50
Ohlson_classic	High	182.00	-1.80	1.06	-4.42	-2.43	-1.90	-1.23	3.34
	Low	244.00	-1.93	1.27	-10.27	-2.51	-1.83	-1.22	2.58
Zmijewski	High	182.00	-1.65	0.74	-3.82	-2.06	-1.65	-1.13	1.00
	Low	244.00	-2.01	1.20	-11.81	-2.36	-1.82	-1.42	0.06

Table 4.3 reports complete descriptive statistics for the four models. Median values show a similar increase in risk as shown by the mean for Zmijewski and Ohlson modified, both of which highlight higher distress risk in the high-rate regime. On the other hand, Ohlson's classic specification displays the opposite trend, while Altman's model exhibits just a thin variation across regimes.

Dispersion indicators provide additional insights. While according to Altman the standard deviation is much larger in the low interest rates regime, the other models display the opposite. The latter behavior can be explained with a great heterogeneity of strategies and leverage used by firms in low rates periods, while distress risk rose more uniformly across the sample when rates rose.

The fact that the mean and median values diverge in Altman signals right-skewness – a few extremely sound firms heavily influence the mean. This can be seen by the large gap between extremes (max and min), which signals the presence of certain significant outliers.

On the other hand, the other models – particularly Zmijewski - display closeness between mean and median, which suggests more symmetric distributions. The interquartile ranges also confirm the pattern of narrow clustering around median values for Zmijewski and Ohlson.

Overall, the findings agree and reinforce that Ohlson modified and Zmijewski models appear most exhaustive and informative and hint to the hypothesis that they are the most adapt for the specific sample of listed European real estate companies.

4.2 Model scores

This section evaluates whether the differences across regimes are statistically significant.

As explained in Chapter 3, a model is considered statistically significant if the p-value is below the 0.05 cut-off. Welch's t-test calculates the standardized difference in means between regimes: the larger |t| is, the stronger the evidence of mean difference. Additionally, Hedge's g measures effect size, capturing the magnitude of differences independently of sample size. Values around 0.2 display small effects, 0.5 is considered medium and 0.8 is redeemed a high effect.

Table 4.4 – Welch and Hedges's tests

	variable	mean_low	mean_high	t	p_value	hedges_g
0	Altman Z″	6.453014	6.046988	0.819059	0.413228	0.074959
1	Ohlson classic	-1.930649	-1.804646	-1.116181	0.264985	-0.106320
2	Ohlson Modified	-2.055639	-1.644706	-2.989913	0.002955	-0.284213
3	Zmijewski	-2.005191	-1.654737	-3.696514	0.000248	-0.338545

Statistical tests reveal several and consistent differences between models. Altman's Z-score fails to capture meaningful differences across regimes. This is shown by its p-value of 0.41 and t-statistic of 0.8 – respectively the largest and smallest in absolute terms of the group -, indicating no statistical significance. The effect size g (0.07) as well is negligible.

Those results suggest that, while being widely used and accepted, Altman's specification underestimates shifts in distress risk among the selected sample.

Ohlson's classic model performs slightly better than Altman's but still fails to show significance. The p-value of 0.26 is in fact extremely high. A plausible explanation is that this classic specification puts too much relevance on operating ratios which do not reflect sector dynamics.

In contrast, once a single industry specific variable is introduced, Ohlson's performance drastically improves. Ohlson's modified model exhibits a p-value below 0.01, a t-statistic close to -3 and an effect size approaching medium power (g = -0.28). Those are very significant results that validate the model selection.

Zmijewski's score displays the strongest results out of all the models. A highly significant p-value (<0.001), the largest t-statistic in absolute terms and the largest effect size (|g| = 0.34) suggest a meaningful deterioration in financial conditions when a stricter monetary policy is underway. The focus on profitability and leverage makes Zmijewski's model the one able to capture the increase in risk better than everyone else and the most suitable for the selected sample of listed European real estate companies.

Altman is the only model that shows a positive Hedge's g. This is obvious and indicates that average Z-scores are lower in the high regime – thus are riskier. On the other hand, Ohlson and Zmijewski assume higher risk with lower values, which is in line with g results.

Overall, the initial statistical checks show that Ohlson's modified and Zmijewski's models are the only statistically significant. They emerge as the most informative models for assessing bankruptcy risk, aligning statistical significance with economic relevance.

Moving to the robustness check analysis, Table 4.5 Displays the results of the regression analysis, conducted for each model as introduced in Chapter 3.3.

Table 4.5 – Regression results

Model	Spec	Coefficient β1	p_value	R²
Altman Z″	Simple OLS	-0.320	0.491	0.001
Altman Z″	Firm Fixed Effects	-0.327	0.041	0.894
Ohlson Classic	Simple OLS	0.182	0.087	0.005
Ohlson Classic	Firm Fixed Effects	0.187	0.003	0.687
Ohlson Modified	Simple OLS	0.448	0.001	0.022
Ohlson Modified	Firm Fixed Effects	0.453	0.000	0.489
Zmijewski	Simple OLS	0.319	0.000	0.020
Zmijewski	Firm Fixed Effects	0.320	0.000	0.614

The coefficient represents the average estimated difference in risk between regimes. Negative values indicate higher risk in Altman, while the opposite is true in Ohlson and Zmijewski.

The results reveal that all models estimate higher distress risk under the high interest rates environment.

The simple OLS regression confirms the same findings as described before: Ohlson Modified and Zmijewski's models are the only ones with statistically significant p-values, while R^2 shows how every model is able to explain only a small proportion of total variance.

Once controlling for firm heterogeneity however, all models point to the same conclusion: there was a statistically significant increase in risk under tighter monetary regime.

Importantly, the coefficient becomes weakly significant (0.041) in Altman and significant in Ohlson classic's model (0.003). By contrast, Ohlson modified and Zmijewski's models produce highly significant coefficients in both regression specifications, confirming that those models are the most reliable.

Interestingly, every model is subject to a jump in R^2 when firm heterogeneity is controlled. Particularly, Altman's model reaches the highest level with an astonishing 89%. This is given by the fact that Altman's score, because of its firm-specific focus, is able to capture most of the static firm differences.

Given the large difference among the firms constituting the data sample - and the real estate industry as a whole - controlling for firm differences uniforms and isolates the model results from unwanted noise. This robustness check highlights the importance of firm-specific differences that affect score results.

4.3 Decomposition analysis

In this section a decomposition of each model introduced beforehand is presented. This is a common practice undertaken by researchers that study the application of bankruptcy models, since this approach allows to understand which ratios contribute the most to the results of the model and helps with interpretations of the outcomes.

The models are going to be analyzed in a methodical and precise order across regimes. Table 4.6 displays Altman's Z-score decomposition.

Table 4.6 – Altman Decomposition

--- Altman Z" mean contributions by regime (levels) ---

Regime	const	X1	X2	X3	X4	Zdd
High	3.25	-0.002	1.067	0.240	1.492	6.047
Low	3.25	-0.048	1.310	0.310	1.631	6.453
na	3.25	-0.022	1.143	0.269	1.613	6.252

--- Altman Z" mean contributions by regime (% of Z") ---

Regime	const	X1	X2	X3	X4	Zdd
High	53.7	-0.0	17.7	4.0	24.7	100.0
Low	50.4	-0.7	20.3	4.8	25.3	100.0

The most notable insight is that most of the contribution in both regimes is given by the constant. This implies that most of the results are not explained by Altman's ratios. Moreover, the contribution of each parameter decreases under higher interest rates environment.

Among the real contributor ratios, Retain Earnings to Total Assets (X2) and Equity to Liabilities (X4) are the dominant drivers, explaining 40-45% of the score. They display a positive value, thus they contribute to mitigating the risk of failure. Moreover, they remain mostly stable across regimes, suggesting that long-term profitability is the key solvency determinant for the firms in the sample.

By contrast, Working Capital to Total Assets (X1) has a nihil contribution, particularly in the tighter environment (-0.002 and 0% of contribution). This suggests that liquidity is not considered a relevant risk mitigator or factor given the characteristics of the selected companies in the sample.

Overall, Altman's decomposition indicates that the model fails to detect the real drivers of distress risk. Together with the earlier findings of statistically insignificance, this suggests that Altman's Z-score has limited applicability to the European real estate industry.

Table 4.7 – Ohlson classic decomposition

--- Ohlson classic mean contributions by regime (levels) ---

Regime	const	SIZE	TLTA	WCTA	CLCA	NITA	EBIT_TL	INTWO	OENEG	CHIN	Ohlson_classic
High	-1.32	-3.514	2.866	0.000	0.235	-0.007	-0.148	0.034	0.0	0.050	-1.802
Low	-1.32	-3.345	2.888	0.010	0.217	-0.202	-0.180	0.004	0.0	-0.003	-1.931
na	-1.32	-3.391	2.879	0.005	0.212	-0.159	-0.169	0.008	0.0	-0.061	-1.973

--- Ohlson classic mean contributions by regime (% of score) ---

Regime	const	SIZE	TLTA	WCTA	CLCA	NITA	EBIT_TL	INTWO	OENEG	CHIN	Ohlson_classic
High	73.3	195.0	-159.0	-0.0	-13.0	0.4	8.2	-1.9	-0.0	-2.8	100.0
Low	68.4	173.2	-149.6	-0.5	-11.2	10.5	9.3	-0.2	-0.0	0.2	100.0

Once again, the greatest relative contribution to the model is the intercept, and in the case of Ohlson's model it accounts for 2/3 of the total.

It is important to note that some variables account for more than 100%, this is possible because some ratios pull in opposite direction, thus counterbalancing each other.

The largest real contribution to the model is performed by Size and Leverage variables. While the former reduces risk (a negative sign in the first column), the latter increases it, almost completely counterbalancing the other. This makes sense, given that larger firms are usually the soundest, while leverage carries more financial burdens and intrinsically more failure risk. In the high-rate regime, the Size effect increases its relative weight more than leverage does.

Liquidity (CLCA) and earnings power (EBIT/TL) ratios have a smaller but still relevant contribution. The former is a destabilizing factor, while the latter decreases the risk of failure (-0.18 in the low regime). Those remain stable across regimes, while NITA (profitability) exhibits a significant gap between the two environments. The protective effect of profitability disappears in the high-rate regime, where it collapsed to zero contribution (-0.007 in absolute level, 0,4% of contribution)- thus making it irrelevant.

Anyhow, the statistical analysis previously conducted showed how this model has low credibility and adaptability for the sample. Because of this, the results of the decomposition should be taken with circumspection.

On the other hand, the modification of just one variable to the Ohlson classic model grants superior results, as was shown in the previous section. The decomposition of Ohlson modified is presented in Table 4.8

Table 4.8 – Ohlson modified decomposition

--- Ohlson Modified mean contributions by regime (levels) ---

Regime	const	SIZE	TLTA	WCTA	CLCA	NITA	FFO_TL	INTWO	OENEG	CHIN	Ohlson_Modified
High	-1.32	-3.514	2.866	0.000	0.235	-0.007	0.011	0.034	0.0	0.050	-1.643
Low	-1.32	-3.345	2.888	0.010	0.217	-0.202	-0.305	0.004	0.0	-0.003	-2.056
na	-1.32	-3.391	2.879	0.005	0.212	-0.159	-0.271	0.008	0.0	-0.061	-2.074

--- Ohlson Modified mean contributions by regime (% of score) ---

Regime	const	SIZE	TLTA	WCTA	CLCA	NITA	FFO_TL	INTWO	OENEG	CHIN	Ohlson_Modified
High	80.3	213.9	-174.4	-0.0	-14.3	0.4	-0.7	-2.1	-0.0	-3.0	100.0
Low	64.2	162.7	-140.5	-0.5	-10.5	9.8	14.8	-0.2	-0.0	0.2	100.0

The constant is again one of the main contributors to the model, and it sharply increases in the high-rate environment. In the latter situation, it contributes 80% of the total. This is the highest among all the models.

Size and Leverage remain the two most relevant variables. Interestingly, while both variables have a slightly lower contribution in the low-rate environment, the respective shares significantly increase during tighter policy period.

The influence of the variables remains the same: size decreases risk, while leverage increases it – as displayed by the level contribution. Moreover, the hierarchy between the two variables is stable: size is a stronger and more influential variable than leverage is.

Liquidity (CLCA) is a mild but persistent indicator, with similar negative contributions in both regimes.

The main difference compared to Ohlson classic is represented by the substitution of EBIT/TL with FFO/TL. In the original specification, EBIT/TL had a slightly stabilizing effect in mitigating failure risk, and the contribution remained stable across regimes. By contrast, FFO/TL has a mild positive effect in the low-rate period but dramatically changes under tighter environment. Under the latter regime, the variable has a positive correlation with the risk of failure.

This suggests that cash flows that under low rates indicate resilience, correlate with risk under tight period. This is because higher interest expenses absorb a larger share of available cash and undermine the capacity to cover liabilities. Once this happens it is reasonable for analysts to conclude that financial distress is more likely and investors to withdraw their capital and invest in some safer and more lucrative asset.

This sole difference implies a much higher statistical significance of the model compared with its classic specification, which means that the interpretation is accurate and depicts what really happens between market participants.

Table 4.9 – Zmijewski decomposition

--- Zmijewski mean contributions by regime (levels) ---

Regime	const	NITA	TLTA	CA_CL	Zmijewski
High	-4.336	-0.013	2.699	-0.004	-1.669
Low	-4.336	-0.385	2.720	-0.005	-2.005
na	-4.336	-0.303	2.711	-0.004	-1.945

--- Zmijewski mean contributions by regime (% of score) ---

Regime	const	NITA	TLTA	CA_CL	Zmijewski
High	259.7	0.8	-161.7	0.3	100.0
Low	216.2	19.2	-135.7	0.2	100.0

The decomposition of Zmijewski's model presents some interesting results.
The intercept is the most relevant contributor to the overall explanation, reflecting below ideal classification power.

Liquidity (CACL) provides zero contribution to the model, suggesting that short-term working capital dynamics are of minimal relevance for the sample firms.

Profitability (NITA) makes a modest contribution in reducing risks in the low-rate regime, but its role drops to zero under tighter monetary situation. This highlights how higher financial expenses affect net income and erode the protective role of profitability.

Leverage (TLTA) offers key interpretations to the model: it is by far the most significant 'real' contributor and has a positive correlation with risk, as shown by its positive coefficient.

The contribution of leverage increases under high-rates environment by nearly 20%, reflecting how highly leveraged firms face more challenges under external pressure – particularly when monetary policy tightens. This implies that leverage increases the overall bankruptcy risk of single firms.

In conclusion, Zmijewski's model individuates leverage as the dominant risk driver, while attributing a minor role to profitability. This model displays the lowest number of variables, yet those contain straightforward and meaningful interpretations.

4.4 Results and interpretations

The overall analysis demonstrated that every model confirms - to different extents - the first hypothesis: European listed real estate companies experienced increased risks under the recent wave of monetary tightening.

Moreover, the analysis tested the second hypothesis - which model better suits the industry and captures the risk dynamic - highlighting that two out of four models show robust and significant empirical performance, thus displaying their suitability for the real estate industry. The other two models show mediocre results, which suggest that they either require adjustments or are not adapt for the specific sample and sector.

Altman's Z-score displayed a slight increase in risk under the tighter regime, yet it classifies the whole sample as extremely healthy during the entire period. Moreover, the results obtained display no size effect and both the Welch test and the simple regression do not reach statistical significance.

On the other hand, the regression that isolates the sample from idiosyncratic characteristics shows significance and demonstrates that the Z-score reaches the highest level of variance explained. This peculiarity is explained by the firm-specific focus of Altman's specification, which enables to capture most of the static differences.

In conclusion, Altman's contribution is not suitable for large European real estate companies. This is explained by the fact that the Z-score is strongly balance-sheet oriented, emphasizing solvency ratios while underrepresenting liquidity and cash-flow dynamics. The latter happens to be crucial for large real estate companies that always maintain high asset levels and strong equity positions. Because of this the Altman score tends to classify the companies as safe even when leverage and cash flow risk are increasing.

Ohlson's classic model includes a broad set of accounting and dummy variables and exhibits higher distress risk under high-rates regime. The preliminary statistical tests display disappointing results, while the firm-adjusted regression showed relevant results.

The model puts too much relevance on operating income, which is often distorted by accounting treatments for REITs and real estate companies. Additionally, the O-score underweights the asset-heavy structure and capital-market dependence of REITs, crucial drivers of risk in the real estate industry.

In conclusion, Ohlson classic is little informative about solvency for large European real estate companies.

The idea of adjusting Ohlson's classic model with a sector-specific variable, as suggested by some authors in the literature, materially alters the outcomes.

Ohlson's modified model indeed shows the most significant deterioration in financial conditions and an augmented failure risk (+25%) as exhibited by the difference-in-mean. This result is statistically significant according to all the tests and has a low-to-moderate effect size.

Surprisingly, the R^2 is the lowest compared with the other specifications. Unlike Altman in fact, Ohlson's modified model depends more on time-varying indicators – particularly the variable FFO/TL - rather than firm characteristics.

The apparent tiny change – FFO/TL instead of EBIT/TL – enables the model to capture industry dynamics that would otherwise be missed. FFO in fact captures recurring cash flows from operations before depreciation and fair-value adjustments, which are considerable industry-specific distortions.

The good results of the model are given by its contributors: size, leverage and cash flow capacity. The former reduces risk, the second increases it, while the latter behaves differently across regimes. This is explained by the fact that when rates quickly rise the buffer provided by FFO shrinks.

Overall, the model has the great contribution of capturing an industry-specific risk channel, which is otherwise excluded by every other model. This shows the relevance and usefulness of adapting classic models to industry dynamics.

The other encouraging result is provided by the fourth model: Zmijewski's specification. This model only considers a handful of variables, much less than Ohlson's model, yet the statistical tests conducted report the best results, particularly with a p-value of <0.01 according to every test. Moreover, the effect size is the largest among all the models, thus implying that the theory translates to real economic impact.

The decomposition of the model shows that all the explanation is provided by leverage, reflecting the threat posed by monetary cycles to leveraged industries and firms. In addition to leverage, profitability is a moderate indicator but ceases to be protective under tighter regimes, while liquidity is irrelevant.

Overall, Zmijewski's model puts strong emphasis on leverage, which is an intrinsic characteristic of many real estate companies. For this reason, the model grants considerable results and is the most suitable for the industry solely according to statistics.

In conclusion, all models point to increased bankruptcy risk under the high-rate regime. Yet only Zmijewski and Ohlson modified's models provide statistically significant and economically meaningful results.

This is in line with the findings of Andriani and Sihombing (2021) and Purwanti (2024), which argue that Zmijewski's contribution is the best performing in the real estate industry. Likewise, the good performance of an industry-tailored model is in line with Manda (2024).

By contrast, Altman and Ohlson's classic models seem poorly suited for large European real estate firms. This conclusion is contradictory to Yendrawati (2020), but in line with Andriani and Sihombing (2021) and others.

The final consideration is that Ohlson's modified formulation considers more variables and allows for more interpretability compared to Zmijewski's model. The capture of industry-specific dynamics suggests that this model is the most relevant to understanding bankruptcy risk in the real estate industry, and is the one suggested for future research and studies.

Conclusions

This research sought to assess whether large European listed firms in the real estate industry experienced an increase in failure risk as predicted by a series of notorious bankruptcy prediction models following the increase in interest rates of the last years.

The rationale for this question was that a series of exogenous shocks have affected the world's largest economies with long-lasting effects. The number of large corporations filing for bankruptcy is on a worrying rise and interesting insights may be gathered by the theoretical literature in the prediction field.

The real estate industry is asset-heavy, highly leveraged, long-term looking and extremely sensitive to changes in monetary policy. That means that the sector is the perfect candidate to study the effects of monetary policy changes.

No previous study is present in the literature that tests bankruptcy prediction models across different monetary regimes, nor that applies a specific analysis to the large-cap European real estate industry.

A number of European companies were selected over ten years to obtain a sample of 420 firm-year observations. This was used to gather information located in the financial statements and construct the ratios needed for the analysis. The observations were split between a high interest rate regime (2022-2025) and low-interest rate regime (2016-2019).

Four notorious bankruptcy prediction models – indicated by the literature – were selected. Those are Altman's Z'' Score, Ohlson's O-score, Zmijewski's score and an industry-tailored specification based on Ohlson's model.

To test whether an increase in risk happened, the results in the two regimes were compared with the techniques of difference-in-mean, Welch's t test, Hedge's g, p-values and a tailor-made OLS regression controlling for firm specific differences.

The results draw the same conclusion: large European real estate companies suffered an increase in bankruptcy risk as displayed by their financial statements following the tightening of monetary policy, thus confirming the main hypothesis.

The research demonstrates that two models are the best suited for the industry: Zmijewski's contribution and Ohlson's modified. This result is in line with other findings in the literature.

While Zmijewski's model exhibits slightly better results, the modification of Ohlson's model to create an industry-specific specification considers more variables and enables more interpretability compared to Zmijewski's model. The capture of industry-specific dynamics makes this model the most relevant to understanding bankruptcy risk in the real estate industry, thus this model is suggested for future applications.

Moreover, the decomposition shed light over the most useful and impactful variables: size, leverage and repayment capacity from cash flows. Those are the ones that managers and policymakers should thoroughly look at when assessing bankruptcy risk in the European real estate industry.

The research successfully confirmed the stated hypothesis, however it suffers from some limitations.

Firstly, the prediction models were not used in their standard specification given that no actual bankrupt sample was analyzed. This is because actual bankruptcies are hardly observed in large real estate companies. This thesis instead tried to assess whether the selected models were reliable in assessing a risk increase and to suggest the best specification, similarly to other contributions in similar contexts.

Secondly, only large capitalization companies were included in the sample and studied. Those firms are indeed less likely to fail and to suffer from exogenous shocks, however a reliable model to assess their risk has great utility and application for researchers and analysts. Future studies may focus on different European samples.

Thirdly, the sample may suffer of survivorship and selection biases. Additionally, many REITs compose the sample, which may skew the results. Future research is encouraged to experiment on a more diversified or specific sample.

Fourthly, only four notorious bankrupt models were reproduced, while other specifications or recent machine learning applications were not applied. Those may give different results and broader interpretations, thus future studies are encouraged to use them in the European industry.

Finally, the methods employed to test the results are robust, but others could be applied to increase the accuracy and interpretation of the results. The regression here used only offers the purpose of answering the first hypothesis, while future research may develop a more specific regression or utilize different methods to evaluate results.

In conclusion, the thesis offered hints and interpretations showing that established bankruptcy prediction models are able to capture meaningful risk variations in European real estate firms under different monetary regimes.

The individuation of the best performing prediction models for the large-cap European real estate industry can be useful for managers and policy makers for when similar inflationary shocks and monetary pressures happen again. In that situation, the approach and results of this analysis can be adopted to assess vulnerability and risk and ultimately structure sound strategies.

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