Financial Distress Prediction Models: An Analysis for Portuguese Listed Companies

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Abstract

This study a comparative analysis of two prominent financial distress prediction models - the Altman Z-Score and Ohlson O-Score - applied to Portuguese companies listed on Euronext Lisbon. Focusing on distinct macroeconomic periods, including the 2011–2013 sovereign debt crisis and the COVID-19 pandemic, the research assesses the models' behaviour, correlation, and sensitivity to economic shocks.

Results show that both models significantly deviate from normality, necessitating nonparametric approaches. The distress levels measured by each score do not differ significantly across economic periods, though they exhibit a strong negative correlation reflecting their inverse risk scales. Sensitivity analyses reveal distinct responses: the Ohlson O-Score displays greater variability and heightened sensitivity to the 2011–2013 crisis, while the Altman Z-Score demonstrates relative stability and significant improvements in post-crisis periods. These findings underscore the complementary nature of the two models and their practical utility in financial risk assessment within volatile economic environments.

The study contributes to the literature by bridging model comparison with crisis sensitivity analysis in a market context, offering enhanced understanding for decision-makers to make more accurate assessments and timely decisions.

Keywords: Financial Distress Prediction, Z-score, O-score, Portuguese Listed Companies, Euronext Lisbon, Sovereign debt crisis, COVID-19, Crisis Sensitivity Analysis, Market

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Sumário

Este estudo apresenta uma análise comparativa de dois modelos proeminentes na previsão de dificuldades financeiras - o Altman Z-Score e o Ohlson O-Score - aplicados a empresas portuguesas cotadas na Euronext Lisboa. Focando em períodos macroeconómicos distintos, incluindo a crise da dívida soberana de 2011–2013 e a pandemia de COVID-19, a presente investigação avalia o comportamento dos modelos, a sua correlação e sensibilidade a choques económicos.

Os resultados indicam que ambos os modelos se desviam significativamente da normalidade, exigindo abordagens não paramétricas. Os níveis de dificuldade financeira medidos por cada score não diferem significativamente entre os períodos económicos, embora exibam uma forte correlação negativa que reflete as suas escalas inversas de risco. As análises de sensibilidade revelam respostas distintas: o Ohlson O-Score apresenta maior variabilidade e sensibilidade aumentada à crise de 2011–2013, enquanto o Altman Z-Score demonstra estabilidade relativa e melhorias significativas nos períodos pós-crise. Estes resultados sublinham a natureza complementar dos dois modelos e a sua utilidade prática na avaliação do risco financeiro em ambientes económicos voláteis.

O estudo contribui para a literatura ao unir a comparação de modelos à análise da sensibilidade às crises num contexto de mercado, oferecendo assim uma melhor compreensão para os decisores tomarem avaliações mais precisas e decisões atempadas.

Palavras-chave: Dificuldades financeiras, Modelo Z-score, Modelo O-score, Empresas Portuguesas Cotadas, Euronext Lisboa, Crise da dívida soberana, COVID-19, Análise de Sensibilidade a Crises, Mercado

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List of Abbreviations

CEO – Chief Executive Officer

EBIT – Earnings Before Interest and Taxes

FCP – Futebol Clube do Porto

GDP – Gross Domestic Product

PD - Probability of Distress

ROA – Return on Assets

SCP – Sporting Clube de Portugal

SLB – Sport Lisboa e Benfica

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1. Introduction

The relevance of predicting financial distress has become increasingly evident considering recent high-profile insolvencies amongst Portuguese listed companies such as Imobiliária Construtora Grão-Pará, S.A. These cases not only resulted in substantial financial losses for shareholders, creditors, and other stakeholders but also highlighted the broader economic consequences of corporate failures, including job losses and diminished market confidence.

Financial distress is generally understood as a condition in which a firm experiences substantial difficulty in meeting its financial obligations to creditors, employees, and suppliers as they become due (Baxter, 1967; Brown et al., 1992; Ofek, 1993). This situation often arises when the company's revenues or cash flows are insufficient to cover operating expenses, debt servicing, and other liabilities, leading to liquidity shortages and mounting financial pressure. If these challenges remain unresolved, the firm may face severe consequences including insolvency, bankruptcy, or liquidation, where it is either unable to continue operations or must be formally dissolved.

The Altman Z-Score (Altman, 1968) and the Ohlson O-Score (Ohlson, 1980) are widely recognized financial models used to identify and predict financial distress in companies. The Altman Z-Score combines multiple accounting ratios derived from corporate income statements and balance sheets to generate a single score that estimates the likelihood of bankruptcy. It has been extensively tested and demonstrates strong predictive power, indicating whether a firm is financially healthy, in a grey zone, or at high risk of distress based on threshold values. Similarly, the Ohlson O-Score applies a logistic regression framework incorporating various financial ratios, firm characteristics and market indicators to estimate the probability of default, offering a probabilistic measure of financial distress risk.

This thesis conducts a comparative analysis of financial distress prediction using the Altman Z-Score and the Ohlson O-Score on a sample of Portuguese companies listed on Euronext Lisbon. The study covers a period characterized by varying economic conditions, including pre-crisis, the 2011–2013 sovereign debt crisis, post-crisis recovery, the COVID-19 pandemic, and the post-COVID period.

By applying rigorous statistical methods such as normality testing, nonparametric hypothesis tests, correlation analysis, variance assessments, and fixed-effects panel regressions, the research aims to clarify the strengths and limitations of each model in capturing financial distress risk by systematically comparing their responses to varying economic conditions and shocks. This analysis seeks to reveal how effectively each model identifies early warning signs of distress, how sensitive they are to external macroeconomic disruptions, and whether they provide consistent, reliable signals across different periods of economic instability. By doing so, the research offers nuanced insights into the practical utility of the Altman Z-Score and Ohlson O-Score, highlighting scenarios where one model may outperform the other or where complementarity exists.

2. Literature review

2.1. Definition of financial distress

Financial distress is broadly defined as a condition in which a firm faces significant difficulty in meeting its financial obligations to creditors, employees, and suppliers as they become due (Baxter 1967; Brown et al.1992; Ofek 1993), potentially culminating in insolvency, bankruptcy, or liquidation if unresolved. Academic literature emphasizes that financial distress is best conceptualized as a continuum - not a single event (Warner 1977; Clark & Weinstein 1983; Gilson et al. 1990). This state typically arises from a deterioration in the firm's financial position, visible through sustained operating losses, eroding liquidity, rising leverage ratios, negative cash flows, and mismatches in working capital, often manifesting years before any formal declaration of default or bankruptcy occurs.

Distress is an important but often underappreciated phase in the financial life cycle of a firm - one that is fundamentally distinct from bankruptcy or formal insolvency proceedings. Bankruptcy is a specific legal state triggered by a court filing, usually as a last resort when a company cannot meet its debt obligations and seeks protection or an orderly liquidation under legal supervision. Insolvency, meanwhile, can be defined either technically (the inability to pay debts as they come due) or through a balance-sheet lens (total liabilities exceed total assets). As pointed out by Whitaker (1999) and Altman & Hotchkiss (2006), this distinction underlines the value of analysing companies "at risk" of failure, not only those that have already failed. Companies "at risk" of failure can either recover, be acquired, undergo out-of-court workouts, or ultimately enter bankruptcy, but the distress phase itself is rich with information about managerial responses, stakeholder negotiation, and the potential for turnaround.

As clarified by Beaver (1966), early signs include an increasing incidence of losses, the consumption of liquid assets, declining profitability, and growing debt ratios. According to

Beaver (1966), Ohlson (1980), and Altman (1966), negative trends in financial statement ratios - such as lower return on assets (ROA), declining cash flow to debt, and a rising debt-to-assets ratio - are crucial for diagnosing the onset of distress well in advance of failure.

2.2. Why predict financial distress?

Anticipating future developments and recognizing potential failure is highly valuable for companies operating in today's dynamic economic environment. By improving their ability to identify the risk of financial distress, businesses can modify their strategies and actions to avoid facing serious financial troubles or bankruptcy. This proactive approach helps minimize the costs and negative impacts associated with financial distress and supports the long-term health and sustainability of the company (Gepp & Kumar, 2015; Kubíčková & Nulíček, 2016).

According to Beaver et al. (2011), while it may seem obvious that predicting financial distress is important, the reasoning is more nuanced. If bankruptcy and contract renegotiation were entirely costless, the probability that a firm would face distress wouldn't impact its value - any issues could be resolved efficiently and equitably among stakeholders. Even in this ideal scenario, individual stakeholders would still need to predict distress, since it influences the likely payout from their investment or claims.

However, bankruptcy and renegotiations involve real costs: from legal fees to lost relationships and reputational damage. This means that knowing the likelihood of distress is vital not just for the firm's overall value, but also for individual stakeholders who must make decisions based on risk and anticipated returns. Predicting financial distress is essential for protecting interests, guiding strategic choices, and responding proactively to mitigate losses or enable recovery.

Ohlson (1980), on the other hand, argued that the real focus shouldn't be simply on predicting if bankruptcy will occur, but instead on estimating the actual losses or negative impacts that arise from different degrees of financial distress. In this view, financial distress isn't just a binary outcome - losses can be zero in some cases or vary in magnitude as distress becomes more severe. Thus, the more meaningful analysis considers not only whether distress might happen but also quantifies the possible financial consequences if it does.

Despite this, predicting the probability of distress (PD) remains a crucial initial step, as it helps identify which firms are at risk and sets the stage for deeper analysis of likely losses. In practice, however, detailed data on actual investor losses during times of distress are hard to obtain, making it much more feasible to first assess risk probabilities before estimating precise outcomes. This layered approach combines Ohlson's perspective with the realities of data availability and modelling.

2.3. Predictive models of financial distress

Distress research on financial distress prediction indicators has evolved significantly, shifting from simple univariate analyses to complex multivariate models and expanding beyond purely financial indicators to incorporate multidimensional factors - such as market variables and macroeconomic conditions. The financial approach remains a vital technique in bankruptcy prediction, as balance sheets and income statements provide detailed, reliable data for early warning of risk (Adamowicz & Noga, 2018; Cultrera & Brédart, 2016). By analysing key metrics such as liquidity, profitability, leverage, and cash flows, financial statement analysis can detect initial signs of distress, enabling firms and stakeholders to intervene before conditions worsen. This approach allows for timely risk assessment and supports informed decision-making through quantitative evidence drawn from core financial documents, which are foundational in forecasting business health and potential insolvency. Weaver et.al. (1932) were the first to empirically investigate which financial ratios best predicted corporate failure, ultimately identifying net equity and equity ratios as particularly effective indicators.

Building on this, Beaver (1966) research selected thirty indicators, including measures of profitability, short-term and long-term solvency, and operational capacity, as a foundation for predictive modelling. Altman (1968) Z-score model combined several ratios - working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value of equity to book value of total debt, and sales to total assets - to forecast bankruptcy with greater accuracy. Ohlson (1980) contributed by developing a financial distress prediction model using nine key financial variables. Zmijewski (1984) took a different approach, employing return on assets and liquidity indicators to distinguish between financially sound firms and those facing insolvency, based on empirical data from hundreds of companies. More recently, Altman expanded his model to include operational margin, asset growth, sales growth, workforce growth, and change in price-to-book, thereby enhancing its ability to capture emerging risks in global and fast-changing environments.

Nevertheless, research has shown that the accuracy and sensitivity of bankruptcy prediction models are closely tied to industry-specific characteristics (Sayari & Mugan 2017). When the same financial ratios are applied across different industries, their predictive power can decrease substantially. Typically, models that use indicators tailored to the structure and dynamics of a particular sector perform well within their original context but lose effectiveness when generalized across diverse industries. Sayari & Mugan (2017) attribute this issue to the inability of many models to account for unique industry features, which impedes their ability to reliably differentiate between distressed and healthy firms.

The cumulative evidence suggests that effective financial distress prediction now requires a multidimensional view: combining market-based and macroeconomic signals, traditional accounting measures, and qualitative factors such as board structure, ownership, and executive psychology.

Researchers have begun to differentiate between market information and accounting information in predicting financial challenges. Market-based data, such as stock prices, volatility, and trading volumes, often offer forward-looking insights into investor sentiment, market expectations, and perceived risk, whereas accounting data typically provides a historical snapshot of a firm's financial standing. Beaver et al. (2005) argued that rising market volatility tends to increase the likelihood of bankruptcy, as it signals higher uncertainty and potential instability. Similarly, Campbell et al. (2008) pioneered the use of logic models to combine both financial and market indicators, confirming that market-driven variables significantly improve the accuracy of distress forecasts.

Further studies by Christidis et al. (2010) took this approach a step further, examining the predictive capacity of several market-based forecasting indicators. Their results show that incorporating macroeconomic variables - such as interest rates, Gross Domestic Product (GDP) growth, and systemic risk factors - into market and accounting models enhances their predictive power both within and across different sample periods. This shift reflects the broader consensus that financial distress prediction must adapt to include real-time market signals and the external context in which firms operate, yielding more accurate and timely warnings of impending financial difficulty.

In recent years, the scope of predictive research has expanded even further, with scholars investigating the role of corporate governance and executive behaviour as important predictors. For instance, Lee et al. (2004) found that family-owned firms were more likely to slip into distress due to their unique governance structure, which can concentrate decision-making and reduce oversight. Khaw et al. (2016) observed that male executives tended to be more aggressive in operational decisions, which might increase risk-taking and affect a company's risk exposure compared to female executives.

Zeng et al. (2021) went deeper into the psychological and behavioural characteristics of Chief Executive Officers (CEO), arguing that executive cognitive foundations, risk preferences, and personal attributes substantially shape organizational decision-making and strategy. Studying Shanghai and Shenzhen A-share listed firms from 2010 to 2018, they empirically linked CEO risk appetite with the likelihood of encountering financial difficulty and committing regulatory violations. They found that companies led by risk-averse CEOs were paradoxically more likely to break the law, but that the major effect was moderated by the degree of financial challenge faced by the business.

2.3.1. Altman's Z-Score Model

First introduced in the 1960s, Altman's pioneering Z-Score model laid the foundation for multivariate analysis in bankruptcy forecasting and transformed the field. Altman constructed this preliminary model with a sample of 66 companies, split evenly between bankrupt and non-bankrupt firms. The bankrupt companies in the dataset, mainly manufacturing enterprises, had filed for bankruptcy under Chapter X of the National Bankruptcy Act between 1946 and 1965. The average asset value for these firms was $6.4 million, reflecting the relatively modest scale common among companies at that time.

To ensure the integrity of his comparison, Altman carefully selected non-bankrupt firms that closely resembled their insolvent counterparts in industry category and size, although the healthy companies tended to be slightly larger by asset value. The financial data for all sample companies was sourced from a single reporting period - the year prior to bankruptcy for the insolvent group - ensuring comparability across both bankrupt and non-bankrupt firms.

Altman's rigorous evaluation included 22 financial ratios that captured essential elements of business performance, spanning liquidity, profitability, leverage, solvency, and operational efficiency. Through statistical analysis, he identified five key financial ratios as the most powerful predictors. These ratios formed the basis of the discriminant function, which ultimately produced the original Z-Score formula - a breakthrough that enabled practical, quantitative bankruptcy prediction for the first time. The success and impact of the Z-Score model prompted numerous adaptations over subsequent decades to match evolving market conditions and industry requirements. The equation representing the final Z-Score is:

$$Z = 1.2 * X1 + 1.4 * X2 + 3.3 * X3 + 0.6 * X4 + 1 * X5$$

Where:

X1 = Working Capital / Total Assets - Working capital results from the difference between current assets and current liabilities. In other terms, it represents the company's available resources to meet its short-term obligations. When divided by total assets, this ratio provides a sense of the company's liquidity relative to its overall size. According to Altman (1968), among all liquidity ratios, this one proved to be the most effective indicator.

X2 = Retained Earnings / Total Assets - The ratio is important because the retained earnings component implicitly reflects the age of the company. According to Altman (1968), a newer company in the market is generally more likely to be classified as bankrupt than an older one.

X3 = Earnings Before Interest and Taxes (EBIT) / Total Assets - This ratio measures the firm's true productivity in utilizing its assets, while ignoring taxes or the effects of leverage. Since a company's existence is based on its ability to generate returns from its assets, this ratio is considered highly suitable for assessing bankruptcy risk (Altman, 1968).

X4 = Market Value of Equity / Total Liabilities - The market capitalization is calculated by multiplying the current stock price by the total number of outstanding shares. This ratio can measure to what extent a company's assets can lose value before liabilities start to exceed assets, potentially leading the company into insolvency. It introduces a market value dimension that sets it apart from other studies (Altman, 1968).

X5 = Sales / Total Assets - This ratio can also be called asset turnover, as it shows the ability of a company's assets to generate sales. According to Altman (1968), it is a measure of management's ability to perform well under competitive conditions.

Altman (1968) employed an F-test to evaluate the individual discriminant capacity of each variable in his model. This statistical procedure identifies whether a statistically significant distinction exists in the mean ratios between bankrupt and non-bankrupt groups. Among the ratios previously discussed, only the initial four exhibited statistical significance at the stringent 0.001 level, indicating marked differentiation between the groups. Although the X5 variable demonstrated minimal statistical significance, Altman nonetheless chose to include it in the model.

In response to the constraints of the initial Z-Score model for non-public companies, Altman suggested modifications, leading to the development of the Z'-Score model. This iteration substituted the market value of equity with the book value of equity, therefore enhancing its applicability to privately held enterprises. The updated equation for the Z'-Score model is as follows:

$$Z' = 0.717 * X1 + 0.847 * X2 + 3.107 * X3 + 0.420 * X4 + 0.998 * X5$$

Due to the absence of an extensive database for private companies, Altman did not verify the accuracy of the Z'-Score model using a secondary sample. In order to broaden the model's relevance to many sectors, he devised the Z"-Score model, which omits the Sales/Total Assets ratio (X5) due to its susceptibility to industry-specific influences. The following equation with four variables creates the Z"-Score model:

$$Z'' = 6.56 * X1 + 3.26 * X2 + 6.72 * X3 + 1.05 * X4$$

Within this improved model, the EBIT/Total Assets ratio (X3) continues to be the most effective differentiator between financially troubled and financially stable companies. The versatility of the Z"-Score model enables its application to non-manufacturing firms as well as both private and public corporate entities, extending beyond manufacturing firms. For instance, Altman et al. (2016) effectively implemented the Z"-Score model on a wide range of privately owned companies in different sectors, showing its robust ability to forecast outcomes in nonmanufacturing environments.

Furthermore, Altman outlined a method for selecting threshold values ("cut-off points") for classifying firms according to their Z-score. Upon reviewing misclassified firms, he established that companies with Z-scores exceeding 2.6 could be reliably classified as financially healthy, while those with scores below 1.1 were classified as bankrupt. The intermediate range between 1.1 and 2.6 was designated as a grey zone reflecting uncertainty and a higher incidence of classification error. Thus, classification guidance is provided as follows:

- $Z < 1.1$: Company is designated as being in the distress zone.
- $1.1 < Z < 2.6$: Company falls within the grey zone.
- $Z > 2.6$: Company is deemed to be in the safe zone.

2.3.2. Ohlson's O-Score Model

Ohlson (1980) was the first to apply logistic regression (logit analysis) to forecast the probability that a company would face bankruptcy in the near future. Ohlson O-score model estimates the level of risk associated with financially distressed firms.

To construct the bankruptcy prediction model, Ohlson (1980) relied solely on publicly available financial data, selecting nine specific financial ratios as explanatory variables. Each ratio holds a coefficient and a constant factor, remaining fixed irrespective of changes in the individual variables. Two of these nine variables act as dummy factors, generally contributing zero impact in most cases. Notably, the GDP price index, which is not present in company financial statements, was incorporated to adjust total assets and reflect inflationary effects.

The sample underpinning the Ohlson model comprised 105 bankrupt companies and over 2,000 non-bankrupt firms, enabling robust statistical inference. Ohlson used these observed data to create his O-score, which has been shown to outperform the Altman model over a two-year prediction horizon in terms of accuracy. Indeed, Ohlson's methodology demonstrated over 90% predictive accuracy, surpassing Altman's model, which achieved just above 70%.

Key determinants in Ohlson's approach include liquidity position, company size, performance, and capital structure. Furthermore, Ohlson considered the availability timing of financial data, noting that whether a company enters bankruptcy before or after data release can influence prediction outcomes. The Ohlson model's innovation lays in its statistical rigor and its capacity for improved early bankruptcy detection in comparison to prior methods. The equation representing the final O-Score is:

$$\begin{aligned} O = {} & -1.32 - 0.407 * X1 + 6.03 * X2 - 1.43 * X3 + 0.0757 * X4 - 2.57 * X5 - 1.83 * X6 \\ & + 0.285 * X7 - 1.72 * X8 - 0.521 * X9 \end{aligned}$$

Where:

X1 = Size (LOG (Total Assets/GDP Index)) - It determines the size of a company by adjusting the total assets for inflation.

X2 = Debt Ratio (Total Liabilities/Total Assets) - It determines the level of indebtedness. The higher the debt, the higher the risk of bankruptcy.

X3 = Working Capital to Total Assets - Measures the percentage of liquid assets in a company.

X4 = Current Liabilities to Current Assets - It shows the level of liquidity of a company.

X5 = Total Liabilities Exceeds Total Assets - Discontinuity correction for leverage measure. Dummy Variable:1 if total liabilities exceed total assets, 0 otherwise. It helps to correct the extreme leverage level of a company.

X6 = Return on Assets - Determines the profit level of a company which is assumed to be negative because of default.

X7 = Funds Provided by Operations to Total Liabilities - Measures the ability of a company to finance its debt using operating cash flow alone.

X8 = Net Income was Negative for The Last Two Years (INTWO) - Discontinuity correction for ROA. Dummy Variable:1 if a net loss for the last two years, 0 otherwise. It helps to correct the two-year losses effect of a company.

X9 = Delta Net Income Divided by the Sum of the Absolute Net Income (CHIN) - It measures possible continuous losses for two consecutive years in the history of company life.

Using the logistic function below, the Ohlson O-score is transformed into a probability value. If the resulting probability is above 0.5, the company is considered risky and faces a high chance of bankruptcy. If the probability falls below 0.5, the company is regarded as financially healthy and relatively safe from bankruptcy risk.

$$Probability\ of\ Default = P = \frac{e^{O\,-\,score}}{1 + e^{O\,-\,score}}$$

3. Research methodology

This chapter focuses on the methodology adopted to determine is Altman's (1993) Z''-score model is more accurate in predicting financial distress for Portuguese listed companies than the Ohlson's O-score model. The chapter is divided into various sub-chapters such as the population of the research, sample of the research, research hypothesis and the data processing and analysis methods. There is also a dedicated subsection providing an overview of the Portuguese economy during the period covered by this research, aimed at contextualizing the hypotheses under study.

3.1. Population of the research

The population of this research consists of all companies currently listed (2025) on Euronext Lisbon, which includes 33 entities representing several economic sectors. This population, or universal set, was identified using official Euronext Lisbon Exchange data, accessible through their online market directory[1] and verified databases. The Euronext Lisbon database provides

[1]Euronext, October 30th, 2025: https://live.euronext.com/pt/markets/lisbon/equities/list

the most recent and comprehensive list of listed companies and is cited as the source for these entities in the reference section of this research.

3.2. Sample of the research

The sample comprises 29 companies listed on Euronext Lisbon during the period from 2010 to 2023. Firms that entered or exited the stock exchange during the sample period were excluded from the analysis, so that only companies continuously listed over the entire horizon were retained, thereby ensuring intertemporal comparability of the data. Although the number of companies is relatively small, the characteristics of the Portuguese market and the long-time frame of fourteen years ensure a total of more than 400 observations, providing sufficient statistical adequacy for the applied tests.

Accordingly, the sample of this study comprises share-issuing companies that were continuously admitted for trading on Euronext Lisbon throughout the period from 2010 to 2023. This extended fourteen-year time frame was deliberately selected to ensure the study's robustness and to facilitate a thorough evaluation of how the key variables evolved over time.

The inclusion criterion required companies to be listed for the entirety of this period, thus excluding any firms with intermittent or partial listings. This methodological choice was crucial to create a balanced panel dataset, which is vital for longitudinal analysis, as it guarantees that all variables of interest are consistently observed for every company across the full research horizon. Such a balanced design not only strengthens the internal validity of the study by controlling for potential biases related to missing data but also enhances the comparability of results across firms and time. Additionally, this approach mitigates distortions that could arise from changing sample compositions and allows for more accurate modelling of temporal dynamics within the Portuguese capital market context.

Regarding data sources, the financial statements and market capitalization were collected from Refinitiv Eikon database, which is a comprehensive financial data platform designed for professionals in the financial markets.

3.3. Portuguese economy during the research timeframe

In 2010, Portugal’s economy was marked by fragile growth amidst ongoing structural challenges. The country’s GDP reached approximately 180 billion euros, with a growth rate of 2.5% for the year - one of the few positive years following the 2008-2009 global recession.

However, this modest recovery masked deeper vulnerabilities: unemployment climbed to nearly 11% and public debt and budget deficits remained high.

Between 2011 and 2023, the Portuguese economy experienced a dynamic trajectory marked by significant challenges and recoveries, as detailed by Banco de Portugal's economic data and projections. The sovereign debt crisis in 2011 led to a deep recession, with GDP contracting sharply and unemployment peaking at over 15% in 2013.

Subsequent recovery, beginning i1n 2014, was underpinned by structural reforms, fiscal consolidation, and an improving global economic environment. During the period from 2014 to 2019, average GDP growth rates hovered around 2%, driven by increased private consumption, strong export performance, and tourism's positive contribution. The labour market also improved substantially, with unemployment falling to approximately 6.7% by 2019.

The COVID-19 pandemic interrupted Portugal's economic recovery, causing a severe contraction estimated at around 7.6% in 2020 according to the European Commission. The sharp decline was initially driven by a cumulative GDP drop of about 17% in the first half of the year as lockdown measures and social distancing protocols were implemented to contain the virus spread. The hospitality and tourism sectors, which comprise a large part of the Portuguese economy, were particularly devastated due to travel restrictions and closures of non-essential services.

By early 2021, stricter lockdowns contributed to a projected GDP decline in the first quarter, but the economy showed signs of accelerating recovery from the second quarter onward. The summer months saw a notable pickup largely driven by the partial return of tourism and domestic demand, though full recovery in tourism was expected to lag other sectors. Actual data shows that Portugal's GDP growth in 2021 evolved more strongly, reaching approximately 4.9%, followed by an even more vigorous expansion of 6.8% in 2022. In 2023, growth moderated to 2.3%, reflecting a return to more sustainable levels after the rapid post-pandemic rebound.

In summary, the evolution of Portugal's GDP can be distinctly categorized into five key periods (Figure 1):

- Pre-crisis: 2010.
- Crisis: 2011-2013.

- Post-crisis: 2014-2019.
- COVID-19: 2020.
- Post-COVID: 2021-2023.

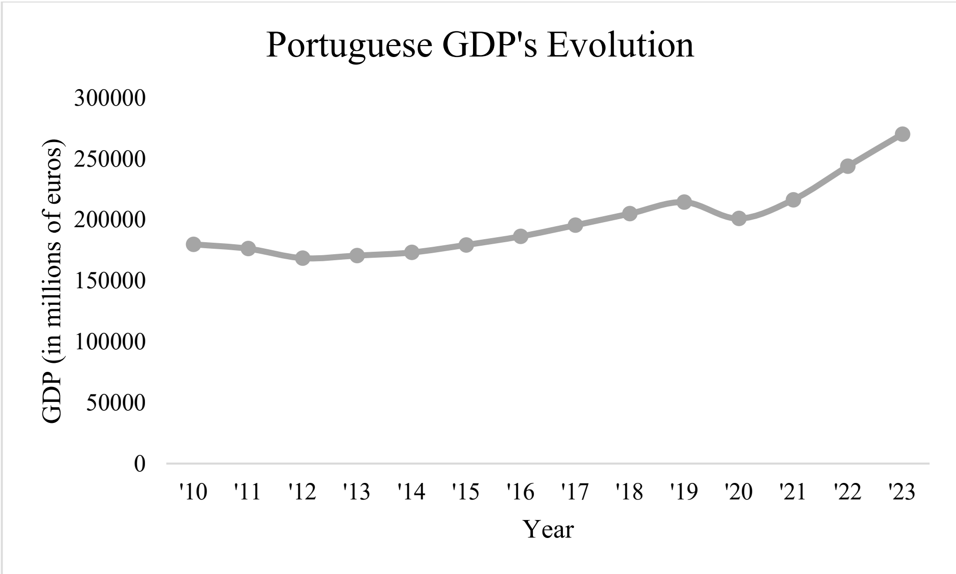

Figure 1 - Portuguese GDP's Evolution
Source: Pordata

3.4. Research hypothesis

Different researchers have utilized various financial distress prediction models to assess the likelihood of corporate failure; however, there remains no clear consensus on which model is the most suitable. Some studies have argued that Altman's model demonstrates superior accuracy, while others have found Ohlson's model to perform better. The selection of a particular model often depends on several factors, including the time horizon of the analysis - whether the focus is on short-term or long-term prediction - as a test of robustness. Moreover, the specific components and underlying variables of each model also play a significant role in determining their relative accuracy.

To analyse the data, the two models of Altman's (1993) Z-score model and Ohlson's (1980) O-score model are used. The revised version of Altman's Z-score model developed in 1993 is adopted, as it is more appropriate for the characteristics of the selected sample, which consists primarily of non-manufacturing listed companies. This adjustment ensures that the model remains contextually relevant and accurately reflects the financial structures of service-oriented and diversified firms. Each model serves as a predictor of likely financial distress of the selected organizations.

The primary objective of this thesis is to examine the degree to which the Altman Z"-Score and the Ohlson O-Score correlate positively and significantly in predicting financial distress. By establishing whether a strong correlation exists between these scores, the thesis aims to clarify whether they offer complementary insights or if one model consistently outperforms the other under varying economic conditions. Understanding this relationship is crucial because the Altman Z-Score, based on multiple discriminant analysis of financial ratios, and the Ohlson O-Score, derived from logistic regression incorporating market metrics, are grounded in different methodological frameworks yet often applied to similar datasets. This study will rigorously test this correlation across multiple economic periods and shocks to assess the consistency and robustness of each model's predictive power.

With this principal objective in mind, the following hypotheses have been formulated to guide the empirical investigation:

Hypothesis 1:

H0 - The mean Altman Z-Score does not differ between economic periods.

H1 - Financial distress measured by the Altman Z-Score varies between economic periods.

Hypothesis 2:

H0 - The mean Ohlson O-Score does not differ between economic periods.

H1 - Financial distress measured by the Ohlson O-Score varies between economic periods.

Hypothesis 3:

H0 - The 2011-2013 sovereign debt crisis has no significant effect on the scores.

H1 - The impact of the 2011-2013 sovereign debt crisis is statistically significant on the scores.

Hypothesis 4:

H0 - The COVID-19 pandemic has no significant effect on the Altman Z-Score or the Ohlson O-Score.

H1 - The impact of the COVID-19 pandemic is statistically significant on the scores.

Hypothesis 5:

H0 - There is no statistically significant correlation between the Altman Z-Score and the Ohlson O-Score.

H1 - The Altman Z-Score and the Ohlson O-Score show a statistically significant correlation.

Hypothesis 6:

H0 - The sensitivity of the scores to economic shocks is not significantly different between the models.

H1 - The sensitivity of the scores to economic shocks (such as 2011-2013 and COVID-19) differs significantly between the two models.

3.5. Data processing and analysis methods

The data analysis process was carried out in two main stages. First, in order to conduct a preliminary examination of the data through descriptive statistics for the variables under study and to provide a characterization of the sample, the dataset was imported and processed using Stata/SE 18.5.

Subsequently, with the objective of testing the hypotheses listed above, a series of statistical procedures was implemented, including normality tests, non-parametric tests, and correlation analyses, to assess the distributional properties of the variables and the significance of the relationships under investigation.

4. Descriptive Analysis

4.1. Descriptive Statistics of Z-score and O-score

The Figure 2 presented below provides an overview of the main financial variables used in the analysis, relevant to the Altman Z-Score and Ohlson O-Score models across all 406 observations as well as the fundamental outputs of the models themselves. The ratios of Z-score are represented by z_x_i and the O-score ratios by o_x_i.

Variable	Obs	Mean	Std. dev.	Min	Max
z_score	406	1.655367	5.918306	-12.43899	48.31209
pd_ohlson	406	.9267745	.1322842	.1057795	.9999954
z_x1	406	-.029659	.2285825	-1.068469	.5837414
z_x2	406	.1085546	.5150789	-1.237608	5.404091
z_x3	406	.0132683	.0862473	-.3608236	.2141036
z_x4	406	1.339885	3.885933	-.4612648	35.58333
o_x1	406	-2.293628	.745942	-3.85406	-.6004927
o_x2	406	.6570535	.2450983	.0273349	1.856199
o_x3	406	-.029659	.2285825	-1.068469	.5837414
o_x4	406	2.755017	10.24381	.0577856	111.1991
o_x5	406	.0665025	.2494658	0	1
o_x6	406	.0072579	.2007743	-2.996938	.390732
o_x7	406	.0801495	.3624488	-4.433391	2.485939
o_x8	406	.1256158	.3318247	0	1
o_x9	406	.0481927	.5042002	-1	1

Figure 2 – Descriptive Statistics of Z-score and O-score
Source: Stata/SE 18.5

The Altman Z-Score's mean sits at 1.66, indicative of moderate financial health in the average firm, but the large standard deviation of about 5.92 flags significant variation across firms. The wide range of values, stretching from -12.44 to 48.31, highlights the presence of firms on extremes - from those clearly at risk of financial distress to those with very strong financial standings. Such variation underscores the complex landscape of financial stability firms face within the sample.

Conversely, the Ohlson model's predicted default probability maintains a mean of approximately 0.93, coupled with a smaller standard deviation of 0.13. This suggests a concentration of firms estimated to have a relatively higher risk, but with less dispersion than the Altman scores. This tighter range is expected given the logistic regression nature of the Ohlson model, which constrains predictions between 0 and 1.

Examining the individual components of both models reveals further complexity. The Altman explanatory variables z_x1, z_x2, and z_x3 all display mean values near zero, which at first glance may suggest average ratios across the sample are fairly balanced around the midpoint. In the case of x1, with a mean close to zero and a moderately sized standard deviation, the results here indicate that, on average, companies in the sample have very little surplus working capital, hinting there is little liquidity for short-term obligations. For z_x2 and z_x3, what is at stake it's the ability to generate profitability continuously in time. A mean value near zero for both z_x2 and z_x3 suggests that, on average, firms in the sample neither consistently accumulate significant retained earnings nor generate robust profits from their assets. This can point to a population that is facing profitability challenges and with low capacity to reinvest in the business.

Turning attention to z_x4, this variable stands out within the Altman Z-Score model due to both its higher mean (approximately 1.34) and substantial standard deviation (about 3.89). Z_x4 also has the highest variance between minimum and maximum which corroborates the highest standard deviation and hints that the population has considerable heterogeneity.

In contrast, the Ohlson model variables encapsulate wider dimensions of firm characteristics and market conditions (o_x1 includes GDP Index). The two variables with the highest mean and the biggest standard deviation are o_x1 (-2.29 and 0.76) and o_x4 (2.76 and 10.24). Considering that o_x1 represents firm size, a negative mean of o_x1 means that despite the fact that population is composed by listed firms, it includes relatively small-cap firms which remains a vulnerability even for listed companies, as they may have less ability to weather financial shocks, less diversified operations, and potentially more difficulty accessing capital in distress scenarios.

For the variable o_x4, which captures the working-capital position, the fact that it displays the largest standard deviation in the O-score model reveals a very high degree of dispersion around the mean, and thus a marked heterogeneity in firms' short-term liquidity profiles. In practical terms, this means that, even within a sample composed exclusively of listed companies, there are firms with very comfortable working-capital surpluses coexisting with others that operate with thin or even structurally negative working capital, which may translate into recurrent tensions in meeting short-term obligations and a heightened vulnerability to cash-flow shocks.

4.2. Classification of companies across economic periods

The Tables 1 and 2 summarizes the annual classification of firms, based on the Altman Z-Score and Ohlson O-Score, in terms of financial stress. The data spans several distinct economic periods, from pre-crisis and crisis years to post-crisis, COVID-19, and post-COVID recovery.

	Pre-crisis	2011-2013 Crisis			Post-crisis						COVID-19	Post-COVID		
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Distress zone	55%	62%	62%	55%	55%	55%	52%	45%	48%	55%	52%	48%	52%	52%
Grey zone	28%	24%	17%	24%	21%	21%	24%	28%	21%	14%	28%	31%	7%	17%
Safe zone	17%	14%	21%	21%	24%	24%	24%	28%	31%	31%	21%	21%	41%	31%
Grand Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Table 1 – Financial distress of firms according to Altman Z-score
Source: Author's computation

	Pre-crisis	2011-2013 Crisis			Post-crisis						COVID-19	Post-COVID		
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Risky	100%	100%	100%	93%	93%	97%	93%	97%	93%	97%	97%	97%	93%	100%
Safe	0%	0%	0%	7%	7%	3%	7%	3%	7%	3%	3%	3%	7%	0%
Grand Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Table 2 – Financial distress of firms according to O-score
Source: Author's computation

During the pre-crisis (2010), over half of the firms (55%) were already classified in the distress zone, with only 17% in the safe zone and 28% in the intermediate grey zone. The proportion in distress surged further during the 2011-2013 crisis, peaking at 62%, while the safe zone declined to as low as 14% in 2011, reflecting severe pressure on firm solvency and heightened risk of bankruptcy in the face of macroeconomic turmoil.

As the post-crisis period unfolds (2014-2019), a gradual recovery is evident - distress zone percentages decrease to 45% by 2017 and safe zone percentages climb steadily, reaching 31% by 2018 and 2019. These shifts suggest improved financial stability and resilience among firms, consistent with macroeconomic recovery and potential recapitalization or restructuring efforts.

With the onset of the COVID-19 period (2020), the proportion in distress remains significant (52%), yet the safe zone shrinks temporarily to 21%, highlighting the renewed stress exerted by the pandemic. However, in the post-COVID subperiod (2022-2023), a notable improvement appears: the safe zone jumps to 41% in 2022, the highest in the observed window, before modestly declining to 31% in 2023, while distress zone proportions stabilize around 52%.

The grey zone exhibits variability throughout, with a major drop in 2022 (to 7%) indicative of more decisive shifts out of ambiguity - firms are either recovering to safety or falling into distress, especially under post-pandemic economic conditions.

Regarding the Ohlson O-Score, the data reveal limited variation in company risk classification across different economic periods, with the vast majority of firms persistently identified as "Risky" throughout the entire timeframe. Notably, even during the crisis years, the proportion of firms classified as "Safe" only rises to 7%, which represents the highest observed share for the safe zone within the thirteen-year span. The lowest points for financial safety, with 0% of firms in the safe zone, occur in 2010, 2011, 2012, and 2023 - covering the pre-crisis period, the apex of the 2011-2013 crisis, and the post-COVID environment.

4.3. Individual classification of companies across economic periods

As illustrated in Appendix A and B, a substantial majority of the observed entities consistently report Altman Z-Scores below the 1.1 threshold for the "grey zone," denoting an elevated risk of financial distress throughout the examined period. This empirical pattern suggests that most of Portugal's listed firms - across sectors - faced persistent financial vulnerability, especially during and immediately following macroeconomic shocks.

From an individual firm perspective, the most robust financial performance was observed in Pharol SGPS SA, Corticeira Amorim SGPS SA, and SONAECOM SGPS SA, each maintaining comparatively high Z-Score values across all years under review. Their consistent achievement of scores exceeding the critical threshold for distress indicates strong financial health and a notable resilience to both sectoral and market-wide economic fluctuations.

Conversely, the entities with persistently distressed scores - Futebol Clube do Porto (FCP), Sport Lisboa e Benfica (SLB), Sporting Clube de Portugal (SCP), and Imobiliaria Grão-Pára - were chronically situated below the safe Z-Score zone. Notably, the three football clubs (FCP, SLB, and SCP) belong to the sports sector and display structural financial weaknesses typical of Portuguese professional football. These organizations are traditionally highly leveraged, which negatively affects the X4 leverage ratio component of the Altman model, and they frequently struggle to generate positive EBIT, directly impacting the X2 profitability component. Such characteristics underscore the sector's systematic difficulty in achieving operational break-even, a trend repeatedly confirmed in industry benchmarking studies of Portuguese football.

Imobiliaria Grão-Pára provides an instructive case of acute and protracted financial distress. The firm's Z-Score trajectory plunged during the 2011–2013 sovereign debt crisis and failed to recover in subsequent years, ultimately resulting in insolvency in the fiscal year 2025 after several consecutive years of negative retained earnings. This outcome, while severe, reflects a broader reality for the construction and real estate sectors in Portugal during the period studied. Both Teixeira Duarte S.A. and Mota-Engil SGPS SA, among other sector peers, recorded their lowest Z-Score values during these crisis years and again in the context of the COVID-19 pandemic, evidencing elevated industry sensitivity to macroeconomic turbulence.

As shown in Appendix A and C, the Ohlson O-Score PD remains elevated for the majority of entities across all macroeconomic periods surveyed, with PD values clustering close to or above

0.9 in most cases. This pattern reflects an overall high risk of financial distress as assessed by the Ohlson model for much of the Portuguese listed corporate landscape.

Relative to the firms identified as the most financially sound according to the Z-score model, the O-score model likewise points to Pharol SGPS SA and SONAECOM SGPS SA as the entities with the lowest estimated probabilities of default (PD), thereby reinforcing the classification of these companies as the least financially distressed in the sample. In relation to the football sector, the clubs exhibit PD values that are very close to 1 that typically is interpreted as signalling an extremely high likelihood of default and, consequently, a situation of pronounced and persistent financial distress which corroborates the Z-score results.

Moreover, the temporal pattern of the PD estimates reveals a salient tendency: for the majority of firms, the PD is lower in the post-COVID period than in the post-crisis period, indicating an improvement in their financial resilience over time. This evidence suggests that the effects of a more prolonged and systemic crisis may require an extended adjustment period before firms can fully recover from crisis-induced financial distress, whereas the shock associated with the COVID-19 pandemic appears to have been followed by a comparatively faster normalization of firms' financial conditions.

5. Empirical Analysis

5.1. Data distribution

The Shapiro-Wilk test is a statistical method designed to assess whether a given sample comes from a population that is normally distributed. The Shapiro-Wilk test is widely recognized for its statistical power compared to other normality tests, especially for small or moderate sample sizes, and is considered a standard for preliminary analysis before performing any parametric or non-parametric tests.

The null hypothesis for the Shapiro-Wilk test is that the population distribution is normal. If the resulting p-value is greater than the chosen significance level (0.05 in this research), the null hypothesis is not rejected, meaning the sample does not significantly deviate from normality. If the p-value is less than or equal to 0.05, the null hypothesis is rejected meaning the data are not described by a normal distribution.

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
z_score	**406**	**0.63586**	**101.593**	**11.003**	**0.00000**

Figure 3 – Z-score Shapiro-Wilk W test for normal data
Source: Stata/SE 18.5

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
pd_ohlson	**406**	**0.49627**	**140.537**	**11.776**	**0.00000**

Figure 4 – O-score Shapiro-Wilk W test for normal data
Source: Stata/SE 18.5

As presented in Figures 3 and 4, both the Altman Z-Score and the PD of Ohlson O-Score in the sample strongly fail the Shapiro-Wilk normality test, indicating that their distributions deviate significantly from the normal curve.

For the Z-score, the Shapiro-Wilk W statistic was 0.64 with a p-value of 0.000, much less than the conventional 0.05 significance threshold. For the PD Ohlson variable, the W statistic was even lower at 0.50, with a similarly compelling p-value of 0.000. Both results compel a rejection of the null hypothesis that these financial distress measurements are drawn from a normally distributed population.

Due to these results, any subsequent hypothesis testing or comparative analysis involving these variables should utilize non-parametric statistical techniques or consider transformation methods to account for the fundamental non-normality of the financial distress scores. This approach will ensure that statistical inferences about company risk and model performance remain robust and valid despite the underlying shape of our data.

5.3. Scores variation between periods

The Kruskal-Wallis test is a nonparametric statistical method used to determine whether there are significant differences between the distributions of three or more independent groups. Kruskal-Wallis test works by ranking all values from lowest to highest across all groups, then comparing the average ranks between groups.

The null hypothesis is that all groups come from populations with the same median (or more precisely, the same central tendency). The test calculates an H statistic, which is compared against a critical value from the chi-squared distribution based on the number of groups. If the calculated p-value is less than the chosen significance level (0.05 in this research), the null hypothesis is rejected and conclude that at least one group's distribution differs from the others.

The Figures 5 and 6 presented below display the output of the Kruskal-Wallis equality-of-populations rank test for both the Altman Z-Score and the Ohlson O-Score, respectively, segmented by economic period. The economic periods are pre-crisis, 2011-2013 crisis, post-crisis, COVID-19 (2020) and post-COVID as presented previously.

Kruskal-Wallis equality-of-populations rank test

period	Obs	Rank sum
Pre-crisis	29	5255.00
2011-2013 Crisis	87	15920.00
Post-crisis	174	36093.00
COVID-19 (2020)	29	5892.00
Post-COVID	87	19461.00

chi2(4) = **6.476**
Prob = **0.1663**

chi2(4) with ties = **6.476**
Prob = **0.1663**

Figure 5 – Z-score Kruskal-Wallis equality of populations rank test
Source: Stata/SE 18.5

Kruskal-Wallis equality-of-populations rank test

period	Obs	Rank sum
Pre-crisis	29	6679.00
2011-2013 Crisis	87	19047.00
Post-crisis	174	33738.00
COVID-19 (2020)	29	6418.00
Post-COVID	87	16739.00

chi2(4) = **5.630**
Prob = **0.2286**

chi2(4) with ties = **5.630**
Prob = **0.2286**

Figure 6 – O-score Kruskall-Wallis equality-of-populations rank test
Source: Stata/SE 18.5

For both scores, the Kruskal-Wallis chi^2 values are 6.476 (Z-Score) and 5.630 (Ohlson O-Score), with p-values of 0.1663 and 0.2286 respectively. These p-values are above the significance threshold of 0.05, meaning the test finds no statistically significant difference in the median financial distress scores between economic periods.

Even though the rank sums differ across periods - indicating some variation in the distribution of scores - these differences are not pronounced enough to reject the null hypothesis that all periods come from populations with the same central tendency. This result suggests that financial distress as measured by either model remains broadly consistent through different macroeconomic contexts, with no single period displaying significantly higher or lower distress according to either score.

Given that the p-values from the Kruskal-Wallis tests for both Altman Z-Score and Ohlson O-Score are greater than 0.05, the null hypotheses are not rejected for H1 and H2. Therefore, there is no statistically significant evidence that financial distress measured by either score varies between economic periods.

5.4. Crisis and COVID-19 impact on the scores

The Wilcoxon rank-sum test, also known as the Mann-Whitney U test, is a nonparametric statistical test used to determine if there is a significant difference between the distributions of two independent groups.

The test works by combining the observations from both groups and ranking them from smallest to largest. Each observation receives a rank, and the test statistic is calculated based on the sum of ranks for observations in each group. The idea is that if both groups come from the same distribution, their ranks should be intermixed randomly. If one group tends to have higher or lower values, its rank sum will reflect that, leading to a significant test statistic.

It evaluates whether the central tendency (median) differs between groups without assuming any specific data distribution. The test produces a z test result and p-value, which indicate whether to reject the null hypothesis that the two groups have the same distribution.

```
Two-sample Wilcoxon rank-sum (Mann-Whitney) test

      crisis |      Obs    Rank sum    Expected
-------------+---------------------------------
           0 |      319       66701     64916.5
           1 |       87       15920     17704.5
-------------+---------------------------------
    Combined |      406       82621       82621

Unadjusted variance    941289.25
Adjustment for ties         0.00
                       ----------
Adjusted variance      941289.25

H0: z_score(crisis==0) = z_score(crisis==1)
         z =   1.839
Prob > |z| =  0.0659
```

Figure 7 – Z-score two-sample Wilcoxon rank-sum (Mann-Whitney) test for the crisis period
Source: Stata/SE 18.5

```
Two-sample Wilcoxon rank-sum (Mann-Whitney) test

      crisis |      Obs    Rank sum    Expected
-------------+---------------------------------
           0 |      319       63574     64916.5
           1 |       87       19047     17704.5
-------------+---------------------------------
    Combined |      406       82621       82621

Unadjusted variance    941289.25
Adjustment for ties         0.00
                       ----------
Adjusted variance      941289.25

H0: pd_ohl~n(crisis==0) = pd_ohl~n(crisis==1)
         z =  -1.384
Prob > |z| =  0.1664
```

Figure 8 – O-score two-sample Wilcoxon rank-sum (Mann-Whitney) test for the crisis period
Source: Stata/SE 18.5

For the Altman Z-Score (Figure 7), the test statistic z = 1.839 with a p-value of 0.0659 indicates that there is no strong statistical evidence to reject the null hypothesis that the median Altman Z-Score is the same for firms during the crisis (crisis = 1) and not during the crisis (Not crisis = 0). The p-value is slightly above the 0.05 significance level, suggesting a borderline difference but not significant at conventional levels.

For the PD of Ohlson O-Score (Figure 8), the test statistic z = -1.384 with a p-value of 0.1664 indicates that there is no strong statistical evidence to reject the null hypothesis of equal distributions between the crisis and non-crisis groups. The p-value, being well above the 0.05 significance level, suggests that any observed differences in Ohlson scores across these groups could be due to random variation rather than an actual effect of the crisis.

This lack of significance contrasts somewhat with the Altman Z-Score's borderline result, implying that the Ohlson model, when applied here, may be less sensitive to changes in financial distress conditions tied explicitly to the crisis variable. It suggests that the Ohlson O-Score, as a predictive indicator combining multiple financial ratios, might reflect a more stable or longer-term financial distress risk unaffected by the crisis classification alone.

Given that the p-values from the Mann-Whitney U test for both Altman Z-Score and PD of Ohlson O-Score for the 2011-2013 period are greater than 0.05, the null hypothesis is not rejected for H3. Therefore, there is no statistically significant evidence that 2011-13 sovereign debt crisis had an impact on the scores.

```
Two-sample Wilcoxon rank-sum (Mann-Whitney) test

       covid |      Obs    Rank sum    Expected
-------------+---------------------------------
           0 |      377       76729     76719.5
           1 |       29        5892      5901.5
-------------+---------------------------------
    Combined |      406       82621       82621

Unadjusted variance    370810.92
Adjustment for ties         0.00
                       ----------
Adjusted variance      370810.92

H0: z_score(covid==0) = z_score(covid==1)
         z =  0.016
Prob > |z| = 0.9876
```

Figure 9 – Z-score two-sample Wilcoxon rank-sum (Mann-Whitney) test for COVID-19 period
Source: Stata/SE 18.5

```
Two-sample Wilcoxon rank-sum (Mann-Whitney) test

       covid |      Obs    Rank sum    Expected
-------------+---------------------------------
           0 |      377       76203     76719.5
           1 |       29        6418      5901.5
-------------+---------------------------------
    Combined |      406       82621       82621

Unadjusted variance    370810.92
Adjustment for ties         0.00
                       ----------
Adjusted variance      370810.92

H0: pd_ohl~n(covid==0) = pd_ohl~n(covid==1)
         z = -0.848
Prob > |z| = 0.3963
```

Figure 10 – O-score two-sample Wilcoxon rank-sum (Mann-Whitney) test for COVID-19 period
Source: Stata/SE 18.5

For the Altman Z-Score (Figure 9), the test statistic z = 0.016 with a p-value of 0.9876 indicates that there is no strong statistical evidence to reject the null hypothesis that the median Altman Z-Score is the same for firms during the COVID-19 (COVID= 1) and not during the COVID-19 (Not COVID = 0). The p-value markedly exceeds the 0.05 significance level, suggesting that COVID-19 did not have the slightest impact on Z-score.

For the PD of Ohlson O-Score (Figure 10), the test statistic z = -0.848 with a p-value of 0.3963 indicates that there is no strong statistical evidence to reject the null hypothesis of equal distributions between the COVID-19 period and non-COVID-19 groups. The p-value, being well above the 0.05 significance level, suggests that suggesting that COVID-19 did not have a significant impact on O-score.

The COVID-19 period contrasts with the 2011-2013 crisis in that the Ohlson O-Score approaches statistical significance more closely than the Altman Z-Score. This difference may be attributed to the fact that the Altman Z-Score does not incorporate market-based indicators, making it less responsive to short-term, one-year volatility compared to the Ohlson O-Score, which includes such variables.

Given that the p-values from the Mann-Whitney U test for both Altman Z-Score and Ohlson O-Score for the COVID-19 period are greater than 0.05, the null hypothesis is not rejected for H4. Therefore, there is no statistically significant evidence that COVID-19 had an impact on the scores.

5.5. Correlation between Altman Z-score and Ohlson O-score

Spearman's rank correlation coefficient is a statistical measure used to evaluate the strength and direction of the monotonic relationship between two continuous or ordinal variables.

Spearman's first converts the raw data into ranks for each variable. Then, it calculates the correlation based on these ranks, which makes it robust to outliers and suitable for detecting both linear and nonlinear monotonic relationships - relationships where variables tend to move in the same or opposite direction, but not necessarily at a constant rate. The coefficient ranges from -1 to +1, where +1 indicates a perfect positive monotonic association, -1 indicates a perfect negative monotonic association, and 0 implies no monotonic relationship at all.

```
Number of observations =      406
         Spearman's rho = -0.7104

Test of H0: z_score and pd_ohlson are independent
                  Prob =  0.0000
```

Figure 11 – Spearman's correlation between Z-score and O-score
Source: Stata/SE 18.5

The calculated Spearman's rank correlation coefficient of -0.7104 based on 406 observations reveals a strong, statistically significant negative monotonic relationship between the Altman Z-Score and the Ohlson O-Score. This means that as one score increases in rank, the other tends to decrease, with a high degree of consistency and predictability across the sample. The extremely low p-value (0.0000) confirms that this relationship is highly unlikely to be the result of random chance, providing strong evidence against the null hypothesis that the two scores are independent.

This strong negative association aligns well with the conceptual design of the two models. The Altman Z-Score uses financial ratios where higher values typically indicate better financial health and lower bankruptcy risk, whereas the Ohlson O-Score computes a PD where higher values suggest increased financial risk. Since these scoring interpretations are inverse, a negative correlation is expected and confirms the models are consistent in ranking firms by financial distress levels but on opposite scales.

The statistical significance and strength of this correlation lend credibility to using these models in tandem or comparative analyses, as they reflect the same underlying distress phenomena though measured differently. Furthermore, this outcome indicates that despite differences in model construction - such as Altman's purely accounting-based approach and Ohlson's inclusion of market factors - the two approaches provide reliable and complementary views of a firm's financial health.

Given that the p-values from the Spearman's correlation is 0.000, the null hypothesis is rejected for H5. Therefore, there is statistically significant evidence that Altman Z-score and Ohlson O-score are strongly correlated.

5.6. Sensitivity of the scores to economic shocks

To rigorously investigate whether the sensitivity of financial distress prediction models to major economic shocks differs, this study adopts a multi-layered statistical approach. Sensitivity, in this context, refers to the extent each model's outputs respond or adapt to adverse macroeconomic events like the 2011-2013 sovereign debt crisis and the COVID-19 pandemic - at both the firm and aggregate level. Given the complex scenario, deploying a single method would not capture the full nuance of both models' behaviour.

By integrating robust variance tests to assess dispersion changes, the Wilcoxon signed-rank test for within-firm reactivity, and fixed-effects panel regression for period-specific mean shifts, this study provides a comprehensive and multifaceted assessment of each model's sensitivity to economic shocks. This methodology ensures both the reliability and interpretability of results, supporting more robust inferences about how and why financial distress predictions differ across analytic tools and economic environments.

- <u>Robust variance testing</u>

To measure how the overall distribution of each model's scores changes during shocks, the robust variance test is used. Variance is a key statistical indicator of dispersion and risk. By testing for equality of variances across different time periods (e.g., crisis vs. non-crisis, COVID-19 vs. pre-COVID-19), this method evaluates whether the spread of model predictions becomes significantly wider under economic stress. A model demonstrating significantly increased variance during a crisis period is more sensitive in terms of its ability to capture increased financial instability and firm heterogeneity during macroeconomic shocks.

- <u>Paired difference testing (*Wilcoxon signed-rank test*)</u>

Beyond changes in spread, sensitivity can also be examined at the firm level - specifically, whether one model systematically produces larger within-firm changes in scores during shocks compared to the other. The Wilcoxon signed-rank test is employed as a nonparametric approach to compare paired differences in score changes between the Altman and Ohlson models for the same firms. This test is suitable for samples that violate assumptions of normality, offering a robust way to identify whether one model consistently responds more to macroeconomic events than the other.

- <u>Fixed effects panel regression</u>

Finally, to isolate the mean effect of economic shocks on each model's scores - separately from firm-specific, time-invariant characteristics - fixed-effects panel regression is applied. This method uses period dummies (e.g., identifying crisis years) to directly estimate the shift in average model score attributable to shocks, net of any persistent individual firm factors. It allows for a nuanced comparison of whether one model's typical output is more affected, in magnitude or direction, by a particular economic event. The use of panel data and fixed effects is recommended, as it enhances robustness by controlling for unobserved heterogeneity between firms and over time. The detailed results of the statistical tests are provided in Appendix D, E and F.

For the Altman Z-Score, the variance did not differ significantly across periods related to either the 2011-2013 crisis or COVID-19, as indicated by p-values well above conventional significance levels. In contrast, the Ohlson O-Score exhibited a significant variance difference between crisis and non-crisis periods during the 2011-2013 crisis (W0 $p = 0.017$), although no such effect was detected in the COVID-19 period. This suggests that Ohlson's model was more sensitive in terms of score variability during the sovereign debt crisis, once again reflecting the market indicators it contains.

Secondly, the Wilcoxon signed-rank test compared the within-firm changes in model scores between periods. The test did not reveal a statistically significant difference in the magnitude of score changes between the Altman Z-Score and Ohlson O-Score, with p-values indicating that neither model consistently produced larger within-firm changes in periods of economic shock. Therefore, at the firm level, neither model appears systematically more reactive during shocks based solely on magnitude of score change.

Lastly, fixed-effects panel regression was conducted to isolate the average effect of economic shock periods on each model while controlling for firm-specific factors. The results reveal a pronounced divergence in the way the two models interpret firms' financial health following shock periods.

In the Altman Z-Score model, significant positive coefficients observed in the post-crisis and post-COVID periods signal an improvement in the average score, which is conventionally interpreted as better financial stability and reduced risk of financial distress. In contrast, the Ohlson O-Score displays significant negative coefficients in the same periods, indicating a decrease in the average score - a signal of increased distress risk according to Ohlson's model. This suggests that Ohlson's approach, which incorporates additional variables such as firm size and market indicators, captures lingering vulnerabilities or risk factors that are not immediately alleviated by macroeconomic recovery. The model's probabilistic nature and emphasis on broader risk determinants reflect persistent uncertainty or elevated risk in the post-shock environment due to market volatility.

The collective results from these robust statistical tests provide strong support for H6, meaning that the null hypothesis is rejected. Notably, the Ohlson O-Score displayed greater variation in response to the 2011-2013 crisis, as evidenced by a statistically significant change in score dispersion, whereas the Altman Z-Score's variance remained comparatively stable. Additionally, fixed-effects panel regression analysis revealed that the average responses of the two models to shocks not only differed in magnitude but moved in opposite directions: improvements in the Altman Z-Score after crisis and post-COVID periods contrasted with declines in the Ohlson O-Score, suggesting increased distress risk.

6. Conclusion

This study set out to assess the predictive performance, behaviour, and sensitivity of two widely used financial distress prediction models - Altman's Z-Score and Ohlson's O-Score - when applied to Portuguese listed companies across various macroeconomic contexts. By combining normality testing, nonparametric hypothesis testing, correlation analysis, and panel econometric techniques, the research provided a comprehensive evaluation of both models' robustness and responsiveness to economic shocks.

A strong and statistically significant negative relationship was identified between the two models, confirming their conceptual consistency: as Altman's Z-Score increases, indicating stronger financial health, the PD of Ohlson O-Score tends to decrease, reflecting lower distress probability. This negative monotonic association demonstrates that both models capture the same underlying financial distress dynamics, although they operate on inverse scales and rely on distinct methodological foundations - Altman's being accounting-based and Ohlson's combining probabilistic and market elements.

The Kruskal–Wallis and Mann–Whitney U tests demonstrated that, at a broad level, median financial distress scores did not vary significantly between economic periods, including during the 2011–2013 crisis and the COVID-19 pandemic. This indicates that both models displayed a certain degree of stability in ranking firms' financial conditions even under adverse macroeconomic environments.

Nevertheless, sensitivity analysis emphasized meaningful contrasts in how each model responds to different economic shocks. Variance analysis revealed that only the Ohlson O-Score displayed a significant increase in dispersion during the 2011–2013 crisis, marking it as more sensitive to systemic instability. In contrast, the Altman Z-Score's variance remained stable, suggesting stronger resilience and lower volatility in stress detection. Fixed-effects regressions further confirmed a divergence in post-crisis and post-COVID responses, with Altman's model showing improvements (implying recovery and greater stability), while Ohlson's predicted elevated distress risk, reflecting persistent uncertainty and potential structural fragility in market valuations following shocks.

Overall, the evidence suggests that combining Altman's Z-Score and Ohlson's O-Score offers a richer and more resilient framework for assessing financial distress in Portuguese listed firms, especially across periods of heightened macroeconomic uncertainty. Used together, these models balance the stability of accounting-based indicators with the heightened responsiveness of market-informed measures, providing decision-makers with a more nuanced view of risk that remains informative under both normal and stressed conditions.

7. Limitations and Future Research

While this thesis provides insights into the financial distress prediction of Portuguese listed enterprises through the comparative analysis of the Altman Z-Score and Ohlson O-Score models, several methodological limitations must be acknowledged. The scope of the research is inherently restricted by the sample size and composition, as the data set is drawn exclusively from publicly traded entities listed in Portugal. As a result, the findings may not readily generalize to unlisted firms or to the wider population of small and medium-sized enterprises, which constitute the vast majority of the national business landscape.

The study relies on only two financial distress prediction models, each utilizing a defined subset of financial report variables over a specified multi-year time series. Although both models have proven efficacy in empirical and applied contexts, they do not encompass all potential indicators of financial distress, thereby limiting the comprehensiveness of risk assessment. The selection of variables is determined by established model methodologies rather than an exhaustive consideration of all financial statement elements.

Looking ahead, future research could benefit from incorporating high-frequency or real-time data streams, affording researchers and decision-makers enhanced responsiveness to emerging economic changes. It would also be worthwhile to investigate the impact of financial distress across different company sizes and sectors, reflecting the heterogeneity of the Portuguese economy and providing tailored risk management insights for both large firms and SMEs.

Additionally, recent advances in machine learning - such as random forests, support vector machines, and gradient boosting algorithms - offer promising avenues for financial distress forecasting. These techniques excel at handling large, complex, and non-linear datasets, potentially capturing latent risk factors that logistic regression-based models may miss. Adopting such approaches could improve predictive accuracy and model robustness, especially in increasingly volatile economic conditions.

Addressing these methodological constraints in future research will advance the robustness and relevance of financial distress prediction models, enabling Portuguese listed companies, investors, creditors, and regulators to make more accurate assessments and timely decisions. In turn, this approach can support improved risk management and strategic planning amongst all stakeholders.

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Appendix

Appendix A – Classification of companies across economic periods

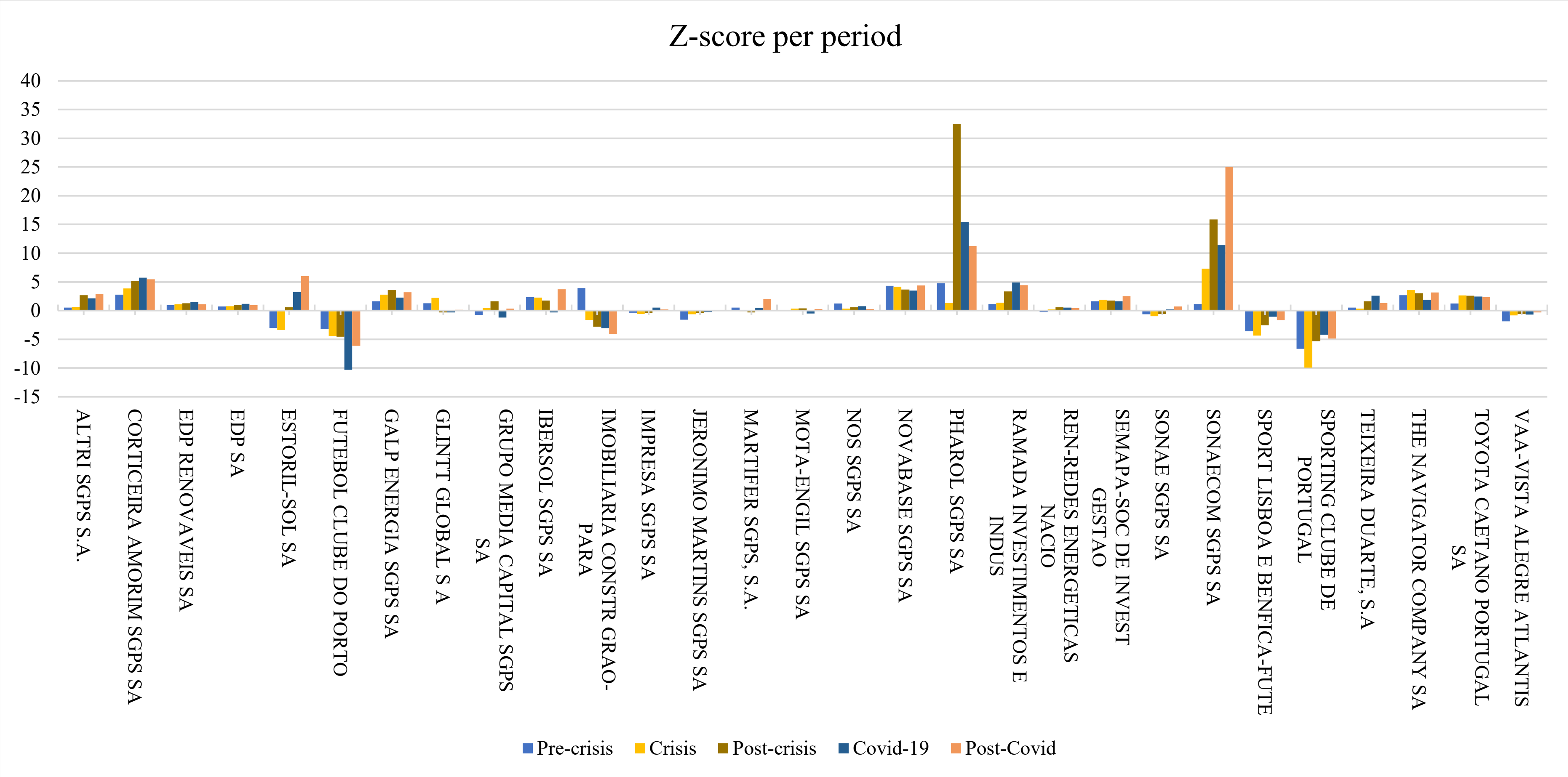
	Mean		Standard deviation		Minimum value		Maximum value	
	pd_ohlson	z_score	pd_ohlson	z_score	pd_ohlson	z_score	pd_ohlson	z_score
firm								
ALTRI SGPS S.A.								
period								
Pre-crisis	.9889383	.5398501	.	.	.9889383	.5398501	.9889383	.5398501
2011-2013 Crisis	.9895795	.6224807	.0045385	.8097547	.9866697	-.2300013	.994809	1.381375
Post-crisis	.969884	2.681849	.0127511	.9341719	.9514053	.8241543	.9884392	3.376875
COVID-19 (2020)	.9806663	2.119044	.	.	.9806663	2.119044	.9806663	2.119044
Post-COVID	.9459211	2.928176	.0448335	.9243555	.8953048	2.027586	.9806385	3.874593
Total	.9711008	2.10014	.0251445	1.254413	.8953048	-.2300013	.994809	3.874593
CORTICEIRA AMORIM SGPS SA								
period								
Pre-crisis	.907622	2.765995	.	.	.907622	2.765995	.907622	2.765995
2011-2013 Crisis	.9158687	3.878755	.0056078	.3057825	.9096339	3.529862	.9205002	4.100191
Post-crisis	.8557518	5.148364	.043627	.5530917	.7704321	4.385402	.8941747	6.039678
COVID-19 (2020)	.8356388	5.750561	.	.	.8356388	5.750561	.8356388	5.750561
Post-COVID	.8286965	5.459205	.0182909	.312879	.8113111	5.112944	.8477753	5.721614
Total	.8651048	4.815759	.0439904	.9416633	.7704321	2.765995	.9205002	6.039678
EDP RENOVAVEIS SA								
period								
Pre-crisis	.9342839	.9628592	.	.	.9342839	.9628592	.9342839	.9628592
2011-2013 Crisis	.921954	1.106168	.0065196	.1842707	.9177503	.9380185	.9294643	1.303158
Post-crisis	.9115061	1.264646	.0233064	.1384173	.8695384	1.113085	.9318953	1.463925
COVID-19 (2020)	.9030341	1.489461	.	.	.9030341	1.489461	.9030341	1.489461
Post-COVID	.9313881	1.104394	.0233338	.2961321	.9044788	.8951827	.9460201	1.443237
Total	.9190272	1.190848	.0200037	.2069665	.8695384	.8951827	.9460201	1.489461
EDP SA								
period								
Pre-crisis	.9648339	.7281601	.	.	.9648339	.7281601	.9648339	.7281601
2011-2013 Crisis	.9658233	.767691	.002626	.067952	.96313	.6968092	.9683763	.8322747
Post-crisis	.9596106	1.008994	.0067688	.2087465	.9483134	.7253753	.9659702	1.34063
COVID-19 (2020)	.9504016	1.193792	.	.	.9504016	1.193792	.9504016	1.193792
Post-COVID	.9651755	.9500603	.0074185	.2985714	.9588834	.6360145	.9733556	1.230275
Total	.9618497	.9377979	.0068137	.2205857	.9483134	.6360145	.9733556	1.34063
ESTORIL-SOL SA								
period								
Pre-crisis	.9948172	-3.059787	.	.	.9948172	-3.059787	.9948172	-3.059787
2011-2013 Crisis	.9843204	-3.379696	.0219601	.6111659	.9589715	-4.071879	.9975627	-2.914503
Post-crisis	.9331283	.5934452	.0330768	2.643473	.8989847	-2.534024	.9741343	4.139837
COVID-19 (2020)	.9122334	3.268866	.	.	.9122334	3.268866	.9122334	3.268866
Post-COVID	.7540694	6.013615	.1984495	3.537107	.5998768	2.505261	.9779672	9.578791
Total	.9086421	.8336792	.1193236	4.075228	.5998768	-4.071879	.9975627	9.578791
FUTEBOL CLUBE DO PORTO								
period								
Pre-crisis	.9975979	-3.220605	.	.	.9975979	-3.220605	.9975979	-3.220605
2011-2013 Crisis	.9953309	-4.459528	.0005596	1.963742	.9947932	-6.699939	.99591	-3.036498
Post-crisis	.9594957	-4.544333	.0535648	1.223535	.8727159	-6.308223	.9987023	-2.859075
COVID-19 (2020)	.99983	-10.31594	.	.	.99983	-10.31594	.99983	-10.31594
Post-COVID	.9960896	-6.139777	.0034813	.920932	.9926606	-7.196735	.9996209	-5.510083
Total	.9806188	-5.185747	.0383031	2.035376	.8727159	-10.31594	.99983	-2.859075
GALP ENERGIA SGPS SA								
period								
Pre-crisis	.959227	1.612724	.	.	.959227	1.612724	.959227	1.612724
2011-2013 Crisis	.915777	2.782112	.0448203	1.286102	.8821841	1.297305	.9666688	3.548358
Post-crisis	.8722123	3.587797	.0484645	.2889612	.8141181	3.098364	.9367631	3.956792
COVID-19 (2020)	.9725695	2.274961	.	.	.9725695	2.274961	.9725695	2.274961
Post-COVID	.9394572	3.187292	.0200384	.5682132	.9164353	2.556381	.9529761	3.658728
Total	.9093409	3.094477	.0512668	.8328489	.8141181	1.297305	.9725695	3.956792
GLINTT GLOBAL S A								
period								
Pre-crisis	.9403762	1.279122	.	.	.9403762	1.279122	.9403762	1.279122
2011-2013 Crisis	.9426236	2.210679	.0097551	.7554029	.9340118	1.356252	.9532176	2.789878
Post-crisis	.9650608	-.2977942	.0177073	.724296	.9385326	-.801821	.9904813	1.130598
COVID-19 (2020)	.9769731	-.3257198	.	.	.9769731	-.3257198	.9769731	-.3257198
Post-COVID	.9737104	.1563084	.0036751	.5927507	.9715396	-.5156762	.9779537	.6049101
Total	.961194	.4476856	.017676	1.198397	.9340118	-.801821	.9904813	2.789878

GRUPO MEDIA CAPITAL SGPS SA								
period								
Pre-crisis	.9875137	-.7744422	.	.	.9875137	-.7744422	.9875137	-.7744422
2011-2013 Crisis	.9767751	.4460112	.012009	.8978412	.9667699	-.5843082	.9900926	1.060922
Post-crisis	.9657925	1.586205	.0135168	.6514882	.9557362	.2981196	.9927176	2.101338
COVID-19 (2020)	.9847799	-1.1982	.	.	.9847799	-1.1982	.9847799	-1.1982
Post-COVID	.8203446	.3540985	.1978007	.2429788	.5978648	.0977304	.9763301	.5810007
Total	.9398863	.7103512	.1017976	1.070326	.5978648	-1.1982	.9927176	2.101338
IBERSOL SGPS SA								
period								
Pre-crisis	.961079	2.356828	.	.	.961079	2.356828	.961079	2.356828
2011-2013 Crisis	.9556219	2.269842	.0099679	.1302589	.9441801	2.156005	.9624257	2.411897
Post-crisis	.9602885	1.749016	.0214681	.6957761	.9308111	.6056405	.9887031	2.50098
COVID-19 (2020)	.9952263	-.2976314	.	.	.9952263	-.2976314	.9952263	-.2976314
Post-COVID	.8882028	3.733593	.1132417	1.988978	.7574427	1.635279	.9537303	5.591354
Total	.9463936	2.183114	.0570581	1.384418	.7574427	-.2976314	.9952263	5.591354
IMOBILIARIA CONSTR GRAO-PARA								
period								
Pre-crisis	.9571268	3.923211	.	.	.9571268	3.923211	.9571268	3.923211
2011-2013 Crisis	.9446601	-1.624547	.063398	3.902567	.8747049	-4.553701	.9983195	2.805678
Post-crisis	.9886187	-2.798693	.0049534	.169087	.9802031	-3.034819	.9934398	-2.559196
COVID-19 (2020)	.9946571	-3.088147	.	.	.9946571	-3.088147	.9946571	-3.088147
Post-COVID	.9999929	-4.057087	3.39e-06	.1579507	.9999891	-4.231213	.9999954	-3.923028
Total	.9798182	-2.357286	.0331551	2.512728	.8747049	-4.553701	.9999954	3.923211
IMPRESA SGPS SA								
period								
Pre-crisis	.983365	-.3491461	.	.	.983365	-.3491461	.983365	-.3491461
2011-2013 Crisis	.9598757	-.605187	.0517204	.0596183	.9004233	-.6628292	.9945063	-.5437719
Post-crisis	.9846097	-.4045427	.0054228	.5455825	.9798171	-1.311981	.9944527	.0583036
COVID-19 (2020)	.9766421	.5466338	.	.	.9766421	.5466338	.9766421	.5466338
Post-COVID	.9830983	.2188143	.0058678	.2645927	.9764402	-.0762682	.9875151	.4349413
Total	.9783277	-.2420633	.0230728	.5159112	.9004233	-1.311981	.9945063	.5466338
JERONIMO MARTINS SGPS SA								
period								
Pre-crisis	.9853878	-1.56379	.	.	.9853878	-1.56379	.9853878	-1.56379
2011-2013 Crisis	.9804713	-.6427431	.0004846	.4522399	.9800798	-1.157825	.9810133	-.31078
Post-crisis	.981882	-.4355462	.0055332	.1547673	.9713	-.5452937	.9878231	-.1263147
COVID-19 (2020)	.9870934	-.2693828	.	.	.9870934	-.2693828	.9870934	-.2693828
Post-COVID	.9850688	-.0195703	.0016484	.0588085	.983167	-.0564228	.9860865	.0482509
Total	.9828853	-.4595278	.0041211	.4364291	.9713	-1.56379	.9878231	.0482509
MARTIFER SGPS, S.A.								
period								
Pre-crisis	.9882762	.5326285	.	.	.9882762	.5326285	.9882762	.5326285
2011-2013 Crisis	.9614097	-.1253811	.0201058	.3277286	.9436279	-.4837119	.9832272	.159166
Post-crisis	.9442322	-.3320547	.0605316	.5892778	.8280164	-1.118516	.990161	.3989031
COVID-19 (2020)	.9973556	.4804061	.	.	.9973556	.4804061	.9973556	.4804061
Post-COVID	.9898313	2.00425	.0046973	.6968461	.9847395	1.20455	.9939957	2.48127
Total	.9646248	.3326651	.0440593	1.061464	.8280164	-1.118516	.9973556	2.48127
MOTA-ENGIL SGPS SA								
period								
Pre-crisis	.9921371	.0575551	.	.	.9921371	.0575551	.9921371	.0575551
2011-2013 Crisis	.990761	.3571526	.0017521	.3056091	.988792	.0966457	.992148	.6935591
Post-crisis	.9907954	.383791	.0031008	.4578629	.9870656	-.3120719	.9941345	1.053414
COVID-19 (2020)	.997449	-.5035558	.	.	.997449	-.5035558	.997449	-.5035558
Post-COVID	.99009	.2699767	.0017405	.2718249	.9886763	.0775289	.9920339	.5809368
Total	.991208	.2670095	.0028482	.4044595	.9870656	-.5035558	.997449	1.053414
NOS SGPS SA								
period								
Pre-crisis	.9901983	1.227075	.	.	.9901983	1.227075	.9901983	1.227075
2011-2013 Crisis	.9869977	.3175725	.0094677	.0874133	.9760655	.226624	.9925181	.4009593
Post-crisis	.9682981	.5568011	.0036283	.3889941	.9643911	-.2183991	.9740837	.7980388
COVID-19 (2020)	.9795917	.7647215	.	.	.9795917	.7647215	.9795917	.7647215
Post-COVID	.979128	.2953432	.0018686	.2825207	.977583	.0680772	.9812049	.6116596
Total	.9769968	.5122393	.0096108	.3692997	.9643911	-.2183991	.9925181	1.227075

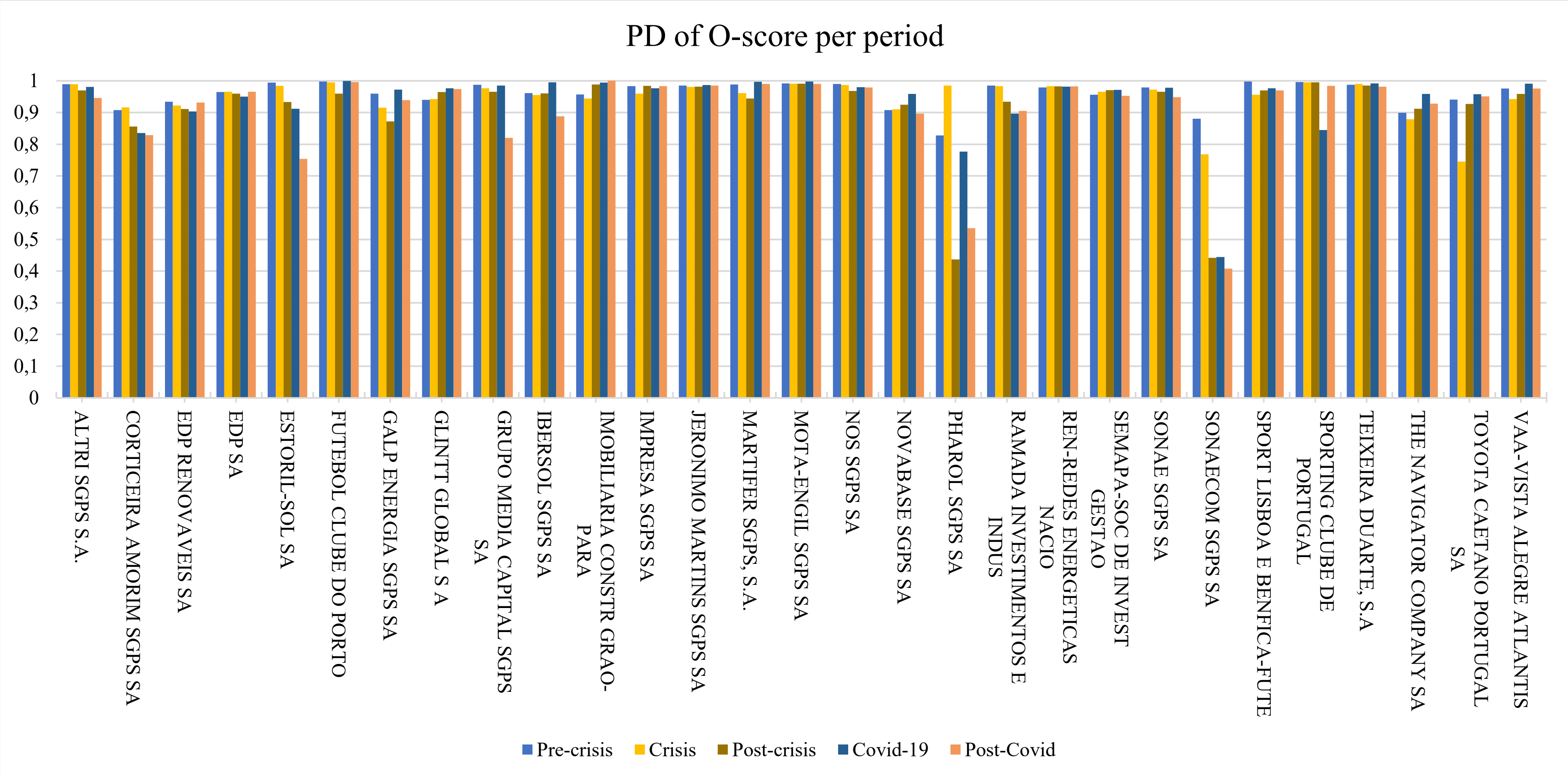
NOVABASE SGPS SA								
period								
Pre-crisis	.9072922	4.320417	.	.	.9072922	4.320417	.9072922	4.320417
2011-2013 Crisis	.9100509	4.133823	.0284317	.2970141	.8786055	3.870327	.9339436	4.455689
Post-crisis	.9247432	3.6468	.024662	.3772262	.8772328	3.048568	.9451335	4.196179
COVID-19 (2020)	.9588756	3.486804	.	.	.9588756	3.486804	.9588756	3.486804
Post-COVID	.8968108	4.369672	.0584574	.9320418	.8298019	3.760674	.9373595	5.442639
Total	.9168009	3.94275	.0340441	.5655281	.8298019	3.048568	.9588756	5.442639
PHAROL SGPS SA								
period								
Pre-crisis	.8277515	4.73119	.	.	.8277515	4.73119	.8277515	4.73119
2011-2013 Crisis	.9854853	1.320205	.0030879	.0588939	.9823389	1.285309	.9885111	1.388202
Post-crisis	.4370245	32.49178	.4139925	14.8264	.1057795	16.27202	.981744	48.31209
COVID-19 (2020)	.7769458	15.41914	.	.	.7769458	15.41914	.7769458	15.41914
Post-COVID	.5350746	11.20434	.1269026	2.059881	.3979659	8.835212	.6484083	12.57205
Total	.6277517	18.04819	.3485556	16.46337	.1057795	1.285309	.9885111	48.31209
RAMADA INVESTIMENTOS E INDUS								
period								
Pre-crisis	.9846826	1.119792	.	.	.9846826	1.119792	.9846826	1.119792
2011-2013 Crisis	.9831073	1.360389	.0017181	.2593641	.9820831	1.15168	.9850908	1.650755
Post-crisis	.9342476	3.341678	.0519971	1.476698	.8614709	1.705008	.9787432	4.823012
COVID-19 (2020)	.8967328	4.867248	.	.	.8967328	4.867248	.8967328	4.867248
Post-COVID	.9051807	4.427999	.0130627	.3251367	.8901361	4.103022	.9136405	4.753296
Total	.9394118	3.100163	.0456911	1.59358	.8614709	1.119792	.9850908	4.867248
REN-REDES ENERGETICAS NACIO								
period								
Pre-crisis	.9792952	-.2901888	.	.	.9792952	-.2901888	.9792952	-.2901888
2011-2013 Crisis	.9830431	.1769079	.0080236	.6706221	.9743209	-.5047604	.99011	.8359089
Post-crisis	.9823624	.5860697	.0022661	.3159469	.9794951	.2159691	.9850802	1.079449
COVID-19 (2020)	.9815029	.5436936	.	.	.9815029	.5436936	.9815029	.5436936
Post-COVID	.9822596	.4319257	.002564	.3484842	.9798389	.0577864	.9849462	.7472768
Total	.9822057	.3997445	.0037087	.4384035	.9743209	-.5047604	.99011	1.079449
SEMAPA-SOC DE INVEST GESTAO								
period								
Pre-crisis	.9562359	1.590039	.	.	.9562359	1.590039	.9562359	1.590039
2011-2013 Crisis	.9659197	1.898231	.010222	.3611401	.9551751	1.66964	.9755234	2.314573
Post-crisis	.9709002	1.722179	.0043796	.2727465	.9670766	1.290655	.9780313	2.101094
COVID-19 (2020)	.9718125	1.62675	.	.	.9718125	1.62675	.9718125	1.62675
Post-COVID	.9526677	2.473738	.0031306	.2626499	.9494324	2.237815	.9556818	2.756746
Total	.9649437	1.904698	.0092626	.4036809	.9494324	1.290655	.9780313	2.756746
SONAE SGPS SA								
period								
Pre-crisis	.9788885	-.6506292	.	.	.9788885	-.6506292	.9788885	-.6506292
2011-2013 Crisis	.9722913	-.9576914	.0213813	.2892399	.947627	-1.288341	.9855798	-.7515892
Post-crisis	.9655948	-.5893363	.0108644	.7113501	.9467644	-1.279794	.979984	.3440013
COVID-19 (2020)	.9781492	.1946765	.	.	.9781492	.1946765	.9781492	.1946765
Post-COVID	.948827	.7320796	.0066707	.1108983	.94131	.6180239	.9540412	.8395248
Total	.965283	-.3334861	.0149473	.7878642	.94131	-1.288341	.9855798	.8395248
SONAECOM SGPS SA								
period								
Pre-crisis	.8806646	1.142615	.	.	.8806646	1.142615	.8806646	1.142615
2011-2013 Crisis	.7679029	7.301793	.2351276	9.496077	.4966777	1.166495	.9141297	18.2399
Post-crisis	.4420739	15.87657	.0588244	4.059649	.3803747	10.36549	.5068858	19.21334
COVID-19 (2020)	.4444736	11.40857	.	.	.4444736	11.40857	.4444736	11.40857
Post-COVID	.4074815	25.00078	.1180741	8.723778	.2953215	15.28343	.5306927	32.15818
Total	.535981	14.62274	.2050789	9.200086	.2953215	1.142615	.9141297	32.15818
SPORT LISBOA E BENFICA-FUTE								
period								
Pre-crisis	.9980763	-3.615453	.	.	.9980763	-3.615453	.9980763	-3.615453
2011-2013 Crisis	.955783	-4.349023	.0286827	.5278334	.939222	-4.720748	.9889029	-3.744862
Post-crisis	.9695332	-2.554957	.0573348	2.151213	.8532539	-5.153726	.9990255	.9272371
COVID-19 (2020)	.9769685	-1.072584	.	.	.9769685	-1.072584	.9769685	-1.072584
Post-COVID	.969417	-1.696266	.0415523	.4886209	.9214368	-2.224922	.9935484	-1.261225
Total	.9691317	-2.72526	.0420347	1.731105	.8532539	-5.153726	.9990255	.9272371

SPORTING CLUBE DE PORTUGAL								
period								
Pre-crisis	.9959737	-6.670499	.	.	.9959737	-6.670499	.9959737	-6.670499
2011-2013 Crisis	.99548	-9.917221	.0065249	2.559503	.987985	-12.43899	.999893	-7.32158
Post-crisis	.9950287	-5.314533	.0046844	3.355812	.9859227	-11.78058	.9996813	-2.346601
COVID-19 (2020)	.8446389	-4.19237	.	.	.8446389	-4.19237	.8446389	-4.19237
Post-COVID	.9839644	-4.85409	.0121039	1.465558	.9755798	-6.539128	.9978406	-3.876126
Total	.9820798	-6.218857	.0403125	3.156728	.8446389	-12.43899	.999893	-2.346601
TEIXEIRA DUARTE, S.A								
period								
Pre-crisis	.9880216	.5024203	.	.	.9880216	.5024203	.9880216	.5024203
2011-2013 Crisis	.9903139	.3373825	.0045125	.2530911	.9871663	.1655306	.9954838	.6280162
Post-crisis	.9848843	1.599472	.0089217	.7433024	.9675012	.7650873	.9918045	2.522188
COVID-19 (2020)	.9915145	2.582121	.	.	.9915145	2.582121	.9915145	2.582121
Post-COVID	.9813385	1.338971	.0182047	.4537181	.9610094	.8792486	.9961352	1.786436
Total	.9859856	1.265031	.0098626	.8268441	.9610094	.1655306	.9961352	2.582121
THE NAVIGATOR COMPANY SA								
period								
Pre-crisis	.8991979	2.687802	.	.	.8991979	2.687802	.8991979	2.687802
2011-2013 Crisis	.8789759	3.568722	.0127141	.47051	.8682449	3.140132	.8930179	4.072175
Post-crisis	.9121744	3.015917	.0242603	.3416965	.8839117	2.416175	.9533604	3.459354
COVID-19 (2020)	.9589539	1.891232	.	.	.9589539	1.891232	.9589539	1.891232
Post-COVID	.9281192	3.163403	.0123737	.5940432	.9154047	2.53936	.9401214	3.722031
Total	.9108917	3.062208	.0277005	.5586335	.8682449	1.891232	.9589539	4.072175
TOYOTA CAETANO PORTUGAL SA								
period								
Pre-crisis	.9410099	1.226555	.	.	.9410099	1.226555	.9410099	1.226555
2011-2013 Crisis	.7452836	2.619574	.3181022	1.499313	.3801314	.9312189	.9623113	3.79546
Post-crisis	.9276468	2.59256	.0338398	.3572298	.8609362	2.213547	.9492314	3.179463
COVID-19 (2020)	.9574615	2.428053	.	.	.9574615	2.428053	.9574615	2.428053
Post-COVID	.9511885	2.349968	.0159301	.3553923	.9377405	2.109412	.9687813	2.758175
Total	.8966978	2.437042	.1513276	.740048	.3801314	.9312189	.9687813	3.79546
VAA-VISTA ALEGRE ATLANTIS								
period								
Pre-crisis	.9761183	-1.853124	.	.	.9761183	-1.853124	.9761183	-1.853124
2011-2013 Crisis	.9425352	-.822486	.0836965	1.060987	.845891	-1.975397	.991003	.1128443
Post-crisis	.9584337	-.5865253	.0233869	.5403593	.9285669	-1.4603	.9892289	.1678436
COVID-19 (2020)	.9908233	-.6762972	.	.	.9908233	-.6762972	.9908233	-.6762972
Post-COVID	.9755768	-.3367377	.0060734	.6008992	.9710415	-.9998415	.9824769	.1717317
Total	.9622771	-.680446	.0388426	.6948457	.845891	-1.975397	.991003	.1717317
Total								
period								
Pre-crisis	.9602065	.3882474	.0412907	2.475115	.8277515	-6.670499	.9980763	4.73119
2011-2013 Crisis	.9470352	.365241	.0876081	3.57314	.3801314	-12.43899	.999893	18.2399
Post-crisis	.9177867	2.261228	.1544264	7.330852	.1057795	-11.78058	.9996813	48.31209
COVID-19 (2020)	.9369998	1.392997	.1094157	4.479611	.4444736	-10.31594	.99983	15.41914
Post-COVID	.9099369	2.243603	.145019	5.67499	.2953215	-7.196735	.9999954	32.15818
Total	.9267745	1.655367	.1322842	5.918306	.1057795	-12.43899	.9999954	48.31209

Appendix B – Z-score per period



Appendix C – PD of O-score per period



Appendix D – Robust variance testing

crisis	Summary of z_score Mean	Std. dev.	Freq.
0	2.00722	6.3699817	319
1	.36524096	3.57314	87
Total	1.6553674	5.9183055	406

W0 = 3.0675309 df(1, 404) Pr > F = 0.08062952

W50 = 2.1482724 df(1, 404) Pr > F = 0.14350826

W10 = 2.1524337 df(1, 404) Pr > F = 0.14312211

crisis	Summary of pd_ohlson Mean	Std. dev.	Freq.
0	.92124885	.1416615	319
1	.94703525	.08760811	87
Total	.9267745	.13228417	406

W0 = 5.7140350 df(1, 404) Pr > F = 0.01728706

W50 = 2.1050577 df(1, 404) Pr > F = 0.14758879

W10 = 2.3660062 df(1, 404) Pr > F = 0.12478675

covid	Summary of z_score Mean	Std. dev.	Freq.
0	1.6755497	6.0189515	377
1	1.3929968	4.4796111	29
Total	1.6553674	5.9183055	406

W0 = 0.07743592 df(1, 404) Pr > F = 0.78094508

W50 = 0.03750345 df(1, 404) Pr > F = 0.84654095

W10 = 0.03386344 df(1, 404) Pr > F = 0.85408992

covid	Summary of pd_ohlson Mean	Std. dev.	Freq.
0	.92598794	.13397226	377
1	.93699983	.1094157	29
Total	.9267745	.13228417	406

W0 = 0.08885947 df(1, 404) Pr > F = 0.76578538

W50 = 0.11209445 df(1, 404) Pr > F = 0.73794588

W10 = 0.04880293 df(1, 404) Pr > F = 0.82527111

Appendix E – Paired difference testing (Wilcoxon signed-rank test)

Wilcoxon signed-rank test

Sign	Obs	Sum ranks	Expected
Positive	206	38666	35626.5
Negative	171	32587	35626.5
Zero	0	0	0
All	377	71253	71253

Unadjusted variance	4483001.25
Adjustment for ties	0.00
Adjustment for zeros	0.00
Adjusted variance	4483001.25

H0: dz = do
z = 1.436
Prob > |z| = 0.1511

Appendix F – Fixed effects panel regression

Fixed-effects (within) regression		Number of obs =	406
Group variable: **firm_id**		Number of groups =	29
R-squared:		Obs per group:	
Within =	0.0538	min =	14
		avg =	14.0
Overall =	0.0203	max =	14
		F(4, 373) =	5.30
corr(u_i, Xb) =	0.0000	Prob > F =	0.0004

z_score	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
period						
2011-2013 Crisis	-.0230065	.7896156	-0.03	0.977	-1.575663	1.52965
Post-crisis	1.872981	.7386178	2.54	0.012	.4206037	3.325358
COVID-19 (2020)	1.004749	.9670777	1.04	0.299	-.8968584	2.906357
Post-COVID	1.855355	.7896156	2.35	0.019	.3026989	3.408011
_cons	.3882474	.6838272	0.57	0.571	-.9563923	1.732887
sigma_u	4.7488153					
sigma_e	3.6825222					
rho	.62447695	(fraction of variance due to u_i)				

F test that all u_i=0: F(28, 373) = 23.28 Prob > F = 0.0000

```
Fixed-effects (within) regression               Number of obs     =        406
Group variable: firm_id                         Number of groups  =         29

R-squared:                                      Obs per group:
     Within  = 0.0360                                         min =         14
                                                              avg =       14.0
     Overall = 0.0155                                         max =         14

                                                F(4, 373)         =       3.48
corr(u_i, Xb) = -0.0000                         Prob > F          =     0.0083
```

pd_ohlson	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
period						
2011-2013 Crisis	-.0131712	.0190428	-0.69	0.490	-.0506159	.0242734
Post-crisis	-.0424198	.0178129	-2.38	0.018	-.077446	-.0073936
COVID-19 (2020)	-.0232067	.0233225	-1.00	0.320	-.0690668	.0226534
Post-COVID	-.0502696	.0190428	-2.64	0.009	-.0877142	-.012825
_cons	.9602065	.0164915	58.22	0.000	.9277785	.9926345
sigma_u	.10146075					
sigma_e	.08880949					
rho	.56619835	(fraction of variance due to u_i)				

```
F test that all u_i=0: F(28, 373) = 18.27                    Prob > F = 0.0000
```