ANALYSIS OF FINANCIAL DISTRESS FACTORS IN THE MINING INDUSTRY: EMPIRICAL STUDY OF THE DEVELOPING MARKET

Satik Movsesyan [*], Lena A. Seissian [**]

[*] American University of Armenia, Yerevan, Armenia
[**] *Corresponding author,* American University of Armenia, Yerevan, Armenia
Contact details: American University of Armenia, 40A Marshal Baghramyan Avenue, Yerevan 0019, Armenia

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Abstract

Bankruptcy and financial distress studies have been among the most intensively researched topics starting from the 1960s, being pioneered by Edward Altman, deploying accounting ratios for assessing the financial healthiness of companies. This research deploys financial, macroeconomic, and company-specific factors to check the movement of a company's classification of financial health. Deploying a generalized ordered logit model on the sample of 11 mining companies listed on the Lima Stock Exchange (*Bolsa de Valores de Lima* — BVL) we revealed a significant impact of leverage, profitability, economic growth, company size and interest rates on the probability of company staying in or moving from one of three financial health groups. The study finds that borrowing costs significantly impact corporate financial distress, with Peruvian mining companies being naturally protected against adverse interest rate fluctuations reflecting their hedging ability. The findings of this research expand the current body of literature review and are consistent with results presented by Sierpińska (2021), Van et al. (2021), and Boďa and Úradníček (2016).

Keywords: Mining, Altman-Z, Financial Distress, Bankruptcy, Generalized Ordered Logit Regression, Corporate Bankruptcy, Early Bankruptcy Detection, Pro-Active Distress Detection, Financial Regulation, Corporate Finance and Governance

Authors' individual contribution: Conceptualization — S.M. and L.A.S.; Methodology — S.M.; Software — S.M.; Validation — L.A.S.; Formal Analysis — S.M.; Investigation — S.M.; Resources — S.M.; Data Curation — S.M.; Writing — Original Draft — L.A.S.; Writing — Review & Editing — S.M. and L.A.S.; Visualization — S.M. and L.A.S.; Supervision — L.A.S.

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1. INTRODUCTION

The proactive detection of financial distress signs is a critical concern for stakeholders, including investors, creditors, and regulatory authorities. This need intensified in recent years, when increased pressure on economies and financial markets resulted in worldwide economic turbulence, intensifying the issue of operational continuity of businesses and hindering corporate financial stability around the world.

Considering the specificities of each industry in terms of their size, cyclicality, business model peculiarities, and the extent of the impact on economic stability, the careful examination revealed a strong need to analyze the financial distress preconditions for companies in the mining industry. The majority of past studies focused on industrial and trade sectors or even skipped sectoral focus taking samples from diverse industries as it was done by Ha et al. (2023). This hinders the tailored applicability of research in specific cases.

The slowing of the global economy, resulting in reduced demand for specific metals and a drop in their pricing, is the primary cause of the downward revision by Moody's on the mining and metals industry from stable to negative. Due to lower production levels in some places, greater input costs, and lower pricing, Moody's anticipates that copper miners would experience declining earnings before interest, taxes, depreciation, and amortization (EBITDA) (Jamasmie, 2022). Amalgamating the current situation described above, the examination of the Peruvian mining sector can help in revealing factors that can drive fruitful inferences of financial distress implications, particularly in the mining industry of developing countries.

The Altman Z-score model serves as the conceptual backbone of our research. Developed by Edward Altman in 1968, the Z-score integrates five financial ratios to provide a single score indicative of a company's financial health (Altman et al., 2016). By employing a generalized ordered logit model, this research accounts for variations in the proportional odds assumption, enabling a detailed examination of how changes in three groups of independent variables (company-specific, macroeconomics, and market-related) affect the probability of transitioning between different risk categories.

The study's relevance lies in its potential to provide early warnings of financial distress, thereby allowing for timely, mitigating interventions. The significance of this research is underscored by its ability to improve the accuracy of distress prediction models, which is crucial in a dynamic economic environment.

The research employs a quantitative approach, utilizing longitudinal data from a sample of companies (see Appendix) covering a period of seven years (2015–2021 included). The Altman Z-score is calculated for each company, and the generalized ordered logit model is used to analyze the relationship between the Z-score. This methodology allows for a multifaceted assessment of the factors influencing financial distress (Sebasian, 2023).

This study distinguishes itself from previous research by integrating the Z-score model into an ordinal framework and applying a generalized ordered logit model specifically to the mining industry, capturing varying levels of financial distress risk and addressing the limitations of the proportional odds assumption inherent in traditional models.

Ultimately, this study aims to support better corporate financial decision-making in the mining sector.

The identified problem statement generated the following research questions:

RQ1: Does capital structure impact the probability of financial distress in the mining industry?

RQ2: What are the company-specific determinants of financial distress for companies in the mining sector?

RQ3: What are the macroeconomic determinants of financial distress for companies in the mining sector?

The following pages will include an understanding of the mining industry globally and down to a discussion of the Peruvian mining industry, the focus of our research. Section 2 will provide a literature review. Section 3 will explain the research methodology. Section 4 will describe the statistical results and categorize the analysis of impacts for each distinct category. Section 5 will discuss the main findings, and finally, Section 6 will present the conclusion and suggestions for further research.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. Global mining industry overview

A recent report on top business risks and opportunities within the mining industry by Ernst & Young (EY, 2022) highlighted that even before the war in Ukraine, energy price inflation was a major concern due to extensive supply chain disruptions and the impact of COVID-19 restrictions. Despite central banks' efforts to control inflation by raising interest rates, structural energy issues in the United Kingdom (UK) and Europe are likely to persist, which could significantly impact the mining sector. The mining industry is also grappling with higher input costs, such as tyres, explosives, and sulphuric acid, which are lowering margins for metal producers and suspending capacity in Europe. Additionally, a talent shortage is driving up wages as mining companies seek to retain employees with critical skills, and rising capital costs may delay new projects. Through 2019, despite production declines, investments continued to rise steadily with significant funding in open pit mines such as Quellaveco (USD 5.3 billion), Toromocho expansion (USD 1.3 billion), and Mina Justa (USD 1.6 billion). This trend positioned the Peruvian mining industry as a moderately detrimental contributor to the overall performance of the mining industry. Regardless, the mining industry remains one of the most complex to assess financially due to its multifaceted lifecycle stages.

2.2. Overview of the Peruvian mining industry

Peru has a long-standing history of mining industry development, creating a heavy economic reliance on this sector. According to the Trade Government Association, Peru is the world's second-largest producer of copper, silver, and zinc, and Latin America's largest gold producer. The Peruvian mining industry is considered the main driver of economic revival after severe economic, social, and political hardships, ranking the state among those with the highest levels of investment, growth, and economic stability in the region. According to a 2019 assessment, Peru had the lowest overall risk in the region (1.25% = 125 basis points), which sustained its investment grade and allowed access to international financial markets. Mining revenues have strengthened investment and savings trends in the Peruvian market (World Bank, 2020). Mining revenue is also the main source of exports and foreign direct investment (FDI) for Peru. However, this dependence on mining creates a risk of exposure to global price volatility, raising the challenge of greater economic diversification. Peru's attractive legal and tax framework and dynamic mining sector have made it the 4th largest place for FDI in Latin America.

2.3. Financial distress and bankruptcy

Profitability indicators are often interpreted as an indicator of strong financial performance if they show growth trends (Hoang et al., 2019). However, more recent studies incorporate accounting values and market indicators to determine financial performance. Negative financial performance indicators, such as measuring financial distress, are also frequently used. Alfaro et al. (2019) identified the interdependence of factors such as leverage, firm size, and the possibility of financial distress. Their application of the Z-score model for emerging markets showed that companies with high financial leverage are in a gray zone, indicating an increased potential for financial distress due to macroeconomic factors. Tinoco and Wilson (2013) developed a predictive model for estimating financial distress likelihood based on earnings coverage insufficiency and negative market capitalization growth. Boďa and Úradníček (2016) applied modifications of the Z-score model to Slovak enterprises, revealing high predictive accuracy and compatibility with financial distress assumptions.

2.4. Altman Z-score: History of development and model description

The pioneer model for bankruptcy prediction was the multivariate model developed by Edward Altman in the 1960s. Altman's work has sparked greater interest in multivariate analysis of bankruptcy prediction among scholars in finance, banking, and credit risk. The model initially faced criticism for its limited applicability outside United States (US) based manufacturing firms. In 1983, Altman re-estimated the model, making it applicable to companies not publicly traded by substituting the market value of equity with book value. Further analysis revealed that the Z-score model performs well internationally, giving it credibility for application to Peruvian companies. Despite criticisms that accounting-based financial distress assumptions can be misleading, studies have shown high predictive accuracy for Altman's Z-score model, such as in Indonesian manufacturing companies and Lebanese manufacturing firms (El Khoury & Al Beaïno, 2014; Salim & Ismudjoko, 2021). Recent studies have shown that mining enterprises face risks such as poor cash liquidity, long investment payback periods, and declining net profit, which concern profitability metrics (Sun & Lei, 2021).

2.5. Distress factors

2.5.1. Capital structure

Capital structure refers to the amount of debt and equity a company uses to finance its long-term initiatives, operational expansion, and capital expenditures. It is important to understand the specificities of financing pertinent to the industry and business model (Sierpińska, 2021). Both macro- and micro-economic factors, including company size, development potential, investment level, asset structure, cost of capital, non-interest tax shields, life cycle, financial risk, and industry-specific activities, impact decisions on equity and external capital proportions. Similar considerations were made by Paredes Gómez et al. (2016) and Santillán Salgado (2018) in their study of listed companies on the Mexican, Colombian, Peruvian, Brazilian, and Chilean stock exchanges. They found that companies' prior period profitability indicated future diminishing levels of debt, suggesting that firms prefer internal resources over external financing. In contrast, Polish mining companies heavily rely on equity financing, in line with global practices (Sierpińska, 2021). Sutomo et al. (2020) found that asset structure positively correlates with leverage in Indonesian mining companies. Khafid et al. (2019) identified that highly leveraged companies have greater financial distress opportunities. Considering the specificities of the mining industry revenues and profitability patterns, analyzing the impact of capital structure on financial distress in Peruvian mining companies is crucial.

2.5.2. Macroeconomic variables

Studies by Mačerinskienė and Mendelsonas (2013) highlight the link between macroeconomic factors, particularly gross domestic product (GDP), and increased corporate insolvency risk. Tinoco and Wilson (2013) take this further by proposing a comprehensive model to predict financial distress, a precursor to bankruptcy. Their model defines financial distress based on two key criteria: 1) negative EBITDA, and 2) declining market value for two consecutive years. It incorporates accounting data reflecting a firm's financial health, market data on its valuation, and macroeconomic variables that influence the broader economic environment demonstrating using all three categories significantly boosts predictive accuracy, with their comprehensive model achieving an impressive 85% success rate. Furthermore, the study acknowledges the "lagging effect" identified by Altman et al. (2016), where financial distress often precedes actual bankruptcy. Their models predicting distress one year in advance achieved higher accuracy (82–85%) which highlights the importance of timely identification for potential interventions.

Economic growth (real GDP growth). Geographical differences among markets in which firms operate can create significant distinctions regarding underlying macroeconomic factors that impact the firm's financial stability. Charalambakis and Garrett (2019) identify determinants of financial distress using a large dataset of 31,000 private firms in Greece considering fundamental determinants and GDP. Employing a series of multi-period logit models with financial and macroeconomic independent variables, the authors identified that the model's predictive ability is statistically significant for identifying financial distress. Of particular interest to our study, is the growth rate of real GDP has a negative effect on the probability of financial distress (Charalambakis & Garrett, 2019).

Interest rate. The interest rate is deemed among the conventional variables while analyzing the financial perspectives of a given company to determine and hedge against its unfavorable spikes. González et al. (2016) identified that stock returns in the integrated oil and gas, commercial services, supplies, and diversified metals and mining industries have a significantly positive relation with unexpected changes in the real rate of interest for the general contraction, and growth sub-periods, which suggest that investments in these industries provide insulation from unexpected changes in the real rate of interest. Significant changes and fluctuations in commodity prices remain among the principal influences upon the economic situation of mining companies and, hence, inevitably, direct mining practices. A conventional cycle in the mining industry is associated with commodities' price fluctuations, which implies respective increases in production as prices go up and vice-versa in case of downward movement. As was outlined by Scope Credit Rating Agency (2022), acredit rating agency, in detailing the approach to rating metals and mining companies as of July 15, 2022, debt servicing and coverage are among key aspects of credit rating for mines, indicating that a considerable number of derivatives that mining companies obtained as a source of hedge against risk and provision for liquidity absorb the impact of commodity price swings, leading to squeezed margins and financial performance. While analyzing non-technical (market-related) factors that expose mining companies to risk, Trench et al. (2014) concluded that "commodity price risk" sensitivity significantly impacts the earnings of mining companies closely related to movements in the price of the respective mineral commodities produced. Augmenting this direct relationship between mining firms' income and commodity price shifts, there is also an association between interest rate shifts and commodity prices claimed by Akram (2009). In addition to previously mentioned results, Akram (2009) suggests the positive relationship between shock-induced increases in interest rates and its corresponding increase in commodity prices, which as we read has a positive impact on the financial sustainability of mining companies' income generation ability. Hence, we will try to estimate whether the same positive effect holds for the Peruvian market.

2.5.3. Company-specific factors

Profitability (return on equity — ROE). Research shows more preference for the measurement of profitability through ROE as a method for representing efficiency in exploiting shareholders capital (equity) for income generation, taking into account more reliance of mining companies on equity financing rather than on significant leverage (Kijewska, 2016). Analyzing factors impacting financial distress likelihood, Van et al. (2021) used four types of ratios: 1) liquidity; 2) financial structure ratios; 3) operating turnover ratios, and 4) profitability ratios as statistically significant factors for classifying a company to safe, gray or distress zone. According to the results, an increase in profitability is deemed to be positively related to the probability of classifying a company as a safe/gray zone (Van et al., 2021).

Company size (market capitalization). Dang et al. (2018) highlight the effectiveness of the inclusion of a market cap if there is a need for controlling the size of the stock market as well as including a more forward-oriented proxy. Additionally, Muigai and Muriithi (2017) state that market capitalization has a significant moderating effect on the relationship between capital structure and corporate bankruptcy. The main finding of this research states that large-scale firms are in a more favorable position with respect to bearing higher levels of leverage and improving their financial distress status, claiming that due to the size, relatively easy access to capital markets, terms of borrowing and costs of debt financing they are in more favorable conditions compared to their small counterparts.

Dividend per share. Bearing in mind the preliminary understanding of the equity-based nature of conservatively financed mining companies, dividends, are an inseparable part of this type of financing method. As it was mentioned earlier, Charalambakis and Garrett (2019) highlighted the dividend payout as a signal for future sustainable earnings, which consequently implies a reduced level of opportunities for financial distress. Hence, the variable was entered into the model presented in this study, in order to reveal whether dividend payout acts as among determinants for financial distress for mining companies.

2.6. Hypotheses development

Based on an exhaustive literature review, the following research hypotheses were formulated:

$H1_0$: An increase in leverage in the company's capital structure does not increase the probability of financial distress.

H1: An increase in leverage in the company's capital structure increases the probability of financial distress.

$H2_0$: Positive economic growth does not impact the probability of a company experiencing financial distress.

H2: Positive economic growth decreases the probability of a company experiencing financial distress.

$H3_0$: An increase in interest rates have no impact on the probability of a company experiencing financial distress.

H3: Increases in interest rates have a negative impact on the probability of a company experiencing financial distress.

$H4_0$: Profitability increases have no impact on the probability of a company experiencing financial distress.

H4: Profitability increases have a negative impact on the probability of a company experiencing financial distress.

$H5_0$: An increase in the size of the company has no impact on the probability of a company experiencing financial distress.

H5: An increase in the size of the company has a significant negative impact on the probability of a company experiencing financial distress.

$H6_0$: An increase in the dividends paid by the company has no impact on the probability of a company experiencing financial distress.

H6: An increase in the dividends paid by the company has a significant negative impact on the probability of a company experiencing financial distress.

3. RESEARCH METHODOLOGY

3.1. Research methods

Adopting secondary quantitative analysis, the study includes a multi-layered approach for obtaining the dependent variable and then the model itself. Extracting financial statements and annual reports of 11 mining companies[1] from the Lima Stock Exchange (*Bolsa de Valores de Lima* — BVL), a panel data for seven years was created (2015–2021). The purposive sampling method was applied due to

[1] Particularly those 11 companies were publicly listed and had available financial statements. Specifically listing criteria gave us granularity and reliability of reported financial data — which became a reason for funneling down to selected companies of our research.

two major constraints related to data extraction which would potentially hinder the model's generalizability, namely: 1) availability of audited financial statements and 2) availability of financial statements for the time interval covering the study. For each Z-score four accounting ratios are calculated and inserted in the predefined model for predicting corporate bankruptcy for non-manufacturing firms which operate in emerging economies (Boďa & Úradníček, 2016; Altman et al., 2016). Below presented is the Z-score model as well as adjusted ranges for classification based on derived Z-scores, which were proposed by Altman (2005) in line with calculation assumptions incorporating various requests for adapting and generalizing models for wider application. Presented below is the pioneer version of the Z-score from 1968:

$$Z = 0.012\,X1 + 0.014\,X2 + 0.033\,X3 + 0.006\,X4 + 0.999\,X5 \quad (1)$$

where, each independent variable represents a separate accounting ratio:

- $X1$ = working capital/total assets;
- $X2$ = retained earnings/total assets;
- $X3$ = earnings before interest and taxes/total assets;
- $X4$ = market value of equity/book value of total liabilities;
- $X5$ = sales/total assets;
- Z = overall index.

Further in 1984, Altman conducted a complete re-estimation of the initial model (Altman, 1984), thus making the model applicable to companies that are not publicly traded, substituting the initially set market value of equity with book value.

$$Z' = 0.717\,X1 + 0.847\,X2 + 3.107\,X3 + 0.420\,X4\,1 + 0.998\,X5 \quad (2)$$

Making further analysis, Altman excluded the $X5$ (sales/total assets) advocating industry-related specificity of this ratio (Altman et al., 2016).

$$Z'' = 3.25 + 6.56\,X1 + 3.26\,X2 + 6.72\,X3 + 1.05\,X4 \quad (3)$$

By adding up variables of size, company age, industry, etc. Altman et al. (2016) revealed that Z'' performs well in the international context, giving us credibility for applying that version, particularly to estimations and analysis of Peruvian companies.

- $Z < 3.75 \rightarrow$ distress zone (Class 1);
- $3.75 < Z < 5.85 \rightarrow$ grey zone (Class 2);
- $5.85 < Z \rightarrow$ safe zone (Class 3).

As for the independent variables debt-to-equity, profitability ratios, and dividend per share data were either extracted or calculated using companies' financial reports. Data for the macroeconomic variables (interest rate and GDP values) was extracted from the World Bank's website. In order to have a smoother fit and minimize errors, a log of the difference between the values for each year was taken. The role of the dependent variable was adopted by applying the Altman Z-score, as a tool for quantifying the financial health state of the companies throughout the whole period of the study. As an alternative method for quantifying dependent variables Springate model can also work (Sebasian, 2023).

3.2. Description and analysis

Dependent variable. The target variable named *FHS* consists of 77 observations ($n = 77$) represented as a Z-score (Altman et al., 2016), calculated for the seven-year period. The average *FHS* score for the years 2015–2021 is 6.78 (see Table 1), which signals that on average the companies within the sample are in a healthy financial state (with 59.2% of companies falling into the class of safe zone for the period under consideration). Transformation to ordinal scale not only deals with skewness but also supports the applicability of the class-based model making further use of results more practical (Williams, 2006; Agresti, 2010).

Table 1. Key characteristics of the data set

Characteristic	*Value/Description*
Dependent variable	*Financial health score* (*FHS*)
Number of obs.	77
Period covered	2015–2021
Average FHS score	6.78
Percentage in "safe" zone	59.2%
Standard deviation of FHS	Larger than mean (indicating possible outliers)
Outlier company (negative values)	PPX Mining Corp. (Min: -34.42, Max: -21.27)
Outlier companies (positive values)	Panoro Minerals Corporation and Bear Creek (for 2015–2017)
Skewness	1.971
Kurtosis	12.453
Average ROE	-15.52%
Companies with 0% ROE	PPX Mining Corp., Panoro Minerals, Bear Creek (consistent zero net income)
Debt-to-equity ratio	0.52 (equity-focused financing)
Average market size	USD 6.73 billion
Largest companies	Southern Copper Corporation (BVL: SCCO), Sociedad Minera Cerro Verde S.A.A. (BVL: CVERDEC1)
Non-parametric analysis	Spearman correlation (due to non-normal distribution)
Correlation results	Moderate relationships between several independent variables and the dependent variable (*FHS*)

Source: Authors' elaboration.

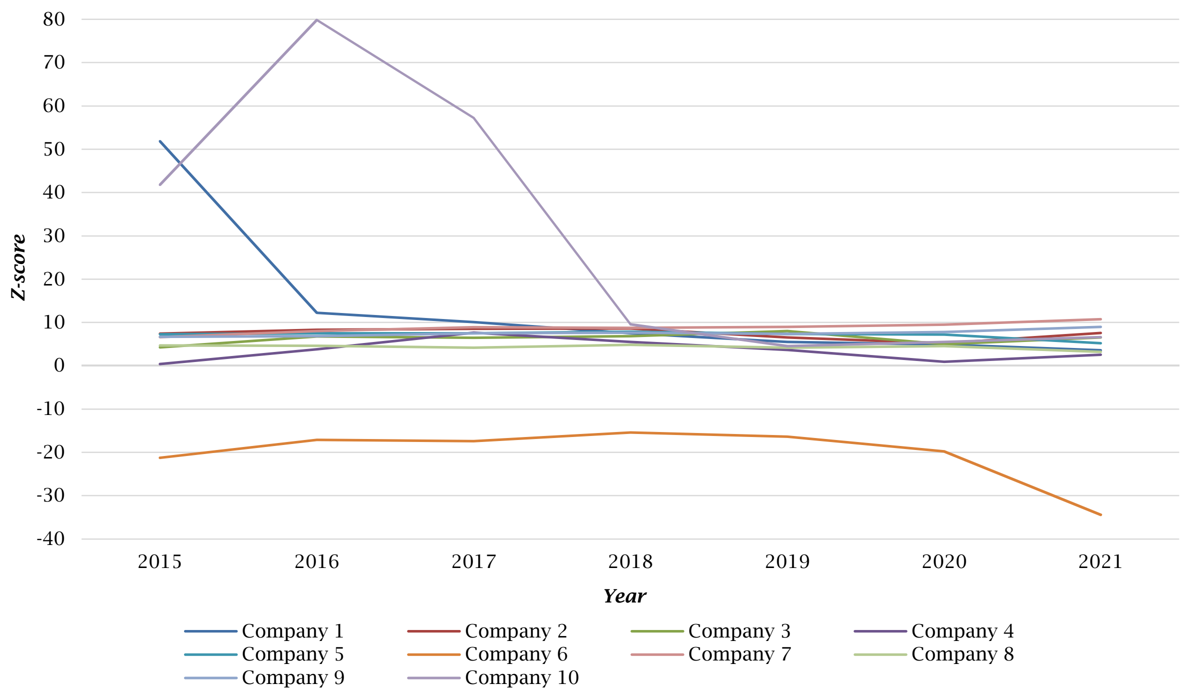
Table 2. Descriptive results

Variables	Obs	Mean	Std. dev.	Min	Max	p1	p99	Skew.	Kurt.
Altman Z	77	6.784	14.879	-34.42	79.85	-34.42	79.85	1.971	12.453
Capital structure	77	0.519	1.279	-7.775	5.731	-7.775	5.731	-2.711	27.642
Profit ratio	77	-0.158	0.632	-4.388	0.35	-4.388	0.35	-4.603	28.536
Company size (market capitalization)	77	6.385	12.415	0	51.935	0	51.935	2.341	7.561
Interest rate	77	0.106	0.037	0.024	0.131	0.024	0.131	-1.538	3.844
GDP growth	77	0.007	0.033	-0.054	0.044	-0.054	0.044	-0.614	2.198
Dividend per share (DPS)	77	0.118	0.362	0	2.2	0	2.2	4.218	21.199

Source: Authors' elaboration.

At the same time standard deviation of this score reveals a spread pattern, considering that it is approximately 2.2 times larger than the mean, which hints possible presence of outliers. The overlay graph displayed in Figure 1 shows one company PPX Mining Corp., which throughout the seven years of observations displays deeply negative values with the minimum and maximum values being -34.42 and -21.27, respectively.

Figure 1. Overlay (2015–2021)



Source: Authors' elaboration.

Box plot (see Figure 2) for our dependent variables reveals true outlier points of PPX Mining Corp. which take on negative values as well as several positive large outliers, which are coming from Panoro Minerals Corporation and Bear Creek values for the three years covering 2015–2017. Skewness and kurtosis test scores for the dependent variable (1.971 and 12.453, respectively) reflect significantly non-normal distribution in the sample of *FHS* with a considerable lack of symmetry and leptokurtic distribution. The general positive trend which departs the outlook of companies from being financially distressed in the upcoming two years, however, is not supported by the positive prospects of wealth generation abilities of mining companies stemming from a negative average value of *ROE*, which is equal to negative 15.52%. Particularly, there are cases for three companies namely (PPX Mining Corp., Panoro Minerals, and Beer Creek), which throughout the seven years' time span produced 0% *ROE*, which was predictable due to their net income consistently showing zero values on the statement of comprehensive income. As net income is after interest and tax results of the company's wealth creation activities, it might signal the indebtedness of the company. It is showing deterioration in financial and economic terms, and the company has no sufficient ability to generate a proper return on net worth.

Figure 2. Boxplot (2015–2021)

Source: Authors' elaboration.

However, the analysis of the debt-to-equity ratio averaged 0.52 indicating that the financing structure of Peruvian mining is more equity-focused, which is in line with the literature. The market size of the companies throughout the period covered was on average USD 6.73 billion, the largest value being taken by Southern Copper Corporation (BVL: SCCO) which in 2018 was ranked 4th out of 25 largest mining companies in the world and Sociedad Minera Cerro Verde S.A.A. (BVL: CVERDEC1).

Prior to delving into the methodology, a preliminary expectation about the potential relationship and impact of selected independent variables and the financial health of the companies was created. Compatible with the results of distribution and symmetry tests, a non-parametric Spearman correlation analysis was conducted (Bishara & Hittner, 2015). Moreover, as the format of our dependent variable applied in the analysis was transformed from continuous to ordered classes, and the assumption is made that the extent of impact among classes will differ — we expect the necessity of considering the curvilinear relationship between predictors and outcome variable, hence releasing on Spearman correlation will produce more robust estimations (Dodge, 2008). Except for several combinations, overall correlations among predictor variables as per Spearman's rank correlation analysis revealed that we are not very likely to experience distortions in explanatory power at the same time several independent variables have moderately strong relationships with the dependent variable (Jones & Hensher, 2004).

4. RESEARCH RESULTS

4.1. Preliminary statistical testing

To have the ability to capture the true impact of predictors on dependent variables, the multicollinearity (variance inflation factor — VIF) test resulted in a VIF equal to 1.69 indicating an absence of major multicollinearity issues (Mansfield & Helms, 1982). Interpretation of the data's normality was in conformity with skewness and kurtosis tests' results which support the data's non-normal (leptokurtic) distribution, which was an essential step in model selection.

While predicting corporate failure, it is important to have a model which will closely capture trends and specificities of data, without bounding to linear relationships. As the review of existing literature showed, there are many variations deploying multiple discriminant analysis (MDA), multiple regression, and supervised/unsupervised machine learning (ML) algorithms for predicting corporate bankruptcy. In this research, following examples of Khafid et al. (2019), and Tinoco and Wilson (2013), logit regression analysis is utilized. Distinctively, the generalized ordered logit regression (*gologit2*) helps omit the necessity of sticking to the parallel lines assumption. Van et al. (2021) used *gologit2* for estimating the change in the probability of classification in one of three groups originally specified by Altman (1968) based on the measurement of changes in input variables of the Z-score equation.

4.2. Generalized ordered logit regression

As Williams (2006) explains, a generalized ordered logit regression model, an extension to the ordered logit model, relaxes the parallel lines constraint only for those variables where it is not justified. An important aspect of deciding to employ *gologit2* was due to the fact that, while having an upward or downward shift in coefficients for explanatory variables, in case of conventional ordinal models, we are unable to see the incremental impact of them on the probability of shifting from one category to the other, depending on the current state. This can potentially lead to the fact of falsely considering improvement in one metric (for example, profitability) as a remedy for the financial health of the company for all cases, while in reality, it might not be sufficient for Class 1 or 2 to merely increase *ROE* for coming out of financial distress. Since initial derivations of the Altman-Z score have continuous variables which cannot be used directly, the dependent variable was transformed into a scale which is subdivided into three classes, respectively: 1 = "distress", 2 = "gray", and 3 = "safe".

The generalized ordered logistic model function is represented below.

$$P(Y > j) = \frac{exp(\alpha_j + X_{1i}\beta_1 + X_{2i}\beta_{2j} + X_{3i}\beta_{3j} + X_{4i}\beta_{4j} + X_{5i}\beta_{5j} + X_{6i}\beta_{6j})}{1 + [exp(\alpha_j + X_{1i}\beta_1 + X_{2i}\beta_{2j} + X_{3i}\beta_{3j} + X_{4i}\beta_{4j} + X_{5i}\beta_{5j} + X_{6i}\beta_{6j})]} \tag{4}$$

$$j = 1, 2, \ldots, M - 1$$

The output provided by generalized ordered logit regression (*gologit2*) in the panel contrasts three categories together (M = 3) providing M - 1 sets of coefficients. In the first panel, Category 1 is contrasted with Categories 2 and 3. The second panel contrasts Categories 1 and 2 with Category 3, respectively (Williams, 2006). According to conventional meaning, positive coefficients indicate that higher values on the explanatory variables make it more likely that the company will be classified in a higher category (moving the *FHS* from 1 = "distress zone" to 2 = "gray zone") of financial health than the current one, whereas negative coefficients indicate that higher values of explanatory variables will lead to the classification of company values on the explanatory variable increase the likelihood of being in the distress zone.

As a starting point, we used a whole set of predictor variables for fitting the regression model and obtained a model with a pseudo-R^2 value of 0.535 which shows the model's predictive ability (Hemmert et al., 2018). In the context of the output provided, the chi-square statistic is used to test the overall significance of the model. In this case, the likelihood ratio (LR) chi-square value of 62.68 with seven degrees of freedom indicates that the model is statistically significant, with a p-value of less than 0.05. This means that the model provides a good fit for the data and can be used to make predictions on relationships between Z-score and selected predictors. Table 3 shows the estimated set of coefficients obtained from generalized ordered logit regression with partial proportional odds assumption. The table presents two sets of outputs, according to the principle of n - 2 (in our case n is 3, since we have three financial health classes) sets of coefficients that compare each class with the remaining set producing a shift in the *FHS* based on the associated changes in different selected factors. The goodness-of-fit result is based on the LR test which tests the appropriateness of partial proportional odds assumption.

Table 3. Generalized ordered logit estimates

Altman Z-score	*Coefficient*	*Std. error*	*Z*	*p > Z*	*[95% conf. interval]*	
Panel A: Class 1 comparison to Class 2 & 3						
Leverage (debt to equity)	-4.421	1.203	-3.670	0.000	-6.780	-2.063
Profitability (ROE)	2.671	1.222	2.190	0.029	0.277	5.066
Company size (market capitalization)	0.971	0.353	2.750	0.006	0.280	1.663
Interest rate	24.011	10.581	2.270	0.023	3.273	44.749
Economic growth	-49.943	26.193	-1.910	0.057	-101.280	1.394
DPS	18.012	25.014	0.720	0.471	-31.013	67.038
Cons_	3.863	1.735	2.230	0.026	0.463	7.264
Panel B: Classes 1 & 2 combined comparison to Class 3						
Leverage (debt to equity)	-4.421	1.203	-3.670	0.000	-6.780	-2.063
Profitability (ROE)	2.671	1.222	2.190	0.029	0.277	5.066
Company size (market capitalization)	0.971	0.353	2.750	0.006	0.280	1.663
Interest rate	24.011	10.581	2.270	0.023	3.273	44.749
Economic growth	20.137	13.515	1.490	0.136	-6.352	46.627
DPS	18.012	25.014	0.720	0.471	-31.013	67.038
Cons_	-1.361	1.221	-1.110	0.265	-3.753	1.031
Number of observations = 70 LR $Chi^2(7)$ = 62.68 Prob = 0.0000 Pseudo R^2 = 0.5357						

Source: Authors' elaboration.

4.3. Analysis of marginal effects from independent variables

With an estimator of marginal effects, coefficients obtained from regression analysis were transformed to the derivative form (dy / dx) for each independent variable, showing the impact of a one-unit change in the independent variable on the odds of being in that particular category if the companies "starting point" class is one among the three ordered classes (Williams, 2022). The marginal effects and respective statistical significance values of the predictor variables on *FHS* values are shown in Table 4.

Table 4. Marginal effect values for generalized ordered logit estimates (Part 1)

Variables	*Class*	*dy / dx*	*Std. error*	*Z*	*p > |Z|*
Leverage (debt to equity)	1. Distress	0.1350	0.0374043	3.61	0.000
	2. Gray	0.2943	0.0566351	5.20	0.000
	3. Safe	-0.4294	0.0648827	-6.62	0.000
Profitability (ROE)	1. Distress	-0.0815	0.0341771	-2.39	0.017
	2. Gray	-0.1778	0.0826104	-2.15	0.031
	3. Safe	0.2594	0.1089699	2.38	0.017
Company size (market capitalization)	1. Distress	-0.0296	0.0109032	-2.72	0.007
	2. Gray	-0.0646	0.0192421	-3.36	0.001
	3. Safe	0.0943	0.0260931	3.61	0.000

Table 4. Marginal effect values for generalized ordered logit estimates (Part 2)

Variables	*Class*	*dy / dx*	*Std. error*	*Z*	*p > |Z|*
Interest rate	1. Distress	-0.7333	0.3524163	-2.08	0.037
	2. Gray	-1.598	0.5742318	-2.78	0.005
	3. Safe	2.332	0.8549283	2.73	0.006
Economic growth	1. Distress	1.5253	0.8973397	1.70	0.089
	2. Gray	-3.4812	1.416381	-2.46	0.014
	3. Safe	1.9558	1.231482	1.59	0.112
DPS	1. Distress	-0.55014-	0.7698911	-0.71	0.475
	2. Gray	1.1992	1.668553	-0.72	0.472
	3. Safe	1.7494	2.421659	0.72	0.470

Source: Authors' elaboration.

• *Capital structure.* A 1% increase in leverage level, increases the odds of being in the "distress" category by 13.5% which conforms to an 11.8% increase in the probability of being in that category. For the firms classified in the "gray'' zone the same positive shift in the amount of debt financing displays an upward change in the probability of staying in this safe zone by 29.4%. Conforming to the theory of predominantly equity-based capital structure of financially stable and successful mining firms — acceleration of leverage levels produces a 42.94% decrease in the odds of being in the "safe" category. Those results are highly statistically significant at a 1% significance level. This finding is in line with Sierpińska's (2021) evidence on the healthy mining industry's debt levels which are kept below global averages.

• *Profitability.* As for the return on equity, a 1 unit increase can produce a negative shift in odds of being in "distress" financial state by -0.0815, while for the "gray" zone, the marginal effect is more profound. Conveying the positive impact of generated return on shareholder's health, the increase in return on equity figures makes the probability of being in the safe zone more profound, increasing the odds of being in the "safe" zone by 0.2594. At a 5% level of significance, we rejected the null hypothesis $H4_0$, since our results reveal a positive impact of profitability indicators on the financial health of the company, hence decreasing the likelihood of experiencing financial distress. Holding everything else equal, improved profitability's incremental effect is reliant on the base-case industry-specific capital structure financing which is reliant on debt, which was also the case for Romanian listed companies (Vătavu, 2015).

• *Company size.* All else equal the odds of being in the "distress" and "gray" category go down by 2.96% and 6.46%, respectively, as the size goes up by 1 unit. This result conforms with other research findings which suggest that forward oriented character of market capitalization and its relative size in the ability to reflect better conditions of larger firms serving elevated debt levels and receiving more favorable terms while acquiring financing (Dang et al., 2018; Muigai & Muriithi, 2017). The hypothesis $H5_0$ with respect to company size having no impact on financial distress is rejected at a 5% level of significance.

• *Interest rate.* 1 unit increase in the real interest rate decreases the odds of being in the "distress" and "gray" category (by 0.7333 and 1.5987, respectively) while increasing the odds of staying in the "safe" zone. In fact, contrasting to Kozlov's (2023) finding, who identified two substantial effects on household consumption: 1) higher interest rates discourage spending and 2) encourage saving, further tailored by consumers' worsened expectations of near-future changes (Kozlov, 2023) and hence commodity prices go down since the demand for the overall amount of goods of regular basket which involve in their production basic commodities goes down.

Contrary to this reality, our research detected results consistent with the claims of Akram (2009), who suggests that equity returns of mining companies provide natural insulation due to moderate volatility against risks associated with shock-spurred interest rate ups and downs. Moderation of returns volatility is also a result of the fact, that pertaining to industry-specific factors of capital structure mining firms are more equity-financed which creates a significant buffer against adversities related to interest expenses. The assumption with respect to interest having no impact on financial distress is rejected at a 5% level of significance, with modification to sign expectation.

• *Economic growth.* Surprisingly, one unit increase in economic growth is expected to produce a statistically significant decrease in odds of being in the "gray" category by -3.4812, while impact throughout other categories is statistically insignificant. As it was noted by Jiang and Wang (2009), survival strategies in case of a shift in economic growth can indeed help a distressed firm, especially those which are in the transitory stage of their financial condition determination which is a class for which vulnerability with positive prospects can be captured as it was highlighted by Altman (2005). Particularly, in line with the authors' argument relating to larger firm size, with a larger intangible assets base and more governmental support and subsidies, mining companies are likely to choose to stay in business when falling into distress and trying to catch up on originated opportunities. Thus, the hypothesis $H2_0$ related to the economic growth variable is rejected at 5% only for companies with Category 2 ("gray zone").

• *Dividend per share.* Display of marginal effects shows that dividend-paying ability and amount of growth are not associated with improvement of classification category on a statistically significant level. We failed to reject the null hypothesis $H6_0$, which implied the absence of impact related to the dividend-paying ability of mining firms on the probability of experiencing financial distress.

5. DISCUSSION AND ANALYSIS OF RESULTS

Throughout the research, we tried to identify major factors that contributed to the increased likelihood of financial failure in the mining industry, incorporating industry peculiarities and traditional indicators. Our main aim was not only to identify the presence of statistically significant impact but also to understand the variability of marginal effects depending on the current classification of the company. Addressing the first research question on the dependency between indebtedness and corporate financial distress, conforming to findings resulting from an estimation of a positive relationship between leverage levels elevation and consequent increase in the probability of financial distress proposed by Alfaro et al. (2019), Sutomo et al. (2020), and Frank and Goyal (2009), we revealed that for the Peruvian mining industry, in case of a company with starting Category 1 ("distress"), increasing the level of indebtedness can result in a higher probability of remaining in the same class, claiming that in $t + 2$ periods company will highly likely to file for bankruptcy. From the perspective of loan covenants and requirements of capital optimization, the riskier the company is, the more costly it will be to use external financing.

Moreover, drawing intersecting lines between the Peruvian and Polish mining sectors, the companies surveyed in 2015–2019 reported a significant increase in assets financed with equity since increased commodity prices drove growth in retained earnings (Sierpińska, 2021), which is supportive of results reported in Table 4, concerning marginal effects produced both, by lower levels of leverage and higher profitability linkage. Our findings of the negative impact of increases in leverage oppose the claims of Muigai and Muriithi (2017) since we focused on the long-term debt having positive and significant effects among large-scale firms while short-term debt is significantly detrimental.

We also identified profitability as being significantly important for corporate financial stability for mining companies, implying a chance to move to the upper category. The result is supported by the findings of Paredes Gómez et al. (2016), who claimed the power of profitability indicators as being decisive of the future financial "destiny" of the firm. While perceiving absolute results of the positive impact of profitability on companies' financial health classification, consciousness should be exercised due to the sensitivity of the denominator for the ratio to changes in equity levels. The company might experience year-over-year artificial inflation of ROE resulting from depreciating levels of equity, eventually turning this metric into meaningless estimation of true profitability (Liu et al., 2021).

Trying to address the question of the presence and extent of dependencies among corporate financial distress and macroeconomic factors, we identified the borrowing cost as one of the macroeconomic determinants that exert a direct impact on the expense side of the firm's financial statements and an indirect one in terms of shaping a company's demand. Analysis of interest rate's impact on miners' financial conditions revealed robust results that link several essential discussions on the relationship between adverse movement in interest rates and commodity prices, acting as potential risk factors. Referring to the identified "insulator" perception of the mining and metals sub-sector investment, this is considered a hedging mechanism against adverse movement in nominal interest rates (Gonzalez et al., 2016). Opposing the fundamental interpretation of the triangular relationship between borrowing costs, commodity prices, and profitability, we claim that companies operating in the Peruvian mining industry possess naturally originated defense against adverse interest rate fluctuations in all financial health classes, which can be primarily supported by industry-specific capital structure consideration.

Given the firm size, the obtained results of our research support claims provided by Frank and Goyal (2009) concerning larger companies being more willing to issue shares as a method of financing. Normally, since they face lower issuance costs, the need to care about marginal tax-shield deductions is not of great concern. Opposite to the revised claims of Modigliani and Miller (1963), who incorporated the impact of interest rate tax shield to reflect a positive impact on returns on common equity and the respective growth in the company's market value, particularly for enterprises operating in the mining industry, it was identified that equity source of capital is most reflective of sustainable financial position pertaining to specific solvency indicators of the mining industry, which decreases the likelihood of a company going bankrupt. This pattern was not surprising since EBITDA revealed that mining industries worldwide are experiencing enlarged cost composition as a consequence of inflationary effects and the inability to pass on costs for sustaining margins.

6. CONCLUSION

Amalgamating scholarly presented determinants of corporate financial distress through literature review and further analysis, we revealed that it is still an underdeveloped niche in the sphere of financial economics, giving us legitimacy to claim that our research sheds light on the concept of multifaceted determination of financial distress by creating a differentiated understanding about the impact of company-specific, macroeconomic, and market-based variables within developing markets. Our suggested model can be used as a proactive signal for corporate distress determination. Summarizing our analysis, we would like to name the model pro-active distress detection and suggest that future scholars further investigate and test the model on enlarged data sets for an extended period, possibly deploying ML algorithms.

Our analysis is important for future research as it addresses a critical gap in understanding the determinants of corporate financial distress, providing a comprehensive model that incorporates multiple variables. The insights from this study can guide policymakers, investors, and corporate managers in better anticipating and mitigating financial distress.

However, there are several limitations to our research. Firstly, the study is constrained by the availability of complete and audited financial statements for a limited number of companies, which may limit the generalizability of our findings. Additionally, the time period analyzed (2015–2021) does not account for longer-term trends or the potential impact of unforeseen future events. Another limitation is the static nature of the Altman

Z-score coefficients, which may not fully capture the dynamic and evolving macroeconomic environment influenced by events such as the COVID-19 pandemic, the Russian-Ukrainian war, and intensifying climate changes. Future studies can build on our findings to develop more accurate and adaptable models for predicting corporate financial distress. As for the Peruvian companies, the results can be borrowed to evaluate their internal decisions and strategies about financing sources and take the necessary precautionary steps to fix their distressed situation or sustain their good class.

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APPENDIX. COMPANY LIST

No.	*Companies*
1	Panoro Minerals Ltd. (PML)
2	Nexa Resources Peru S.A.A.
3	Minsur S.A.
4	Compañía de Minas Buenaventura S.A.A.
5	Compañía Minera San Ignacio de Morococha S.A.A.
6	Sociedad Minera Cerro Verde S.A.A.
7	Volcan Compania Minera S.A.A.
8	Southern Copper Corporation
9	Bear Creek Mining Corporation
10	PPX Mining Corp.
11	Alturas Minerals S.A. (Alturas Perú)