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Predicting Business Continuity in Italian Luxury Firms: a Dual Logistic Regression Approach

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ABSTRACT - SOMMARIO

Business continuity prediction is a topic of great relevance, as it affects the economic well-being of all countries and the stability of production systems. In this context, the study develops two logistic regression models to predict business continuity in the Italian luxury sector. The analysis is conducted on 114 firms operating in the fashion, jewellery and watchmaking, and automotive luxury subsectors, selected from the AIDA database and observed over the 2021–2023 period (342 observations). The dependent variable is business continuity, as defined by Altman's Z''-score. The independent variables include six financial indicators: current ratio, current assets/total assets, equity ratio, natural log of total assets, return on assets, and retained earnings/total assets. The two logistic regression models differ by validation criterion: the first employs a time-based split (training set covering 2021–2022 and test set for 2023), while the second applies a firm-based split (training set with 84 companies and test set with the remaining 30, randomly selected). Both models show good predictive performance, with overall classification accuracies of 96.49% and 94.44%, respectively. The results suggest that logistic regression represents an appropriate tool for predicting business continuity in the Italian luxury sector, a field characterized by a distinctive combination of resilience and vulnerability.

La previsione della continuità aziendale è un tema di grande rilevanza, poiché influisce sul benessere economico di tutti i paesi e sulla stabilità dei sistemi produttivi. In questo contesto, lo studio sviluppa due modelli di regressione logistica per prevedere la continuità aziendale nel settore del lusso italiano. L'analisi è stata condotta su 114 aziende che operano nei sottosettori moda, gioielleria, orologeria, e lusso automobilistico, selezionate dal database AIDA e osservate nel periodo 2021–2023 (342 osservazioni). La variabile dipendente è la continuità aziendale, come definita dal punteggio Z'' di Altman. Le variabili indipendenti includono sei indicatori finanziari: indice di liquidità corrente, attività correnti/attività totali, rapporto di capitale netto, logaritmo naturale delle attività totali, rendimento sugli attivi e utili trattenuti/attività totali. I due modelli di regressione logistica differiscono in base al criterio di validazione: il primo impiega una suddivisione basata sul tempo (set di addestramento che copre il 2021–2022 e set di test per il 2023), mentre il secondo applica una suddivisione basata sull'azienda (set di addestramento con 84 aziende e set di test con le restanti 30, selezionate casualmente). Entrambi i modelli mostrano buone prestazioni predittive, con accuratezze complessive della classificazione rispettivamente del 96,49% e del 94,44%. I risultati suggeriscono che la regressione logistica rappresenta uno strumento appropriato per prevedere la continuità aziendale nel settore del lusso italiano, un settore caratterizzato da una combinazione distintiva di resilienza e vulnerabilità.

Keywords: business continuity; financial distress prediction; financial ratios; logistic regression; Italian luxury sector

1 – Introduction

Financial distress prediction is a central issue for researchers, investors, and individuals worldwide (Sura & Di Ventura, 2025; Wanke et al., 2015). In Italy, the number of business failures has changed significantly in recent years. Following the decline observed during the pandemic period, business bankruptcies increased in 2023, as evidenced by the data published by the Italian National Institute of Statistics (ISTAT, 2023). This confirms the need for effective tools to prevent and promptly manage corporate crises, in line with the proactive approach introduced by the Italian Code of Business Crisis and Insolvency, which came into force in 2022.

Consequently, having an accurate predictive model, which detects early signs of financial distress and prevents business crises, is essential for all firms. In recent decades, financial prediction analysis has undergone significant development, from univariate and multivariate discriminant analysis to logistic regression and artificial intelligence.

This study aims to develop two reliable models for predicting business continuity by leveraging specific financial indicators. The analysis was carried out on 114 Italian companies operating in the luxury sector, identified in the AIDA database and observed over the three-year period 2021–2023, for a total of 342 observations. The analysis focuses particularly on three key luxury subsectors: fashion, jewellery and watchmaking, and automotive.

The luxury sector, a key pillar of the Italian economy and a symbol of "Made in Italy" worldwide, experienced a transition phase during the three-year period under review.

In 2021, with the easing of post-pandemic restrictions, the fashion and luxury industries benefited from a burst of pent-up consumer demand accumulated during the lockdowns, achieving significant global revenue growth (McKinsey & Company, 2023). With 23 companies listed among the global Top 100, Italy confirmed its position as the leading country in terms of the number of major industry players (Deloitte, 2022).

In 2022, the sector once again showed its resilience (McKinsey & Company, 2024). The reopening of retail stores in most countries, the recovery of travel and tourism, and the rebound in consumer demand confirmed the strong health of the industry (Deloitte, 2023).

In 2023, however, the growth momentum of the luxury market slowed, influenced by persistent and mounting challenges. Troublesome inflation in many major economies led central banks to roll out back-to-back interest rate hikes, ending a lengthy period of ultra-low and even negative rates, in a bid to temper rising prices and help steer economies away from recession (McKinsey & Company, 2023). Europe and the United States experienced modest growth; Europe, in particular, was penalized by the energy crisis triggered by the war in Ukraine and by the weakening of the euro against the strong U.S. dollar (McKinsey & Company, 2023). China, meanwhile, after a solid start to the year, slowed in the second half due to new waves of Covid-19 and the resulting containment measures (McKinsey & Company, 2024).

Overall, the 2021–2023 period outlines a dynamic and robust sector, yet one exposed to macroeconomic and geopolitical challenges that test its adaptive capacity. This balance between resilience and vulnerability represents the most distinctive feature of the Italian luxury industry. The sector in fact is characterized by high profit margins, the central role of intangible assets (brand, creativity, know-how), and strong exposure to international markets. At the same time, the cyclical nature of luxury demand makes the sector both resilient, thanks to brand value and consumer loyalty, and vulnerable to rapid downturns when market conditions deteriorate. These characteristics make the sector particularly suitable for the development of business continuity prediction models, aimed at promptly identifying early signs of financial fragility and assessing firms' ability to maintain operational continuity over time.

In this context, the study adopts a quantitative approach based on logistic regression to build two business continuity prediction models: the first based on a time-based split of the dataset, and the second on an independent firm-level validation, to assess their predictive ability. The choice of logistic regression is consistent with previous studies that have demonstrated its effectiveness in predicting financial distress across different national contexts (Binh et al., 2020; Bulut & Şimşek, 2018; Tew & Nordin, 2006).

The rest of this paper is organized as follows: section 2 details the literature review; section 3 illustrates the data and the methodology adopted; section 4 discusses the empirical results obtained; finally, section 5 provides the conclusions of the research.

2. Literature Review

The existing literature on business continuity and bankruptcy risk prediction is extensive and multifaceted and has evolved over time through the progressive refinement of analytical methodologies.

One of the seminal studies that laid the foundation for bankruptcy prediction models was conducted by Beaver (1966). He employed univariate discriminant analysis on 30 financial ratios for 79 pairs of failed and non-failed firms, identifying the cash flow to total debt ratio as the most effective predictive indicator.

However, the development of bankruptcy prediction models gained particular attention with Altman's (1968) Z-score model, based on multivariate discriminant analysis (MDA). By examining the financial statements of 66 U.S. firms, Altman identified five key financial ratios — profitability, liquidity, solvency, leverage, and activity — capable of anticipating corporate failure.

Subsequent studies (Altman et al., 1998; Altman, 2013) confirmed the robustness of the Z-score model, suggesting adjustments for different economic sectors, economic contexts, and time periods. In line with this approach, other authors such as Deakin (1972), Grice and Ingram (2001), and Agarwal and Taffler (2007) proposed similar approaches to predict financial distress and bankruptcy.

Nevertheless, the MDA technique has been criticized for its restrictive assumptions regarding multivariate normality and the independence of explanatory variables (Ohlson, 1980). In response, Ohlson (1980) proposed a logit model based on nine accounting ratios, thereby introducing logistic regression as a new methodology for predicting the probability of default. Subsequently, Zmijewski (1984) employed probit regression analysis, developing a financial distress prediction model based on three variables: profitability, leverage, and liquidity.

In recent years, the development of artificial intelligence has led to the introduction of new methods — such as machine learning techniques, neural networks, and genetic algorithms — in financial prediction analysis. On the one hand, these methods can enhance predictive accuracy (Liang et al., 2016; Tian & Yu, 2017). On the other hand, they may limit the interpretability of results due to the complex nature of the analytical techniques employed (Laitinen & Laitinen, 2000).

Despite the extensive scientific production in the field of business continuity, the bankruptcy and business continuity prediction models proposed in the literature have been applied mainly to generic sectors such as manufacturing (Nair & Sachdeva, 2022; Rafiei et al., 2011), trading and services (Alifiah, 2014), and technology (Bulut & Şimşek, 2018).

In the luxury sector, the literature has paid increasing attention to themes such as strategy, sustainability, digitalization, brand awareness, and diversification (Garzia & Grampa, 2025; Moisello & Pellicelli, 2025). However, empirical evidence concerning the development and application of quantitative models for predicting business continuity specifically within this sector remains limited. The sector, in fact, exhibits structural and cyclical characteristics that make it particularly relevant for the study of business continuity.

Furthermore, the literature has paid limited attention to the Italian context, favouring empirical analyses of predictive models in other national markets, such as Belgium (Cultrera & Brédart, 2016), Iran (Rafiei et al., 2011), Kenya (Ogachi et al., 2020), Slovakia (Svabova et al., 2020), and Taiwan (Chi & Chu, 2021). This research therefore aims to fill this dual gap by developing specific models for Italian luxury firms, a sector characterized by a distinctive combination of resilience and vulnerability.

In addition, while previous studies typically rely on a single validation approach for predictive models, this study employs a combined time-based and firm-based validation to assess their predictive ability. This approach is particularly relevant in the post-COVID context, in which a more careful validation of models is required to ensure their accuracy (Hammond et al., 2023).

Considering the specific features of the sector and the challenges that emerged during the 2021–2023 period, this study proposes an innovative methodological approach, thereby contributing to the expansion of logistic regression applications in predicting business continuity.

Finally, the expected results may provide practical implications for various stakeholders — such as managers, investors, and financial institutions — in monitoring and preventing corporate crises.

Building on the evidence discussed in the literature, the following section presents the data and the methodology employed to develop the two prediction models.

3. Data and Methodology

The analysis is based on firms that, within the AIDA database (Analisi Informatizzata delle Aziende) provided by Bureau van Dijk, jointly satisfy the following criteria:

1. inclusion in the ATECO codes corresponding to the luxury fashion, jewellery and watchmaking, and automotive subsectors: 1411, 1413, 1414, 1419, 142, 143, 15, 2652, 2910 and 3212. These codes correspond respectively to: manufacture of leather apparel (1411), manufacture of other outerwear (1413), manufacture of underwear (1414), manufacture of other wearing apparel and accessories (1419), manufacture of articles of fur (142), manufacture of knitted and crocheted apparel (143), manufacture of leather and related products (15),

manufacture of watches and clocks (2652), manufacture of motor vehicles (2910), and manufacture of jewellery and related articles (3212);

2. active status;

3. the presence, in the business description, of at least one of the following keywords: *"luxury", "luxury brand", "high end", "premium", "exclusive" or "unique";*

4. availability of financial statements for the 2021–2023 period.

By jointly applying these requirements, the final dataset consists of 114 firms, for a total of 342 observations (a balanced panel over three fiscal years). The dataset thus defined does not represent a random sample of Italian firms operating in the luxury sector, but rather the set of firms that simultaneously meet the above-mentioned selection criteria.

Logit analysis, implemented using Stata 19.5, was employed to develop the two predictive models of business continuity. Logit analysis provides the probability of occurrence of an event (financial distress/ non-financial distress) described by a dichotomous dependent variable using coefficients of the independent variables. The logistic regression model is specified as follows:

$$P(Y_i = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}}$$

where:

a. $P(Y_i=1)$ = the probability of a company becoming financially distressed;
b. Y_i = the dependent variable; $Y_i = 1$ if the event occurs (a company is in financial
c. distress); $Y_i = 0$ if the event does not occur (a company is not in financial distress);
d. $X_1, X_2 \dots X_n$ = the independent variables;
e. β_0 = the intercept;
f. β_n = the regression coefficients of independent variables.

If the probability estimated by the model is greater than or equal to 0.5, the firm is classified as financially distressed; if it is lower than 0.5, the firm is classified as a going concern. On the other hand, negative coefficients in the logistic model reduce the probability of financial distress, while positive coefficients increase the probability of financial distress.

In this study, the use of a binary logit model is justified by the dichotomous nature of the dependent variable. The dependent variable used is business continuity and is coded as 0 when the firm is classified as a going concern and 1 when it is identified as distressed. It does not therefore represent an observed default event, but rather an operational criterion for distinguishing between going-concern and distressed firms, based on Altman's Z''-score (2013). This indicator, widely validated in the literature for predicting bankruptcy risk (Sura & Di Ventura, 2025), constitutes an adaptation of the original Z-score model for private firms. The index is calculated as:

$$Z'' = 6.56 \text{ WCTA} + 3.26 \text{ RETA} + 6.72 \text{ EBTA} + 1.05 \text{ VETL}$$

where:

a. Z'' is Z-score representing the going concern;
b. WCTA is defined as the net working capital divided by total assets;
c. RETA is the retained earnings divided by total assets;
d. EBTA is earnings before interest and taxes divided by total assets; and

e. VETL is the book value of equity over total liabilities.

After the computation, the results were grouped into two categories, according to Altman's thresholds:

(A) if Z''-score is higher than or equal to 2.6, the firm is classified as a going concern;

(B) if Z''-score is below 2.6, the firm is classified as distressed.

As indicated in Table 1, of the 342 observations, 146 were classified as distressed (Y=1), while the remaining 196 observations as going concern (Y=0), based on the computed Z''-score.

Table 1 – Classification of dependent variable (Source: Authors' own elaboration)

Status	Frequency	Percent (%)
Going concern (Y = 0)	196	57.3
Distressed (Y = 1)	146	42.7
Total	342	100

The independent variables used in the logistic regression analysis are:

1 – Current ratio

2 – Current assets/total assets

3 – Equity ratio

4 – Natural log of total assets

5 – Return on assets (ROA)

6 – Retained earnings/total assets

These variables, shown in Table 2, were selected based on their relevance in the business continuity literature and are categorized by financial indicator type.

Table 2 – Independent variables (Source: Authors' own elaboration)

Code	Variable	Grouping	Definition
X1	Current ratio	Liquidity ratio	Current assets/current liabilities
X2	Current assets/total assets	Asset structure ratio	Current assets/total assets
X3	Equity ratio	Capital structure ratio	Shareholders' equity/total assets
X4	Natural log of total assets	Size indicator	Ln (total assets)
X5	Return on assets (ROA)	Profitability ratio	EBIT/total assets
X6	Retained earnings/total assets	Solvency ratio	Retained earnings/total assets

In order to obtain unbiased and efficient parameters, the independent variables should not be multicollinear, meaning that there should be no perfect correlation between them (Chopra et al., 2020). To test the presence of multicollinearity, Pearson's correlation coefficients between the independent variables were calculated. As shown in the correlation matrix given in Table 3, none of the correlation coefficients exceed 0.7, indicating that there was no strong correlation among the independent variables.

Table 3 – Correlation matrix (Source: Authors' own elaboration based on Stata output))

Variables	Current ratio	Current assets/ total assets	Equity ratio	Natural log of total assets	ROA	Retained earnings/ total assets
Current ratio	1					
Current assets/total assets	-0.0298	1				
Equity ratio	0.3259	-0.1597	1			
Natural log of total assets	-0.0399	-0.3791	0.3329	1		
ROA	0.0875	0.2074	0.3483	-0.0471	1	
Retained earnings/ total assets	-0.3138	-0.0065	0.2344	0.1302	0.1635	1

Moreover, multicollinearity was checked with the help of tolerance and variance inflation factor (VIF). The tolerance denotes the percentage of variance in a given predictor that cannot be explained by the other independent variables, while VIF represents the reciprocal of the tolerance (Senaviratna & Cooray, 2019). The results reported in Table 4 show that VIFs are well under the suggested value of 10, with a mean VIF of 1.37, showing no issue of multicollinearity (Kianifard et al., 1990).

Table 4 – Collinearity statistics (Source: Authors' own elaboration based on Stata output)

Variable	VIF	1/VIF
Current ratio	1.40	0.714060
Current assets/total assets	1.24	0.805418
Equity ratio	1.69	0.590530
Natural log of total assets	1.33	0.749924
ROA	1.26	0.793522
Retained earnings/total assets	1.30	0.768508

Before proceeding with the estimation of the models, Table 5 reports the descriptive statistics for all the variables included in the logistic regression, showing for each explanatory variable the minimum and maximum values, the first quartile (Q1, 25th percentile), the second quartile (Q2, 50th percentile or median), the third quartile (Q3, 75th percentile), the mean, and the standard deviation.

Table 5 – Descriptive statistics of the independent variables (Source: Authors' own elaboration based on Stata output)

Variable	N	Min	Max	Q1	Q2	Q3	Mean	Std. Dev.
Current ratio	**342**	0.17	30.98	1.23	1.75	2.59	2.37	3.11
Current assets/total assets	**342**	0.16	1.00	0.58	0.74	0.87	0.71	0.20
Equity ratio	**342**	-0.10	0.90	0.18	0.37	0.57	0.38	0.24
Natural log of total assets	**342**	6.87	15.84	8.89	9.63	10.75	10.02	1.73
ROA	**342**	-0.95	0.56	0.01	0.05	0.13	0.06	0.15
Retained earnings/ total assets	**342**	-11.33	0.52	0.00	0.00	0.02	-0.13	1.20

The joint analysis of the mean, median, and quartiles allows for a more detailed examination of the variables' distribution and the identification of potential asymmetries or extreme values.

The current ratio exhibits a positively skewed distribution. The mean (2.37) exceeds the median (1.75), and the maximum value reaches 30.98, indicating the presence of high-value outliers that generate a long right tail and contribute to increase both the mean and the standard deviation (3.11).

The current assets/total assets ratio, by contrast, shows a relatively compact distribution around the median (0.74), with Q1 and Q3 ranging between 0.58 and 0.87, a mean of 0.71, and a limited standard deviation (0.20), suggesting a low dispersion of values.

The equity ratio displays a substantially symmetric distribution, with the median (0.37) very close to the mean (0.38) and quartiles (Q1 = 0.18; Q3 = 0.57) approximately equidistant from the central value.

The natural log of total assets presents a broadly balanced distribution, with a mean of 10.02 and quartiles (Q1 = 8.89; Q3 = 10.75) relatively close to the median (9.63).

ROA shows an approximately symmetric distribution in its central part, with a median of 0.05 very close to the mean (0.06), although some extreme negative values (min = -0.95) generate a slight left tail.

Finally, the retained earnings/total assets ratio exhibits a strongly left-skewed distribution. While Q1 and Q2 are equal to 0 and Q3 is equal to 0.02, the mean is negative (-0.13) due to the presence of a limited number of particularly negative outliers (min= -11.33), whereas the maximum value remains relatively limited (0.52).

Overall, the descriptive statistics reveal a degree of heterogeneity in the distribution of the financial indicators, with some variables characterized by asymmetries and extreme values. Since the explanatory variables are primarily expressed as financial ratios and, in one case, in logarithmic form, their scale and distribution may influence the magnitude of the estimated β coefficients in the logistic regression model.

All statistical analyses, including multicollinearity tests (Tables 3 and 4), logistic regression estimations (Tables 6 and 8), and the assessment of the models' predictive performance (Tables 7 and 9), were conducted using Stata software.

Based on the data and methodology described, the following section presents the results of the empirical analysis.

4. Results

To assess the ability of the logistic regression model to predict business continuity, two distinct models were developed: the first with a year-based data split and the second with a firm-based split. For the first model, the dataset consisting of 342 observations was divided into two samples: a training set and a test set. The 228 observations covering the years 2021 and 2022 were used to construct the training set, which was employed to estimate the logistic regression model. The remaining 114 observations, covering 2023, were selected to build the test set, which was used to evaluate the predictive accuracy of the model estimated on the training set. Splitting the dataset into training and test sets helps to mitigate the risk of overfitting. Overfitting occurs when the parameters fit the training data so well that noise and the peculiarities of the training data are memorized, but they do not fit an unknown (hold-out) sample well (Santos et al., 2009). As a result, the model's performance drops when it is tested in a hold-out sample.

The model was trained on the training set and subsequently validated on the test set. Table 6 presents the results of the logistic regression estimated on the training set. The findings include six predictor variables that contribute to the model. The logit analysis was conducted to evaluate the impact of independent variables on the probability that companies will be classified as either in business continuity or in financial distress.

The final model was statistically significant, with a chi-square value of 282.30, six degrees of freedom and $p < 0.005$. This indicates that the model was able to distinguish between distressed and non-distressed firms.

The variables current ratio, current assets/total assets, equity ratio, and ROA are significant at the 1% level, while natural log of total assets and retained earnings/total assets are significant at the 5% level.

The coefficients of current ratio, current assets/total assets, equity ratio, ROA and retained earnings/total assets are negative, indicating that an increase in these variables reduces the risk of financial distress. In contrast, the coefficient of the natural log of total assets is positive, suggesting that larger companies in the luxury sector are more exposed to the risk of financial distress, possibly due to more complex organizational structures or higher fixed costs.

The signs of the coefficient of each significant variable are consistent with economic-financial theory. Specifically, the negative coefficient of current ratio indicates that an increase in short-term liquidity reduces the probability of doubts arising about business continuity. The negative coefficient of current assets/total assets indicates that an increase in current assets reduces the probability of financial crisis.

Table 6 – Logistic regression results – time-based estimation model (Source: Authors' own elaboration based on Stata output)

Variable	β	Std. Err.	Z	p-value
Current ratio	-15.467	4.714	-3.28	0.001***
Current assets/total assets	-28.702	11.003	-2.61	0.009***
Equity ratio	-42.271	15.357	-2.75	0.006***
Natural log of total assets	1.342	0.547	2.45	0.014**
ROA	-68.250	22.978	-2.97	0.003***
Retained earnings/total assets	-29.162	12.113	-2.41	0.016**
Constant	48.550	17.138	2.83	0.005***
***statistically significant at 1% level. **statistically significant at 5% level.				

The equity ratio also shows a protective effect: as the incidence of equity capital on total assets increases, the risk of crisis decreases, confirming the importance of a solid capital structure. The positive coefficient of the natural log of total assets suggests, however, that larger companies in the luxury sector are more vulnerable to the risk of financial distress. Finally, ROA and retained earnings/total assets are negatively associated with the probability of being classified as distressed, highlighting the crucial role of profitability and self-financing in corporate resilience.

It is also observed that some estimated β coefficients appear numerically large. In the logistic model, the estimated coefficients measure the change in the logarithm of the ratio between the probability of financial distress and non-distress associated with a one-unit increase in the independent variables. Consequently, their magnitude may be influenced by the scale of the explanatory variables.

Based on Table 6, the logistic regression model can be expressed as shown below:

$$P\ (Y = 1) = \frac{1}{1 + e^{-(48.550 - 15.467\ X1 - 28.702\ X2 - 42.271\ X3 + 1.342\ X4 - 68.250\ X5 - 29.162\ X6)}}$$

where:

X1 – Current ratio

X2 – Current assets/total assets

X3 – Equity ratio

X4 – Natural log of total assets

X5 – Return on assets (ROA)

X6 – Retained earnings/total assets

If the calculated probability from the logit model is equal or greater than 0.5, the firm is classified as financially distressed, otherwise it is classified as a going concern.

After evaluating the model's performance on the training set, it was then tested on the test set, on which the predictions were made.

Table 7 below tabulates the percentage of correct classifications for the logistic model, calculated on the test set. It includes the confusion matrix, which summarizes the model's classification results:

- True Positives (TP): 45 distressed firms correctly identified as distressed
- True Negatives (TN): 65 going concern firms correctly identified as going concern
- False Positives (FP): 1 going concern firm incorrectly classified as distressed (Type I error, α)
- False Negatives (FN): 3 distressed firms incorrectly classified as going concern (Type II error, β)

Based on these values, standard classification metrics are calculated as follows:

- Accuracy = (TP + TN) / (TP + TN + FP + FN) = (45 + 65) / 114 = 96.49%
- Specificity (True Negative Rate) = TN / (TN + FP) = 65 / 66 = 98.48%
- Sensitivity (True Positive Rate) = TP / (TP + FN) = 45 / 48 = 93.75%

The model indicates good predictive performance, correctly classifying 96.49% of overall cases, also known as the percentage accuracy in the classification. Specifically, the model correctly classified 98.48% of going concern firms and 93.75% of distressed firms as such. However, the high accuracy observed should be interpreted considering the nature of the dependent variable, internally constructed using Altman's Z''-score. It should also be considered in relation to the scope defined by the selection criteria adopted in the AIDA database, which results in a relatively limited number of firms operating in the luxury sector.

Table 7 – Classification table – time-based model validation (Source: Authors' own elaboration based on Stata output)

Observed	**Predict**		**Percentage Correct (%)**
	0 (Going Concern)	1 (Distressed)	
0 (Going Concern)	65	1	98.48
1 (Distressed)	3	45	93.75
Overall Percentage			96.49

The results indicate that the time-based logistic model represents an appropriate tool for classifying firms as either distressed or non-distressed.

In Figure 1, the receiver operating characteristic (ROC) curve, which gauges the predictive ability of the logit model (Shrivastava et al., 2018), has also been plotted. The area under the curve (AUC) is equal to 97.66%, indicating that the model is able to distinguish between distressed and non-distressed companies. According to Hosmer and Lemeshow (2000), an AUC value above 0.90 indicates high discriminative accuracy, in line with the existing literature.

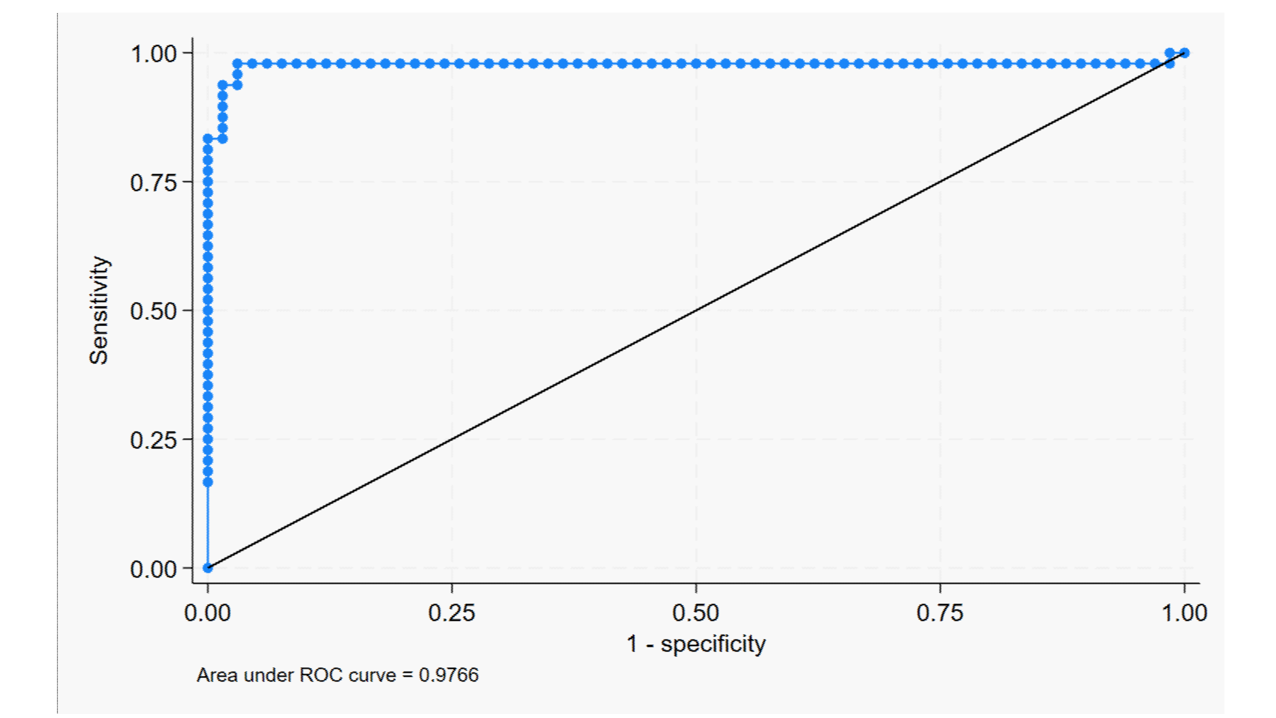

Fig. 1 – ROC Curve for the time-based model (Source: Stata)

Subsequently, to test the independence of the model, a test set was constructed not consisting of a full year of observations, but a subset of enterprises. Starting from the dataset including 114 firms, each observed over three years, 30 companies were randomly selected with all their respective observations (30 x 3 = 90) to be used as test set. The remaining 84 enterprises (114 – 30 = 84) with their respective observations (84 x 3 = 252) formed, instead, the training set.

The logistic regression model was estimated on the training set and then validated on the independent test set to evaluate the predictive capacity of the model on a data subset not influenced by the time structure of the data.

The results of the logistic regression estimated on the new training set are reported in Table 8. In this configuration as well, in line with the time-based model, the results confirm the statistical significance of the explanatory variables and the stability of the coefficient signs in determining the probability of financial distress.

The final model was statistically significant, with a chi-square value of 314.69, six degrees of freedom and $p < 0.005$.

All six predictive variables are significant at the 1% level. The current ratio, the current assets/total assets, the equity ratio, the ROA and the retained earnings/total assets have negative coefficients, consistently with what emerged in the previous model. This indicates that an increase in these indicators reduces the likelihood of financial difficulties. The natural log of total assets, however, maintains a positive coefficient, suggesting that even in this test the largest companies in the luxury sector show higher exposure to risk.

In this case as well, some β coefficients appear numerically large. However, their magnitude should be interpreted in light of the scale of the explanatory variables, as discussed in the previous model.

Table 8 – Logistic regression results – firm-level estimation model (Source: Authors' own elaboration based on Stata output)

Variable	β	Std. Err.	Z	p-value
Current ratio	-12.070	3.508	-3.44	0.001***
Current assets/total assets	-24.108	8.049	-3.00	0.003***
Equity ratio	-38.439	12.612	-3.05	0.002***
Natural log of total assets	1.214	0.414	2.93	0.003***
ROA	-53.313	18.312	-2.91	0.004***
Retained earnings/total assets	-34.290	9.881	-3.47	0.001***
Constant	39.598	12.884	3.07	0.002***
***statistically significant at 1% level.				

The results show consistency in the estimated coefficients even when the logistic model is tested on an independent test set constructed on a firm-based rather than time-based split, suggesting the relevance of the selected predictors of business continuity.

Table 9 below tabulates the percentage of correct classifications for the logistic model, calculated on the independent test set. It includes the confusion matrix, which summarizes the model's classification results:

- True Positives (TP): 39 distressed firms correctly identified as distressed
- True Negatives (TN): 46 going concern firms correctly identified as going concern
- False Positives (FP): 2 going concern firms incorrectly classified as distressed (Type I error, α)
- False Negatives (FN): 3 distressed firms incorrectly classified as going concern (Type II error, β)
- Based on these values, standard classification metrics are calculated as follows:
- Accuracy = (TP + TN) / (TP + TN + FP + FN) = (39 + 46) / 90 = 94.44%
- Specificity (True Negative Rate) = TN / (TN + FP) = 46 / 48 = 95.83%
- Sensitivity (True Positive Rate) = TP / (TP + FN) = 39 / 42 = 92.86%

The model correctly classified 94.44% of overall cases. Specifically, the model correctly classified 95.83% of going concern firms and 92.86% of distressed firms as such. Also in this case, the observed accuracy should be interpreted within the previously outlined methodological framework, relating to the nature of the dependent variable and the relatively limited number of firms analyzed.

The results suggest good discriminative ability of the firm-level validation model, enabling it to distinguish business continuity firms from distressed firms, even when applied to an independent test set distinct from the estimation phase.

Overall, the results obtained from the two models suggest that logistic regression represents an appropriate tool for predicting business continuity in the Italian luxury sector, providing insights for the study's conclusions and the related implications discussed in the following section.

Table 9. Classification Table – firm-based model validation (Source: Authors' own elaboration based on Stata output)

Observed	**Predict**		**Percentage Correct (%)**
	0 (Going Concern)	1 (Distressed)	
0 (Going Concern)	46	2	95.83
1 (Distressed)	3	39	92.86
Overall Percentage			94.44

5 – Conclusion

This paper proposes two predictive models for business continuity, thereby contributing to the analysis of the Italian luxury sector. The luxury sector represents a particularly relevant context for the analysis of firms' financial soundness, due to its economic relevance and structural characteristics that make it particularly suitable for the development of predictive models. Models based on specific financial ratios can, in fact, play a fundamental role in supporting business continuity, enabling firms to adopt preventive financial measures.

The analysis is based on 114 Italian firms operating in the fashion, jewellery and watchmaking, and automotive luxury subsectors, observed over the three-year period 2021–2023 (342 observations).

To mitigate the risk of overfitting, the dataset was divided into two groups: a training set, used to estimate the model, and a test set, used to evaluate its performance. The two predictive models of business continuity developed in this study differ in the criterion used to split the dataset:

1) a time-based model, in which the training set includes data from 2021–2022 and the test set comprises data from 2023;

2) a firm-based model, in which the training set includes 84 companies and the test set comprises the remaining 30, randomly selected.

Both models, through logistic regression, estimate the probability of financial distress as a function of the same six explanatory variables: current ratio, current assets/total assets, equity ratio, natural log of total assets, ROA, and retained earnings/total assets. The estimated coefficients show consistent signs across the two models: five variables — current ratio, current assets/total assets, equity ratio, ROA, and retained earnings/total assets — have negative β coefficients, indicating that higher values reduce the likelihood of financial distress. Conversely, the natural log of total assets exhibits a positive β coefficient, suggesting that, within the luxury sector, larger firms may be more exposed to financial difficulties, possibly due to more complex organizational structures.

Both the time-based and the firm-based validation models show good predictive performance, with overall classification accuracies of 96.49% and 94.44%, respectively, considering the relatively limited number of firms analyzed in the luxury sector.

The combined use of two approaches, time-based and firm-based, highlights the ability of logistic regression to predict business continuity in the luxury sector, a sector characterized by a distinctive combination of resilience and vulnerability. These results are consistent with the dynamics observed during the 2021–2023 period, when the Italian luxury sector demonstrated a remarkable ability to adapt in the face of significant macroeconomic and geopolitical challenges (Deloitte, 2022, 2023; McKinsey & Company, 2023, 2024). The evidence obtained further suggests that the estimated models may be useful to various stakeholders such as policymakers, financial institutions, creditors, managers, bankers, investors, and shareholders. They can promptly identify signs of financial fragility and the most financially vulnerable firms in the luxury sector, thereby facilitating timely corrective actions and recovery strategies.

Based on the analyses carried out, the developed models represent an appropriate tool for predicting business continuity in the Italian luxury sector and provide insights for further methodological developments and practical applications, while requiring careful consideration of the study's limitations.

6 – Limitations and Future Developments

The results of this study and the related implications should be interpreted in light of their limitations, as well as future development perspectives.

First, the analysis is based on a relatively limited number of firms, reflecting the structural size of the Italian luxury sector and the scope defined by the selection criteria applied within the AIDA database. In this perspective, further research could intervene along two main directions. On the one hand, expanding the dataset—both in terms of the number of firms and the time horizon— would allow for a deeper analysis and a further examination of the results obtained. On the other hand, the inclusion of additional financial and non-financial variables (such as governance, sectoral, or macroeconomic variables) could help deepen the determinants of business continuity in the luxury sector and enhance the explanatory power of the models.

Second, the dependent variable is internally constructed based on Altman's Z''-score and represents an operational classification criterion distinguishing going-concern from distressed firms. Although the Z''-score constitutes a benchmark widely used in the literature for measuring financial distress, its construction based on financial indicators may influence the evaluation of predictive performance. In this regard, future research could adopt alternative definitions of business continuity.

Third, given the dichotomous nature of the dependent variable, the analysis adopted logistic regression as the reference methodology. However, future research could explore the use of alternative or more advanced methods to compare predictive performance across different application contexts. For example, Samara and Shinde (2025) show that machine learning models, particularly random forest and neural networks, can improve prediction accuracy compared to traditional statistical approaches, such as logistic regression.

Fourth, the group of going-concern firms was not matched with the group of distressed firms, which may have influenced the classification performance of the model.

Finally, the study focuses on the luxury sector within the Italian context. Therefore, further research could extend the analysis to other sectors and countries. In particular, cross-country analyses could help verify the robustness and transferability of the model across different institutional and economic environments.

6 – References

Agarwal, V., & Taffler, R. J. (2007). Twenty-five years of the Taffler z-score model: Does it really have predictive ability? *Accounting and Business Research*, *37*(4), 285–300. DOI: https://doi.org/10.1080/00014788.2007.9663313

Alifiah, M. N. (2014). Prediction of financial distress companies in the trading and services sector in Malaysia using macroeconomic variables. *Procedia - Social and Behavioral Sciences*, *129*, 90–98. DOI: https://doi.org/10.1016/j.sbspro.2014.03.652

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589–609. DOI: https://doi.org/10.2307/2978933

Altman, E. I. (2013). Predicting financial distress of companies: Revisiting the Z-score and ZETA® models. In Bell A. R., Brooks C., & Prokopczuk M. (Eds.), *Handbook of Research Methods and Applications in Empirical Finance* (pp. 428-456). Edward Elgar Publishing. DOI: https://doi.org/10.4337/9780857936080.00027

Altman, E.I., Hartzell, J., & Peck, M. (1998). Emerging market corporate bonds — a scoring system. In Levich, R. M. (Ed.), *Emerging Market Capital Flows* (pp. 391–400). Springer, Boston, MA. DOI: https://doi.org/10.1007/978-1-4615-6197-2_25

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

Binh, D. T. T., Loan, B. T. T., & Anh, V. T. K. (2020). The application of the logistic model in analyzing the risk of bankruptcy of Small and medium Enterprises (SMEs): a case study. *Academy of Accounting and Financial Studies Journal*, *24*(3).

Bulut, E., & ŞïMşek, A. İ. (2018). Financial failure estimation with logistic regression model: A study on technology sector companies treated in BIST (ICEESS' 18). *Anemon Muş Alparslan Üniversitesi Sosyal Bilimler Dergisi*, *6*, 177–183. DOI: https://doi.org/10.18506/anemon.452622

Chi, D., & Chu, C. (2021). Artificial intelligence in corporate sustainability: Using LSTM and GRU for going concern prediction. *Sustainability*, *13*(21), 11631. DOI: https://doi.org/10.3390/su132111631

Chopra, A., Bansal, A., & Wadhwa, A. (2020). Evidence of predicting early signs of corporate bankruptcy using financial ratios in the Indian landscape. *arXiv*. DOI: https://doi.org/10.48550/arxiv.2008.04782

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

Deakin, E. B. (1972). A discriminant analysis of predictors of business failure. *Journal of Accounting Research*, *10*(1), 167–179. DOI: https://doi.org/10.2307/2490225

Deloitte. (2022). *Global powers of luxury goods 2022: A new wave of enthusiasm in luxury*. Retrieved from: https://www.deloitte.com/it/it/industries/consumer/analysis/2022-global-powers-luxury-goods.html

Deloitte. (2023). *Global powers of luxury goods 2023: Game-changing steps in luxury*. Retrieved from: https://www.deloitte.com/global/en/industries/consumer/analysis/gx-cb-global-powers-of-luxury-goods.html

Garzia, C., & Grampa, D. (2024). Food experience and brand awareness consolidation in the luxury industry. *Economia Aziendale Online*, *16*(2), 661–674. DOI: 10.13132/2038-5498/16.2.661-674

Grice, J. S., & Ingram, R. W. (2001). Tests of the generalizability of Altman's bankruptcy prediction model. *Journal of Business Research*, *54*(1), 53–61. DOI: https://doi.org/10.1016/s0148-2963(00)00126-0

Hammond, P., Opoku, M. O., Kwakwa, P. A., & Berko, D. (2023). Comparison of going concern models with and without corporate governance. *Cogent Business & Management*, *10*(2). DOI: https://doi.org/10.1080/23311975.2023.2234152

Hosmer, D. W., & Lemeshow, S. (2000). *Applied Logistic Regression* (2nd ed.). Wiley. DOI: https://doi.org/10.1002/0471722146

ISTAT. (2023). *Registrazioni e fallimenti di imprese* [Business registrations and bankruptcies]. Retrieved from: https://www.istat.it/wp-content/uploads/2023/11/fallimenti-imprese-IIItrim2023.pdf

Kianifard, F., Neter, J., Wasserman, W., & Kutner, M. H. (1990). Applied linear regression models. *Technometrics*, *32*(3), 352–353. DOI: https://doi.org/10.2307/1269127

Laitinen, E. K., & Laitinen, T. (2000). Bankruptcy prediction. *International Review of Financial Analysis*, *9*(4), 327–349. DOI: https://doi.org/10.1016/s1057-5219(00)00039-9

Liang, D., Lu, C., Tsai, C., & Shih, G. (2016). Financial ratios and corporate governance indicators in bankruptcy prediction: A comprehensive study. *European Journal of Operational Research*, *252*(2), 561–572. DOI: https://doi.org/10.1016/j.ejor.2016.01.012

McKinsey & Company. (2023). *The state of fashion 2023: Resilience in the face of uncertainty.* Retrieved from: https://www.mckinsey.com/~/media/mckinsey/industries/retail/our%20insights/state%20of%20fashion/2023/the-state-of-fashion-2023-holding-onto-growth-as-global-clouds-gathers-vf.pdf

McKinsey & Company. (2024). *The state of fashion 2024: Finding pockets of growth as uncertainty reigns.* Retrieved from: https://www.mckinsey.com/industries/retail/our-insights/state-of-fashion-2024

Moisello, A. M. & Pellicelli, M. (2025). Sustainable Innovation and Digitalization in Luxury Brand Management. *Economia Aziendale Online*, *16*(2), 389–412. DOI: 10.13132/2038-5498/16.2.389-412

Nair, J., & Sachdeva, J.K. (2022). Predictive modelling for financial distress amongst manufacturing companies in India. *Journal of Global Economy*, *18* (4), 261-276. DOI: 10.1956/jge.v18i4.665

Ogachi, D., Ndege, R., Gaturu, P., & Zoltan, Z. (2020). Corporate bankruptcy prediction model, a special focus on listed companies in Kenya. *Journal of Risk and Financial Management*, *13*(3), 47. DOI: https://doi.org/10.3390/jrfm13030047

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, *18*(1), 109–131. DOI: https://doi.org/10.2307/2490395

Rafiei, F. M., Manzari, S., & Bostanian, S. (2011). Financial health prediction models using artificial neural networks, genetic algorithm and multivariate discriminant analysis: Iranian evidence. *Expert Systems With Applications*, *38*(8), 10210–10217. DOI: https://doi.org/10.1016/j.eswa.2011.02.082

Samara, K., & Shinde, A. (2025). Bankruptcy prediction using machine learning and data preprocessing techniques. *Analytics*, *4*(3), 22. DOI: https://doi.org/10.3390/analytics4030022

Santos, E. M. D., Sabourin, R., & Maupin, P. (2009). Overfitting cautious selection of classifier ensembles with genetic algorithms. *Information Fusion*, *10*(2), 150–162. DOI: https://doi.org/10.1016/j.inffus.2008.11.003

Senaviratna, N. a. M. R., & Cooray, T. M. J. A. (2019). Diagnosing multicollinearity of logistic regression model. *Asian Journal of Probability and Statistics*, 1–9. DOI: https://doi.org/10.9734/ajpas/2019/v5i230132

Shrivastava, A., Kumar, K., & Kumar, N. (2018). Business distress prediction using Bayesian logistic Model for Indian firms. *Risks*, *6*(4), 113. DOI: https://doi.org/10.3390/risks6040113

Sura, A., & Di Ventura, E. (2025). The predictive limit of Beta in the corporate default risk. *Economia Aziendale Online*, *16*(3), 921–932. DOI: 10.13132/2038-5498/16.3.921-932

Svabova, L., Michalkova, L., Durica, M., & Nica, E. (2020). Business failure prediction for Slovak small and medium-sized companies. *Sustainability*, *12*(11), 4572. DOI: https://doi.org/10.3390/su12114572

Tew, Y. H., & Nordin, E. (2006). Predicting corporate financial distress using logistic regression: Malaysian evidence. *Social and Management Research Journal*, *3*(1), 123–132. DOI: https://doi.org/10.24191/smrj.v3i1.5108

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

Wanke, P., Barros, C. P., & Faria, J. R. (2015). Financial distress drivers in Brazilian banks: A dynamic slacks approach. *European Journal of Operational Research*, *240*(1), 258–268. DOI: https://doi.org/10.1016/j.ejor.2014.06.044

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