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The predictive limit of Beta in the corporate default risk

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ABSTRACT

This study investigates the relationship between market beta and corporate default risk, measured using Altman's Z-Score. The objective is to determine whether beta - commonly used as a proxy for systemic risk - can serve as a reliable predictor of financial fragility at the firm level. The analysis is based on a panel of 510 observations of Italian companies over the period 2019–2023. Several econometric approaches are employed, including panel data models (Pooled OLS, Fixed Effects, First Differences), parametric and non-parametric Generalised Additive Models (GAM), and LASSO regression for automatic variable selection. The independent variables include beta and a set of accounting indicators (ROE, leverage, interest coverage, net margin, asset turnover, current ratio). The Z-Score is used as a continuous dependent variable to capture default risk. Across all model specifications, beta is consistently found to be statistically insignificant. Its contribution remains null or negligible even in non-linear and penalised models. In contrast, all accounting variables display strong, stable, and significant relationships with the Z-Score, underscoring their superior predictive power. The findings indicate that market beta is not a useful metric for estimating corporate default risk. This suggests a clear empirical separation between systemic risk and firm-level financial fragility. The evidence reinforces the reliability of accounting-based indicators in assessing default probability and highlights the limitations of using beta outside the theoretical scope of the CAPM.

Questo studio indaga la relazione tra beta di mercato e rischio di default aziendale, misurata utilizzando lo Z-Score di Altman. L'obiettivo è determinare se il beta, comunemente utilizzato come proxy del rischio sistemico, possa fungere da predittore affidabile della fragilità finanziaria a livello aziendale. L'analisi si basa su un panel di 510 osservazioni di aziende italiane nel periodo 2019-2023. Vengono impiegati diversi approcci econometrici, tra cui modelli di dati panel (Pooled OLS, Effetti fissi, Prime differenze), modelli additivi generalizzati (GAM) parametrici e non parametrici e regressione LASSO per la selezione automatica delle variabili. Le variabili indipendenti includono il beta e una serie di indicatori contabili (ROE, leva finanziaria, copertura degli interessi, margine netto, rotazione degli asset, current ratio). Lo Z-Score viene utilizzato come variabile dipendente continua per catturare il rischio di insolvenza. In tutte le specifiche del modello, la versione beta risulta essere statisticamente insignificante. Il suo contributo rimane nullo o trascurabile anche nei modelli non lineari e penalizzati. Al contrario, tutte le variabili contabili mostrano relazioni forti, stabili e significative con lo Z-Score, sottolineando il loro superiore potere predittivo. I risultati indicano che il beta di mercato non è una metrica utile per stimare il rischio di default aziendale. Ciò suggerisce una chiara separazione empirica tra rischio sistemico e fragilità finanziaria a livello aziendale. L'evidenza rafforza l'affidabilità degli indicatori basati sulla contabilità nella valutazione della probabilità di default ed evidenzia i limiti dell'uso del beta al di fuori dell'ambito teorico del CAPM.

Keywords: Beta, Z-Score, default risk, panel regression, GAM, LASSO, fundamentals of the firms, CAPM

1 – Introduction

Predicting corporate bankruptcy risk is a central issue for scholars, investors and regulators. Since the formulation of the Z-Score by Altman (1968), the literature has identified accounting data as an effective tool for identifying signs of financial fragility. Subsequent models, such as Ohlson's logit (1980) and Zmijewski's probit (1984), confirmed the informative value of indicators such as profitability, financial leverage, liquidity and asset turnover (Beaver et al., 2005; Agarwal & Taffler, 2008).

At the same time, financial theory developed tools to measure market risk, first and foremost beta, introduced in the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965). Beta measures the sensitivity of a security's return to market movements and is commonly used in estimating the cost of capital (Fama & French, 1992). French, 1992). However, in practical contexts, beta is sometimes extended — arguably — to the assessment of corporate default risk, based on the assumption that greater volatility relative to the market is associated with greater financial instability (Chen et al., 1986).

This extension is methodologically fragile: beta only reflects comovariance with the market and does not consider structural factors such as operating profitability or indebtedness. Studies such as those by Roll (1977), Campbell et al. (2008) and Bali et al. (2009) show that beta has little or no significance in predicting corporate insolvency. In contrast, empirical evidence favours hybrid or purely accounting models.

In light of this, this study aims to critically assess the contribution of market beta in predicting corporate financial fragility, measured using the Z-Score, considering a broad set of accounting variables.

To achieve this objective, a comprehensive and methodologically rigorous empirical strategy is adopted. The analysis is based on fixed and random effects panel models, accompanied by pooled OLS regression, using the Hausman test to select the most appropriate structure. All these models, including the first difference model and both parametric and non-parametric GAM specifications, are estimated using Driscoll-Kraay corrected standard errors to account for heteroscedasticity, serial autocorrelation and cross-sectional dependence. Finally, a LASSO regression is estimated to automatically select the most relevant variables. This multiplicity of approaches allows for a robust assessment of the role of beta in predicting the financial vulnerability of firms.

The paper is organised as follows: Section 2 provides a review of the literature; Section 3 describes the sample, variables and methodologies used; Section 4 presents the empirical results; Section 5 concludes with a discussion of the theoretical and managerial implications, limitations and future research prospects.

2 – Literature review

The literature on insolvency risk has historically favoured the use of accounting variables, which are considered more stable and directly linked to the economic and financial performance of companies. Models such as those proposed by Altman (1968), Ohlson (1980) and Zmijewski (1984) are based on measures of profitability, liquidity and financial leverage and have been widely validated as reliable and reliable te predictors of corporate default (Beaver et al., 2005; Agarwal & Taffler, 2008). This line of research has also been consolidated in more recent applications, where Altman's Z-Score continues to represent a benchmark for measuring financial fragility.

At the same time, classical finance has promoted the use of **market beta** as a synthetic measure of systemic risk. Introduced by Sharpe (1964) in the Capital Asset Pricing Model (CAPM) and subsequently expanded by Fama and French (1992, 2004), beta expresses the sensitivity of a security's return to the market as a whole. However, several authors have criticised the empirical robustness of beta, raising doubts about its predictive effectiveness. Roll (1977) pointed out that the estimation of beta depends heavily on the choice of market index, making it unstable and theoretically fragile. Gangemi et al. (1999) documented beta's tendency to regress towards the mean over time, while Black, Jensen and Scholes (1972) challenged the linearity of the risk-return relationship predicted by the CAPM. From an applied perspective, Campbell, Hilscher and Szilagyi (2008) and Bharath and Shumway (2008) demonstrate that the information contained in beta is already reflected in accounting variables and that its contribution to default prediction is marginal or insignificant.

More recently, the literature has sought to improve the predictive power of beta through alternative approaches. Among these, we note the introduction of the so-called fundamental beta, estimated not from historical market series but from structural characteristics of the company (Rosenberg & Guy, 1976; Rosenberg & Guy, 1995; Di Ventura & De Luca, 2025). However, even in this case, empirical evidence does not seem to attribute to beta a greater explanatory power than traditional balance sheet indicators.

In light of this debate, this study aims to re-examine the role of beta in predicting financial fragility, with a particular focus on its significance after controlling for accounting fundamentals. This gives rise to the first research hypothesis**:**

> **H1.** *Market beta is significantly associated with the financial fragility of companies, measured using the Z-Score, even after controlling for accounting fundamentals.*

However, assuming a linear relationship between beta and risk may be an oversimplification. Recent studies, such as Wood (2017), have shown that the links between financial variables can be non-linear and subject to discontinuities, thresholds or non-constant marginal effects. Shumway (2001) and Chava and Jarrow (2004) show that the impact of market risk can vary depending on the sectoral context and company conditions, while Duffie, Saita and Wang (2007) propose dynamic approaches that capture more complex variations in risk. Furthermore, Gray, Merton and Bodie (2007) emphasise the importance of considering more complex interactions between market risk and financial structure, which often escape linear analysis.

This leads to the second research hypothesis**:**

> **H2.** *The relationship between beta and financial fragility is not linearly monotonic, but has non-linear components that can be detected using non-parametric models.*

This hypothesis is part of a growing body of research that adopts flexible statistical tools, such as Generalised Additive Models (GAMs), to explore the financial behaviour of companies in a more realistic way. This study therefore contributes to the existing literature by verifying both the significance of beta and the nature - linear or non-linear - of its relationship with corporate vulnerability.

3 – Methodology

The empirical analysis aims to verify whether systematic market risk, represented by beta, is a valid predictor of corporate financial fragility, measured using Altman's Z-Score (1968). The dataset used is a balanced panel of Italian companies in the period 2019-2023, consisting of 510 observations in total.

3.1 – *Variables*

3.1.1 – Dependent variable

The dependent variable is Altman's Z-Score (1968), a widely validated indicator in the literature for predicting bankruptcy risk. It summarises five key accounting indicators relating to profitability, leverage, liquidity and efficiency.

3.1.2 – Main variable of interest

The key explanatory variable is market beta, understood as a measure of the sensitivity of a stock's return to movements in the overall market. The data was extracted directly from the Orbis – Bureau van Dijk database, based on the Milan Index, in line with the geographical and sectoral context of the sample. Beta is commonly used as a proxy for systematic risk and, although traditionally used in estimating the cost of capital, is sometimes extended to the assessment of corporate financial stability.

3.1.3 – Control variables

The model includes the main accounting fundamentals as control variables extracted from the Orbis – Bureau van Dijk database, in line with the literature on default prediction (Ohlson, 1980; Zmijewski, 1984; Agarwal & Taffler, 2008). The variables used are: ROE, Leverage, Net_Margin, Interest_Coverage, Current_Ratio and Asset_Turnover. All variables have been winsorised at the 2nd and 98th percentiles to reduce distortion from outliers.

3.2 – *Econometric models*

3.2.1 – Static panel models

Following the approach suggested by Wooldridge (2010), the initial strategy involves estimating Pooled OLS, fixed effects (FE) and random effects (RE) models. The Pooled OLS treats the data as a simple regression ignoring the panel structure, while the FE and RE models explicitly take into account the differences between firms and over time. The Hausman test is used to determine the most appropriate model. Standard errors are corrected according to the Driscoll-Kraay procedure (Driscoll & Kraay, 1998), which provides robust estimates even when the data present heteroscedasticity (unequal variability of errors), serial autocorrelation (dependence over time within the same firm) and cross-sectional dependence (correlation between firms). This correction makes the inference more reliable in applied economic and financial contexts (Hoechle, 2007).

$$Z - SCORE = \beta_0 + \beta_1 BETA + \beta_2 ROE + \beta_3 LEVERAGE + \beta_4 NET\_MARGIN + \beta_5 INTEREST\_COV + \beta_6 CURRENT\_RATIO + \beta_7 ASSET\_TURNOVER + Years + Industry + \varepsilon_i$$

3.2.2 – First difference model

To eliminate the influence of unobservable, time-invariant characteristics, a first difference (FD) model is also estimated, in accordance with the methodological recommendations of Wooldridge (2010). In practice, this approach focuses on the variation of variables over time within each firm, removing the effect of constant features such as sectoral affiliation or managerial style that could bias the estimates. The estimate is corrected with Driscoll-Kraay errors, as in the previous specifications.

$$\Delta Z - SCORE = \beta_0 + \beta_1 \Delta BETA + \beta_2 \Delta ROE + \beta_3 \Delta LEVERAGE + \beta_4 \Delta NET\_MARGIN + \beta_5 \Delta INTEREST\_COV + \beta_6 \Delta CURRENT\_RATIO + \beta_7 \Delta ASSET\_TURNOVER + Years + Industry + \varepsilon_i$$

3.2.3 – GAM models

To explore the possible non-linearity of the relationship between beta and financial fragility, Generalised Additive Models (GAM) are used. These models are more flexible than traditional regressions, as they allow the data to "speak" without imposing a rigid functional form. Two specifications are estimated: a parametric one, which preserves linearity for all covariates, and a non-parametric one, in which each variable is modelled using penalised splines. Splines are smooth curves that adapt to the shape of the data, making it possible to detect threshold effects, discontinuities or other complex patterns in the relationship between variables. The approach follows the methodological proposal of Wood (2017), who shows how GAMs can capture hidden non-linearities in economic and financial data that linear models may overlook.

Model 1

$$Z - SCORE = \beta_0 + \beta_1 BETA + \beta_2 ROE + \beta_3 LEVERAGE + \beta_4 NET\_MARGIN + \beta_5 INTEREST\_COV + \beta_6 CURRENT\_RATIO + \beta_7 ASSET\_TURNOVER + Years + Industry + \varepsilon_i$$

Model 2

$$Z - SCORE = \beta_0 + \beta_1 s(BETA) + \beta_2 s(ROE) + \beta_3 s(LEVERAGE) + \beta_4 s(NET\_MARGIN) + \beta_5 s(INTEREST\_COV) + \beta_6 s(CURRENT\_RATIO) + \beta_7 s(ASSET\_TURNOVER) + Years + Industry + \varepsilon_i$$

This formulation allows us to verify whether the beta effect manifests itself in a non-linear, discontinuous or threshold-dependent form, improving the explanatory power of the model.

All models are estimated on a data frame free of outliers, filtered using interquartile thresholds (IQR) at the 2nd and 98th percentiles.

3.2.4 – LASSO regression

To complete the analysis, a LASSO regression is estimated, which allows the most relevant accounting variables for explaining the Z-Score to be automatically identified. This method introduces a penalty that reduces the weight of less important variables, effectively performing variable selection and avoiding overfitting.

The lambda penalty parameter is selected through 10-fold cross-validation, a procedure that repeatedly divides the sample into training and validation sets to find the value of lambda that minimises prediction error while keeping the model simple and interpretable. (Tibshirani, 1996; Belloni et al., 2014).

4 – Results

4.1 – *Descriptive statistics*

The descriptive statistics (Table 1) provide an initial summary of the variables used in the model. The Z-Score, used as a proxy for the risk of failure, has a mean value of 1.68, with a standard deviation of 0.78, indicating a moderately dispersed and asymmetric distribution. Beta, the central variable of interest, takes values between -0.02 and 1.09, with an average of 0.49, consistent with average or below-average levels of volatility.

The main balance sheet indicators show considerable heterogeneity: ROE has an average of 7.58% but a high standard deviation (12.92%), indicating a wide dispersion in profitability levels. Average leverage is 3.06, while the current ratio stands at 1.55. Asset turnover averages 0.72, suggesting reasonable operating efficiency.

Table 1 – Descriptive statistics (*Source*: Authors' elaboration)

Variables	No	Mean	Sd	Min	Max	Pctl(25)	Pctl(75)	Median
NET_MERGIN	510	1.68	0.78	0.03	5.02	1.12	2.09	1.58
INTEREST_COV	510	0.49	0.27	-0.02	1.09	0.29	0.70	0.46
CURRENT_RATIO	510	7.58	12.92	-59.77	35.43	2.43	14.30	8.34
ASSET_TURNOVER	510	3.06	1.63	1.23	10.89	2.01	3.59	2.59
NET_MERGIN	510	4.88	9.27	-56.49	45.54	1.31	8.65	4.05
INTEREST_COV	510	6.70	14.06	-43.25	97.52	1.32	8.71	3.73
CURRENT_RATIO	510	1.55	0.74	0.50	5.16	1.06	1.88	1.36
ASSET_TURNOVER	510	0.72	0.34	0.11	2.17	0.49	0.90	0.70

4.2 – *Correlation matrix*

The correlation matrix (Table 2) shows no significant relationship between Beta and Z-Score, with a correlation of -0.065, which is not statistically significant. On the contrary, there are significant correlations between Z-Score and key balance sheet variables, such as ROE (0.407), financial leverage (-0.467), the current ratio (0.632) and asset turnover (0.440), consistent with the hypothesis that the probability of failure is more closely linked to the accounting structure of the company than to measures of market volatility.

Table 2 – Correlation matrix (*Source*: Authors' elaboration)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Z-SCORE (1)	1							
BETA (2)	-0.065	1						
ROE (3)	0.407	0.112	1					
LEVERAGE (4)	-0.467***	0.191	-0.060	1				
NET_MERGIN (5)	0.331***	0.016	0.735	-0.173***	1			
INTEREST_COV (6)	0.447	-0.047	0.363	-0.174***	0.325***	1		
CURRENT_RATIO (7)	0.632***	-0.107*	0.136**	-0.442***	0.202	0.262***	1	
ASSET_TURNOVER (8)	0.440	0.046	0.127	0.141	-0.125**	0.120***	-0.035	1
Note(s): * *ρ < 0.10; ** ρ < 0.05; *** ρ < 0.01*								

4.3 – *Static panel models and parametric GAM*

The results of the linear regressions presented in Table 3 consistently show that Beta is never statistically significant in predicting the Z-Score, regardless of the specification adopted. In the Fixed Effects, Pooled OLS, parametric GAM and first differences models, the Beta coefficient varies between 0.013 and 0.223, but with p-values always above the 10% significance threshold. On the contrary, all the main accounting variables are significant and have the expected signs: ROE, net margin, interest coverage, current ratio and asset turnover show a positive and significant relationship with the Z-Score, while leverage is negatively and significantly correlated with bankruptcy risk. The validity of the model is confirmed by R^2 values ranging from 0.641 to 0.778.

Table 3 – Regression results (*Source*: Authors' elaboration)

Variables	*Fixed Effects (FE)*	*Pooled OLS*	*GAM -Parametric Part*	*First Difference Model*
BETA	0.223 (0.145)	0.013 (0.034)	0.013 (0.064)	0.075 (0.133)
ROE	0.001* (0.003)	0.009*** (0.001)	0.009*** (0.002)	0.003*** (0.001)
LEVERAGE	-0.081*** (0.020)	-0.139*** (0.013)	-0.139*** (0.012)	-0.095*** (0.009)
NET MARGIN	0.014*** (0.005)	0.008*** (0.002)	0.008*** (0.003)	0.010*** (0.002)
INTEREST_COV	0.003* (0.002)	0.008** (0.004)	0.008* (0.001)	0.002** (0.001)

CURRENT_RATIO	0.484*** (0.064)	0.472*** (0.025)	0.472*** (0.025)	0.439*** (0.041)
ASSET TURNOVER	1.541*** (0.126)	1.101*** (0.029)	1,101*** (0.053)	1.567*** (0.010)
SE TYPE	Driscoll-Kraay	Driscoll-Kraay	Driscoll-Kraay	Driscoll-Kraay
INDUSTRY FE	Yes	Yes	Yes	Yes
YEAR FE	Yes	Yes	Yes	Yes
Obs.	510	510	510	510
R-Squared	0.641	0.778	0.778	0.644
Adjusted R-squared	0.389	0.775	0.775	0.636
F-STATISTIC	76.30	251.68	251.68	76.99
HAUSMANN TEST	$p < 0.005$			
VIF	1.60			

4.4 – *Generalised Additive Model – smooth specification*

Table 4 shows the results of the non-parametric specification of the GAM model. The term s(beta) is weakly significant (p = 0.014), but with a high effective degree of freedom (EDF = 7.242), indicating an unstructured and difficult to interpret relationship. On the contrary, the accounting variables show well-defined and highly significant functional forms.

The model explains 90.8% of the deviance ($R^2 = 0.901$), confirming that the Z-Score depends mainly on balance sheet indicators.

Table 4 – GAM – Smooth specification regression results (*Source*: Authors' elaboration)

y = Z-SCORE			
Smooth Term	**EDF**	**F-Stat**	**p-value**
s(BETA)	7.242	2.360	0.014
s(ROE)	2.148	13.985	4.34e-07 ***
s(LEVERAGE)	8.534	78.331	< 2e-16 ***
s(NET_MARGIN)	2.605	6.225	0.000275 ***
s(INTEREST_COV)	8.663	6.621	< 2e-16 ***
s(CURRENT_RATIO)	7.434	27.500	< 2e-16 ***
s(ASSET_TURNOVER)	2.634	279.452	< 2e-16 ***
Obs.	510		
R-squared	0.901		
Deviance explained	90.8		
GCV	0.066252		
Scale est.	0.06099		

Note(s): * *ρ < 0.10; ** ρ < 0.05; *** ρ < 0.01*

Figures 1 and 2 show the estimated smooth functions. In Figure 1, beta shows a flat curve with no structure, while ROE, leverage and interest coverage show relationships consistent with economic theory, confirming the reliability of accounting fundamentals in predicting default risk. In Figure 2, increasing relationships are observed for asset turnover and current ratio, while net margin shows a convex trend.

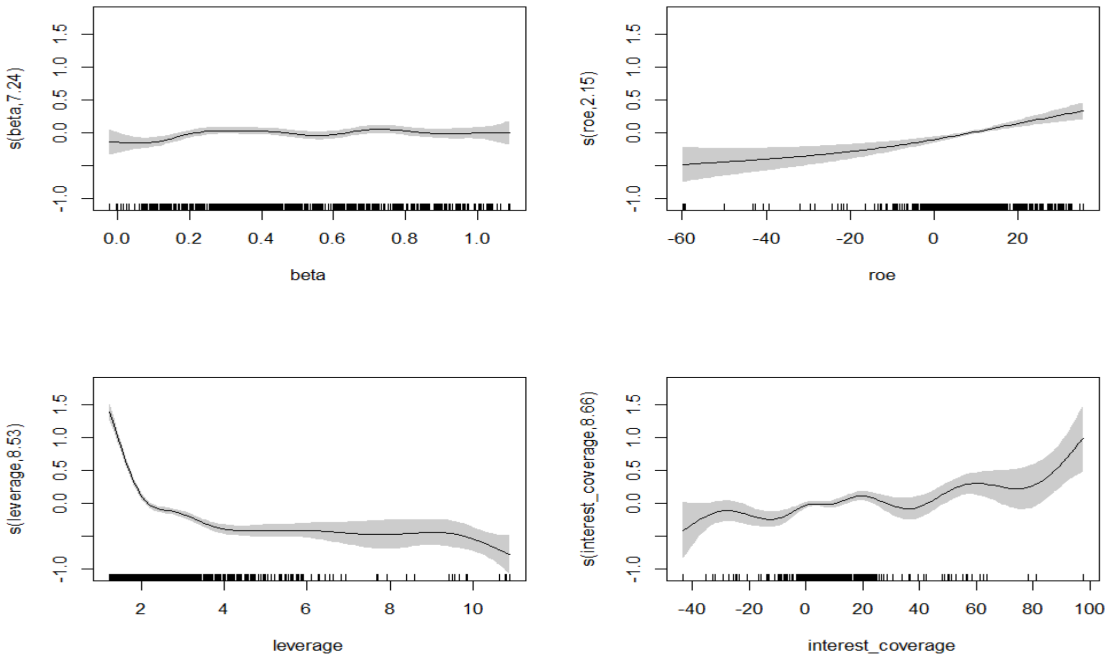

Fig. 1 – Smooth estimate (*Source:* Rstudio)

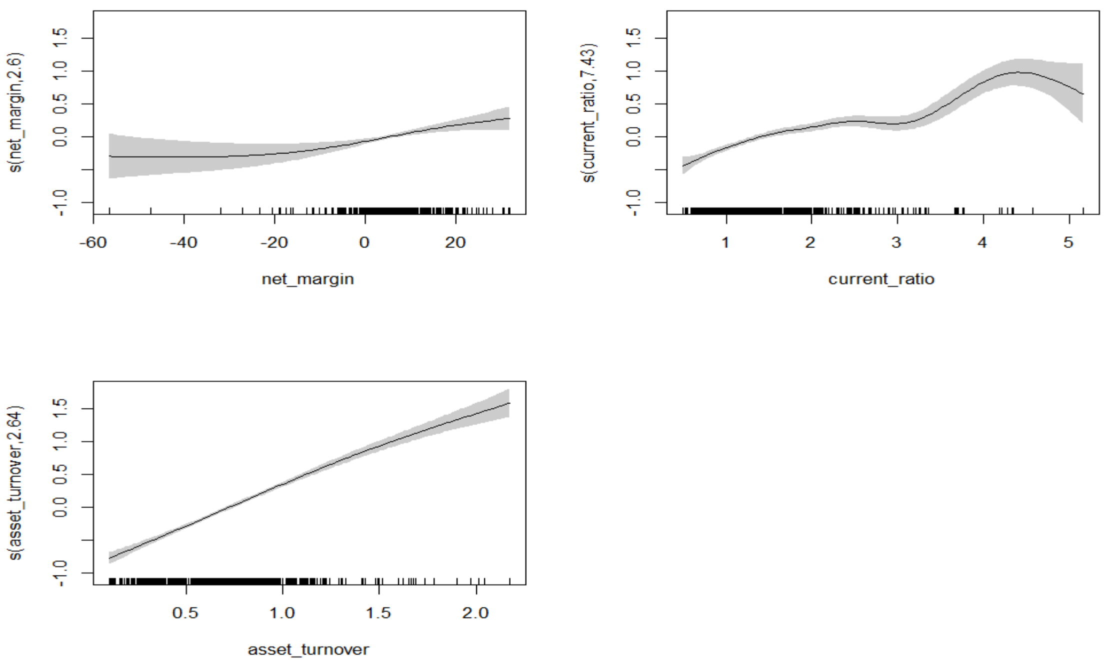

Fig. 2 – Smooth estimate (*Source:* Rstudio)

4.5 – *Lasso regression*

The LASSO model (Table 5) confirms the irrelevance of Beta even in a context of automatic variable selection. The estimated coefficient is 0.0204, with a p-value of 0.7497, which is completely non-significant (Table 6). However, the model maintains a validation R^2 of 0.763, demonstrating strong predictive power even without the contribution of Beta. The automatic penalisation performed by LASSO effectively excludes Beta from the list of relevant variables.

Table 5 – Lasso regression results (*Source*: Authors' elaboration)

LASSO Regression					
Sample	**Lambda**	**Out-of-sample training**	**R-squared validation**	**CV MSE**	**Validation**
Selected Lambda	0.00599	0.786	0.763	0.12	0.17
No. of Obs		357	153	357	153
No. of covariates	7				

Table 6 – Inference on full sample (Lasso regression) (*Source*: Authors' elaboration)

	Coefficient	**z**	**p-value**
Beta	0.0204	0.32	0.7497
Controls	6		
Prob. & gt; χ2	< 0.0001		

5 – Conclusions

This study systematically analysed the relationship between market beta and the financial fragility of companies, measured using the Z-Score. The aim was to assess whether beta, commonly used as a proxy for systemic risk in financial valuation models, could offer relevant information in predicting default risk.

Empirical evidence from multiple econometric specifications — including static panel models, parametric and non-parametric GAM, and LASSO regression — converges on a clear conclusion: beta is never significant in any model, either in linear or non-linear form. Even when estimated with flexible approaches such as GAM or automatically selected through LASSO penalisation, beta shows a negligible or zero impact on the probability of default. This result is consistent with the observations of Fama and French (1992), according to whom beta, although theoretically relevant in the CAPM framework, fails to explain either the expected return or the actual risk observed in the markets. Similarly, Roll (1977) had already pointed out the logical impossibility of fully testing the CAPM in the absence of the true market portfolio, reducing the interpretative scope of beta.

On the contrary, all the accounting variables used — profitability, financial leverage, liquidity and asset turnover — show a strong and statistically significant relationship with the Z-Score, confirming their centrality in the assessment of business risk. This evidence fits in ly with the literature developed by Altman (1968), Ohlson (1980) and, more recently, Campbell, Hilscher and Szilagyi (2008), which values accounting data as reliable predictors of default probability.

The robustness of the results is further strengthened by the use of standard errors corrected for heteroscedasticity, autocorrelation and cross-sectional dependence. The fact that these conclusions remain consistent even in flexibly or penalised modelling contexts suggests that beta not only adds no explanatory power, but may also be an irrelevant measure of risk in this type of analysis.

These results have important theoretical and operational implications. From an academic point of view, they confirm the limitations of beta already widely highlighted in the literature (i.e. Blitz and van Vliet, 2007; Ang et al., 2006) and place further emphasis on the importance of fundamental data for risk measurement. From a managerial and financial point of view, they suggest caution in using beta outside the context for which it was designed, i.e. the determination of the cost of capital (Sharpe, 1964; Lintner, 1965), and highlight the need to complement, if not replace, market indicators with structural metrics in the assessment of financial stability.

Among the main limitations of the study are its focus on a small and geographically homogeneous sample (Italian companies, 2019-2023) and the use of the Z-Score as the sole measure of fragility. Future developments could extend the analysis to international contexts, different risk measures (such as default probabilities, credit spreads or ratings) and the inclusion of alternative forms of beta, such as fundamental beta (Gebhardt et al., 2001), or dynamic measures of systemic risk.

Ultimately, the work contributes to the critical literature on beta, reinforcing the idea that market risk and insolvency risk are conceptually and empirically distinct, and that accounting fundamentals remain the most reliable tool for assessing the financial stability of companies.

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