No easy way out: dissecting firm heterogeneity to enhance default risk prediction[1]

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Abstract

Frame of the research: *Effective risk assessment is central to managerial decision-making in financial institutions, corporate finance, and strategic planning. Drawing from prior studies on default risk, this paper investigates how the predictive ability of financial indicators varies depending on firm characteristics.*

Purpose of the paper: *This study seeks to explore how firm-level heterogeneity is associated with varying levels of predictive strength of financial indicators for default risk, examining how industry, technological levels, size, and age shape the extent to which such indicators are able to predict a firm's likelihood of default.*

Methodology: *The analysis relies on a sample of 121,809 Italian firms sourced from the AIDA database. Logistic regression and random forests are employed to assess the extent to which financial indicators - grouped into liquidity, efficiency, profitability, and growth - predict default risk across firm-specific contingencies.*

Findings: *Results indicate that default risk is more strongly associated with: (a) liquidity indicators in service-oriented firms, (b) efficiency ratios in high-tech firms, (c) profitability measures in smaller firms, and (d) growth indicators in younger firms. These findings support the use of tailored prediction models rather than generalized approaches to default risk prediction.*

Research limits: *The study mainly focuses on incorporated firms and relies primarily on quantitative financial indicators, potentially overlooking qualitative factors and unincorporated micro enterprises.*

Practical implications: *The study points toward the refinement of risk assessment models through the incorporation of firm-level contingencies. This, in turn, has implications for managers, policymakers and institutions involved in SME financing or credit scoring.*

Originality of the paper: *The paper contributes to research on default prediction by combining an integrative theoretical perspective with both statistical and machine learning techniques.*

Key words: *default risk; risk prediction; firm survival; logistic regression; random forests; Italian firms.*

1. Introduction

In times of financial uncertainty, corporate defaults affect firms across industries, organizational scales, and developmental stages (Altman *et al.*, 2017; Bertoni *et al.*, 2023; Ciampi, 2015; He *et al.*, 2023). In this vein, accurate risk assessment informs decisions by financial institutions, policymakers, investors, and managers (Altman *et al.*, 2023b; 2024; Modina *et al.*, 2023). Financial institutions refine lending decisions and stabilize credit markets; policymakers design restructuring policies; investors allocate capital more effectively; managers develop tailored strategies to mitigate risk and sustain growth. Consequently, predictive models of default risk remain a prominent locus of academic and practical interest, spanning from statistical approaches like logistic regression to machine learning methods and big data analytics (Cheraghali and Molnár, 2024).

In spite of the acknowledged relevance of highly accurate default risk models (Cheraghali and Molnár, 2024), exposure to financial distress is not uniform due to the "varying degree of vulnerability" across firms (Igan *et al.*, 2023, p. 102340). For instance, service firms' cash flow constraints, high-tech firms' efficiency requirements, or young firms' growth imperatives suggest that financial signals may carry different predictive weight depending on firm context (Aretz and Pope, 2013; Cathcart *et al.*, 2020).

Yet, empirical evidence remains limited regarding how these differences moderate the predictive power of key financial indicators. Against such a backdrop, this study asks: *How do financial indicators differently predict default risk across various industries, technological levels, firm sizes, and ages?*

To address this research question, we build on an integrative perspective to derive a novel set of hypotheses encompassing the overall assumption that predictive models should reflect firm-specific contingencies. We test our hypotheses on a dataset of 121,809 Italian firms sourced from the Computerized Analysis of Italian Companies (AIDA) database (Bureau van Dijk, 2024) using logistic regression and random forests. The choice of logistic regression is motivated by its longstanding reputation in providing a good balance between flexibility and interpretability in the prediction of firm default (Altman *et al.*, 2023a). Instead, random forests are selected among machine learning methods for their increasing use in the literature of default risk prediction (Li *et al.*, 2020; Perboli and Arabnezhad, 2021; Yıldırım *et al.*, 2021). Compared to logistic regression, random forests have the ability to handle high-dimensional data, non-linear relationships, and complex interactions, which nevertheless comes at the expense of interpretability likewise other machine learning methods (Magrini, 2025).

Building on the gained insights, our paper presents both theoretical and practical contributions. Examining the predictive relationships between key financial indicators and default risk across various firm dimensions, this study seeks to provide a more contingent logic underpinning the predictive value of financial indicators within corporate systems.

2. Theory background and hypotheses development

2.1 Firm heterogeneity in default prediction

Default risk prediction has traditionally focused on financial ratios as key signals of a firm's financial health and likelihood of failure. Early work (e.g., Altman, 1968) established the predictive utility of ratios such as liquidity, profitability, and leverage. Subsequent studies extended this approach, noting that specific indicators capture different dimensions of firm viability under financial stress (e.g., Altman *et al.*, 2023b; Beaver *et al.*, 2019; Bernini *et al.*, 2014; Ciampi, 2015). In particular, liquidity ratios (e.g., current and quick ratios) assess a firm's ability to meet short-term obligations; efficiency indicators (e.g., asset turnover) capture operational effectiveness in converting resources into revenue; profitability ratios reflect the capacity to generate surplus from operations; and growth indicators signal the ability to expand revenue and assets over time, a proxy for market success and future stability (Arbelo *et al.*, 2021; Cheraghali and Molnár, 2024).

The rationale for focusing on these four families of indicators is both theoretical and empirical. Theoretically, they correspond to distinct, complementary dimensions of organizational performance under risk: liquidity aligns with working capital theory, emphasizing short-term solvency; efficiency relates to resource-based and operational perspectives on competitive advantage; profitability reflects sustainability of operations over time; and growth signals the potential for future survival through expansion (Altman *et al.*, 2023a; Ciampi, 2015; Brinckmann *et al.*, 2011; Phelps *et al.*, 2007). Empirically, these indicators are the most widely examined and validated predictors of default risk in both SMEs and large firms (Altman *et al.*, 2023a; Ciampi, 2015; Igan *et al.*, 2023).

At the same time, it is key to acknowledge that firms are highly heterogeneous in both their characteristics (e.g., age and size) and the industries in which they are operating (e.g., services vs. products; high tech vs low tech). In this sense, research increasingly suggests that the appropriateness and predictive power of financial metrics may depend on the specific organizational and environmental context (Aretz and Pope, 2013; Sun and Cui, 2014).

Firm size and age reflect resource access, managerial capability, and stage in the organizational life cycle, which moderate the relevance of profitability and growth indicators (Carreira and Silva, 2010; Cathcart *et al.*, 2020; Coad *et al.*, 2016). For example, smaller enterprises are more likely to exhibit negative shifts in financial indicators such as cash flow ratios or debt levels (e.g., Duarte *et al.*, 2018). This is because these firms may lack the financial resilience to withstand economic downturns (Cathcart *et al.*, 2020), making them more vulnerable to liquidity constraints (Altman and Sabato, 2007).

Industry differences (e.g., services vs. products) shape operational and financial structures, which influence sensitivity to liquidity or profitability. Industry-specific variables, such as demand cycles and regulatory impacts, can significantly influence the risk profiles of firms (Aretz and Pope, 2013). Firms in cyclical industries such as construction or automotive manufacturing may be more exposed to changes in economic conditions compared to those in more stable industries like utilities or healthcare (Drobetz *et al.*, 2016; Öcal *et al.*, 2007; Peric and Vitezic, 2016). Moreover, the rapid pace of innovation and the need to utilize assets efficiently to generate revenue (Dagnino *et al.*, 2021; Yu *et al.*, 2019) make these ratios particularly pertinent for high-tech industries. These firms need to maximize the output from their assets to sustain competitiveness and manage the high costs associated with constant technological upgrades and research and development activities.

Building on such lines of reasoning, this study advances prior research by examining how the predictive ability of liquidity, efficiency, profitability, and growth indicators varies across firm-specific contexts. By grounding variable group selection in established finance and management literature, we test whether the commonly used financial indicators are equally informative across heterogeneous firm characteristics.

2.2 Industry type and liquidity indicators

We propose that the sensitivity of firms to liquidity indicators depends on their industry type. Service-oriented firms, due to their operational characteristics and financial structures, are hypothesized to exhibit greater sensitivity to liquidity indicators than product-oriented firms. This expectation rests on two main arguments.

First, the business model of service firms entails recurring and immediate operational expenses, such as payroll, rent, and utilities (Kumar *et al.*, 2018). These expenses must be met regularly to sustain operations, whereas product firms can partly manage liquidity by liquidating inventory or deferring capital expenditures (Kim, 2021). The constant need to cover frequent expenses makes liquidity management particularly salient for service firms. Liquidity shortfalls often coincide with operational disruptions and elevated default risk, which makes liquidity indicators highly predictive of financial distress in these firms (Safari and Saleh, 2020).

Second, service firms generally possess fewer tangible assets than product firms (Xue *et al.*, 2013). This limited collateral restricts their ability to secure loans or absorb financial shocks, increasing their dependence on operational cash flows to meet short-term obligations. Liquidity indicators, which measure a firm's capacity to cover short-term liabilities with its most liquid assets (Zhang *et al.*, 2020), are therefore especially informative for assessing the financial health and default risk of service firms. Additionally, the revenue model of service firms relies more heavily on operational cash flows than on sales of physical products. Shorter billing cycles and quicker payment terms (Malos and Campion, 2000) further underscore the relevance of liquidity. By contrast, product firms often benefit from longer sales cycles and more flexibility to manage cash flows through inventory and receivables. Hence, liquidity indicators such as the current or quick ratio more effectively signal financial stability and default risk in service firms, reflecting their reliance on timely cash flow generation. Accordingly, we propose the following hypothesis:

Hypothesis 1: Service industry firms' default risk is more strongly predicted by liquidity indicators than that of product industry firms.

2.3 Technology level and efficiency indicators

We argue that high-tech firms, operating in environments defined by fast-paced innovation and intense competition (e.g., Dagnino *et al.*, 2021; Yu *et al.*, 2019), are more sensitive to efficiency indicators when predicting default risk than low-tech firms.

First, high-tech firms depend heavily on ongoing investments in research and development to remain competitive (Han *et al.*, 2024). In this context, high asset turnover reflects efficient use of resources, supporting stronger revenue streams and financial stability in line with the cost structures of these firms (Ausloos *et al.*, 2018; Florackis and Ozkan, 2009).

Second, the operational models of high-tech firms often involve significant upfront investments in technology, infrastructure, and intellectual property, making efficient asset utilization essential to sustaining financial health (Gedajlovic *et al.*, 2012; Roberts and Grover, 2012). Indicators such as asset turnover ratios capture how effectively these firms convert assets into sales, with lower efficiency typically associated with weaker revenue and higher financial distress (Spitsin *et al.*, 2023; Habib *et al.*, 2020).

Third, competitive pressures and rapid technological obsolescence in high-tech industries intensify the need for operational efficiency to maintain market position (Liu *et al.*, 2014; Pangburn and Sundaresan, 2009). By contrast, low-tech firms operate in more stable environments with slower technological change (Huang *et al.*, 2023), which reduces the urgency to optimize asset utilization and weakens the association between efficiency indicators and default risk. Accordingly, we propose the following hypothesis:

Hypothesis 2: High-tech firms' default risk is more strongly predicted by efficiency indicators, such as asset turnover ratios, compared to low-tech firms.

2.4 Firm size and profitability indicators

In this section we advance that smaller firms, characterized by their constrained capital access and focused market presence, are expected to exhibit greater sensitivity to profitability indicators than larger firms. This is underpinned by various reasons.

First, smaller firms often have more limited access to external financing options as compared to their larger counterparts (Altman and Sabato, 2007; Beck and Demirguc-Kunt, 2006; Beck *et al.*, 2008; Revest and Sapio, 2012). Due to their smaller scale and lesser financial clout, they may face higher borrowing costs and more stringent lending conditions (Altman *et al.*, 2023b; Dieperink *et al.*, 2024). Consequently, maintaining adequate profit margins is associated with financial sustainability. Profitability indicators measure a small firm's ability to generate income relative to its asset base (Arbelo *et al.*, 2021; Sydler *et al.*, 2014). High profitability reflects efficient use of assets and operational effectiveness, which supports self-financing and is associated with lower observed financial distress. In contrast, larger firms with broader access to financing can rely more on external capital (Carreira and Silva, 2010; Nguyen and Canh, 2021), making profitability indicators relatively less critical in predicting their default risk.

Second, smaller firms often cover relatively small markets with limited customer bases and product diversification (Odlin and Benson-Rea, 2021). This lack of diversification is associated with greater vulnerability to market fluctuations and downturns. In such contexts, profitability serves as an important indicator of resilience. Higher profits are associated with the ability to sustain operations during periods of revenue volatility and economic shocks. Profitability indicators like ROA thus provide insights into the financial health and default risk of small firms (Gharsalli, 2019). Conversely, larger firms, with diversified income streams and broader market presence, can absorb market fluctuations more effectively (Mills and Schumann, 1985), making profitability indicators less predictive of their default risk.

Third, smaller firms generally have less financial resilience and fewer accumulated reserves compared to larger firms (Igan *et al.*, 2023; Lai *et al.*, 2016). This limited financial cushion is associated with greater exposure to liquidity crises and financial distress. Smaller firms with high profitability are better able to manage cash flows and meet short-term liabilities, which is associated with lower observed default risk. In contrast, larger firms, with substantial financial reserves and diversified assets, can rely on their financial strength to weather periods of low profitability, making profitability indicators less central to assessing their default risk.

Taken together, such arguments collectively highlight the heightened relevance of profitability indicators in assessing the default risk of smaller firms compared to larger firms[2]. As a result, we propose the following hypothesis:

Hypothesis 3: Smaller firms' default risk will be more closely related to profitability indicators, such as return on assets (ROA), than larger firms.

2.5 Firm age and growth indicators

In this section, we contend that younger firms' default risk is more closely predicted by growth indicators, such as revenue growth rate, than that of older firms. This relationship rests on two main arguments.

[2] We acknowledge that the adopted database (AIDA) mostly includes incorporated firms, thus our analysis of "small firms" pertains to the subset of small incorporated entities. Many small firms in the broader economy, particularly micro and family-run businesses, are unincorporated and may rely more on owners' personal resources, which are not observable in our data. Accordingly, the findings of Hypothesis 3 should be interpreted within the population of small incorporated firms. This limitation is also discussed in the "Limitations and conclusions" section.

First, younger firms are typically in the growth phase of their organizational life cycle, prioritizing high resource endowments expansion and market penetration (Bruderl and Schussler, 1990; La Rocca *et al.*, 2011; Phelps *et al.*, 2007). During this stage, earnings are reinvested to support marketing, product development, and scaling operations. High growth rates signal successful market entry and customer acquisition, which contribute to stronger cash flows and lower observed financial distress (Brinckmann *et al.*, 2011). In contrast, older firms, with established market positions, rely less on rapid growth, making growth indicators less predictive of their default risk.

Second, younger firms face greater operational and market uncertainty than older counterparts (Bertoni *et al.*, 2023). Limited diversification, fewer customer relationships, and restricted financial resources make their stability more dependent on rapid growth. Growth indicators thus serve as signals of future viability and help attract investors and lenders, who provide the capital needed to sustain operations and mitigate financial distress (Ahmed and Safdar, 2017). Conversely, stagnating or declining growth is often associated with heightened financial constraints and increased default risk among younger firms. Older firms, with more stable revenue streams and financial histories, tend to rely more on profitability and efficiency measures when assessing financial health.

In sum, the strategic emphasis on growth highlights the relevance of growth indicators as predictors of default risk in younger firms, reflecting their need to demonstrate potential and secure external financing. Accordingly, we propose the following hypothesis:

Hypothesis 4: Younger firms' default risk will be more closely associated with growth indicators, such as revenue growth rate, than older firms.

3. Data and Methods

3.1 Setting and sample

The dataset utilized in this study is sourced from the Computerized Analysis of Italian Companies (AIDA) database (Bureau van Dijk, 2024), which comprises detailed financial statements from a large number of Italian firms. We argue that this setting is particularly suitable for testing our hypotheses for several reasons. First, the Italian economic context - characterized by periods of significant financial stress and recovery (Bruzzi *et al.*, 2021) - provides an appropriate setting to examine how economic fluctuations are associated with firm default risk. As a European member state, Italy has consistently been studied by previous research on default prediction (e.g., Ciampi, 2015). This setting provides an ideal environment to test the robustness of models for default risk prediction under varying economic conditions, and enhances the generalizability of the findings to other contexts facing similar economic dynamics. Second, the extensive coverage of the AIDA database allows for a comprehensive analysis across a wide range of firm characteristics including industry type, size, age, and technological level. The inclusivity of this database ensures that the results of our study are not confined to a narrow segment of the market but are representative of the broader Italian business ecosystem. Third, the diversity within the Italian economy - with a mix of traditional manufacturing, high-technology industries, and robust service industries - provides a unique opportunity to examine the contingencies of default risk across different market conditions and business models. This diversity allows for exploring how financial indicators vary in their predictive power of default risk among firms operating in different economic environments (Broglia and Corsi, 2024). Fourth, the longitudinal aspect of the data, with many firms having multiple years of financial records, allows for dynamic analysis and the ability to track changes in financial health over time. This feature is crucial for investigating how the relationship between financial indicators and default risk evolves as firms grow, adapt, or face economic challenges.

To enhance the representativeness of our sample, we consider all firms present in the database that meet the following three criteria: (i) the legal status is "active" or "failed", (ii) at least three financial statements are available, and (iii) equity is positive for all financial statements. The obtained sample consists of 138,720 firms, of which 127,420 (91.9%) are active and 11,300 (8.1%) are failed. Data cleaning is performed in two steps: (i) companies with anomalous values for any indicator (e.g., when the denominator is very small) are eliminated, and (ii) the set of indicators is pruned until all variance inflation factors indicate no multicollinearity, i.e., they are below the threshold of 5 (O'Brien, 2007). The final sample consists of 121,809 companies, of which 111,612 (91.6%) are active and 10,197 (8.4%) have failed. For most of them (83.8%), the latest available financial statement is for year 2023. The main characteristics of the sample are reported in Table 1.

Tab. 1: Sample characteristics (n = 121,809)

Legal status			*Industry*		
Active	111,612	91.6%	Product-centered	38,588	31.7%
Failed	10,197	8.4%	Service-centered	83,221	68.3%
Firm age			*Firm size*		
≤ 10 years from foundation	9,992	8.2%	Less than 50 employees or total assets < 10 million euros	101,956	83.7%
> 10 years from foundation	111,817	91.8%	More or equal than 50 employees and total assets ≥ 10 million euros	19,853	16.3%
Technological level			*Legal form*		
Low	70,127	57.6%	Capital	117,611	96.6%
High	51,682	42.4%	Consortium	3,703	3.0%
			Other	495	0.4%
Geographical area					
North-West	37,634	30.9%			
North-East	30,807	25.3%			
Center	28,116	23.1%			
South and islands	25,252	20.7%			

Source: our elaboration

3.2 Measures

The dependent variable in this study is the legal status of firms, which is categorized as either "active" or "failed". This binary outcome enables the examination of how various managerial and financial characteristics are associated with default.

Our moderating variables include the industry, firm size, technological level, and firm age. Based on Ettlie and Rosenthal (2011), firms are classified as "product-centered" based on their ATECO 2019 codes if their main activities include manufacturing, agriculture, or retail trade, such as those involved in producing goods or selling products. Examples include manufacturing companies, agricultural businesses, and retail stores. On the other hand, firms are classified as "service-centered" if their activities involve providing services rather than goods, such as healthcare providers, financial services, and IT support companies. To represent the industry, the dummy variable *Industry* is created, coded as 1 if the firm is "service-centered" and 0 otherwise.

Firm size is determined based on the number of employees, revenues and total assets. Firms are classified as "small" if they have fewer than 50 employees or revenues and total assets not exceeding 10 million euros (European Commission, 2024); otherwise, they are considered "medium/large". To represent firm size, the dummy variable *Size* is created, coded as 1 if the firm is "medium/large" and 0 otherwise.

Technological level is determined by the main economic activity similarly to Czarnitzki and Thorwarth (2012) and He *et al.* (2023) , i.e., firms are classified as "high-tech" if their activities are in industries like high-tech manufacturing, IT services, or financial services. Examples include software development firms, biotech companies, and advanced engineering firms. The other firms are considered "low-tech", such as those in traditional manufacturing or basic service industries. To represent the technological level, the dummy variable *Tech* is created, coded as 1 if the firm is "high-tech" and 0 otherwise (Balzano and Marzi, 2023; He *et al.*, 2023).

Firm age is categorized based on the number of years the firm has been in existence. As in Coad *et al.* (2016), a firm is considered "young" if it is 10 years old or less and "established" otherwise. To represent firm age, the dummy variable *Age* is created, coded as 1 if the firm is "established" and 0 otherwise.

Key independent variables include financial indicators, divided into liquidity, efficiency, profitability, and growth. Each indicator is computed two years prior to the date of the latest financial statement in order to predict default risk two years into the future. Liquidity indicators include current ratio (current assets divided by current liabilities) and quick ratio (current assets excluding inventory, divided by current liabilities). Efficiency indicators consist of assets to sales ratio (total assets divided by sales revenue), inventory to sales ratio (inventory divided by sales revenue), and receivables to sales ratio (account receivables divided by sales revenue); these indicators are defined as the reciprocal of turnover ratios to deal with null values of inventory and account receivables. Profitability indicators comprise return on assets (ROA, calculated as earnings before interest and taxes divided by total assets), return on sales (ROS, calculated as earnings before interest and taxes divided by sales revenue), and return on equity (ROE, calculated as net income divided by equity). Growth indicators are assets change (total assets at time t divided by total assets at time t-1), sales change (sales revenue at time t divided by sales revenue at time t-1), and income change (difference in net income between time t and time t-1, divided by total assets at time t-1).

Control variables include leverage indicators and other firm characteristics. As leverage indicators, we consider the debt to assets ratio (total liabilities divided by total assets), the debt to equity ratio (total liabilities divided by equity), the fixed assets to equity ratio (fixed assets divided by equity), and the interest to debt ratio (interest charges divided by total liabilities). Other firm characteristics encompass legal form and geographical region. Legal form is classified into "capital", "consortium", or "other", with "capital" serving as the reference category, thus two dummy variables are created to represent the categories "consortium" and "other". Geographical region is divided into "north-west", "north-east", "center", and "south and islands", with "north-west" as the reference category, thus three dummy variables are created to represent the categories "north-east", "center", and "south and islands". All the adopted measures are listed and described in Table 2, while their descriptive statistics are reported in Table 3.

Tab. 2: Description of the adopted measures

Dependent variable
Legal status: "active", or "failed"
Moderators
Industry: "product-centered" ($Industry_i$=0), or "service-centered" ($Industry_i$=1)
Firm size: "small" ($Size_i$=0), or "medium/large" ($Size_i$=1)
Technological level: "low-tech" ($Tech_i$=0), or "high-tech" ($Tech_i$=1)
Firm age: "young" (Age_i=0), or "established" (Age_i=1)
Liquidity indicators
Current ratio: current assets / current liabilities
Quick ratio: (current assets - inventory) / current liabilities
Efficiency indicators
Assets to sales ratio: total assets / sales revenue
Inventory to sales ratio: inventory / sales revenue
Receivables to sales ratio: account receivables / sales revenue
Profitability indicators
ROA: earnings before interest and taxes / total assets
ROS: earnings before interest and taxes / sales revenue
ROE: net income / equity
Growth indicators
Assets change: total assets at time t / total assets at time t-1
Sales change: sales revenue at time t / sales revenue at time t-1
Income change: (net income at time t - net income at time t-1) / total assets at time t-1
Control variables
Debt to assets ratio: total liabilities / total assets
Debt to equity ratio: total liabilities / equity
Fixed assets to equity ratio: fixed assets / equity
Interests to debt ratio: interest charges / total liabilities
Legal form: "capital", "consortium", or "other"
Geographical region: "north-west", "north-east", "center", or "south and islands"

Source: our elaboration

Tab. 3: Descriptive statistics: mean, standard deviation, and Pearson's correlations

	Mean	Std. dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	1.633	1.325	1.000														
(2)	1.152	0.946	0.789	1.000													
(3)	1.519	1.498	0.090	-0.002	1.000												
(4)	0.312	0.581	0.217	-0.150	0.519	1.000											
(5)	0.256	0.336	-0.018	0.045	0.285	0.124	1.000										
(6)	0.053	0.071	0.148	0.250	-0.230	-0.168	-0.118	1.000									
(7)	0.056	0.101	0.182	0.226	-0.010	-0.026	-0.070	0.695	1.000								
(8)	0.076	0.381	0.061	0.112	-0.163	-0.136	-0.101	0.559	0.477	1.000							
(9)	1.519	0.255	-0.043	0.026	-0.077	-0.067	-0.015	0.245	0.176	0.211	1.000						
(10)	1.260	0.598	0.049	0.033	-0.082	-0.053	-0.097	0.192	0.144	0.167	0.257	1.000					
(11)	0.021	0.071	0.050	0.089	-0.072	-0.061	-0.062	0.518	0.362	0.365	0.302	0.287	1.000				
(12)	0.724	0.188	-0.354	-0.407	-0.101	0.088	0.086	-0.301	-0.284	-0.135	0.050	-0.028	-0.083	1.000			
(13)	6.800	11.837	-0.130	-0.171	0.043	0.146	0.098	-0.194	-0.148	-0.305	-0.002	-0.048	-0.076	0.516	1.000		
(14)	1.995	3.594	-0.203	-0.194	0.142	-0.029	-0.007	-0.198	-0.141	-0.283	-0.050	-0.057	-0.067	0.372	0.624	1.000	
(15)	0.014	0.015	-0.018	-0.041	0.001	0.031	0.017	0.041	0.007	-0.110	-0.062	0.005	0.002	0.156	0.111	0.080	1.000

(1) Current ratio; (2) Quick ratio; (3) Assets to sales ratio; (4) Inventory to sales ratio; (5) Receivables to sales ratio; (6) Return on assets (ROA); (7) Return on sales (ROS); (8) Return on equity (ROE); (9) Assets change; (10) Sales change; (11) Income change; (12) Debt to assets ratio; (13) Debt to equity ratio; (14) Fixed assets to equity ratio; (15) Interests to debt ratio.

Source: our elaboration

3.3 Analytical techniques

The proposed hypotheses are tested using logistic regression, which is a statistical model widely known in the literature on default risk prediction for its good balance between flexibility and interpretability (Altman *et al.*, 2023a). All indicators are standardized by subtracting their sample mean and dividing by their sample standard deviation in order to ease interpretation and allow comparisons among parameters (Menard, 2011). We formulate the model as follows:

$$\log\left(\frac{\pi_i}{1-\pi_i}\right) = \boldsymbol{z}_i'\boldsymbol{\alpha} + \boldsymbol{l}_i'\left(\boldsymbol{\beta}^{(l)} + \boldsymbol{\gamma}^{(l)} \cdot Industry_i\right) + \boldsymbol{e}_i'\left(\boldsymbol{\beta}^{(e)} + \boldsymbol{\gamma}^{(e)} \cdot Tech_i\right) + \boldsymbol{p}_i'\left(\boldsymbol{\beta}^{(p)} + \boldsymbol{\gamma}^{(p)} \cdot Size_i\right) + \boldsymbol{g}_i'\left(\boldsymbol{\beta}^{(g)} + \boldsymbol{\gamma}^{(g)} \cdot Age_i\right) \qquad (1)$$

where, for a generic firm i:

- π_i is the probability of default, thus $\frac{\pi_i}{1-\pi_i}$ is the odds of the event "failed" versus the event "active", here called default risk;
- $\boldsymbol{z}_i$ is a vector including value 1 followed by the value taken by leverage indicators, dummies for moderating variables (Industry, Tech, Size, and Age), dummies for the legal form, and dummies for the geographical region;
- $\boldsymbol{l}_i$ is a vector including the value of liquidity indicators;
- $\boldsymbol{e}_i$ is a vector including the value of efficiency indicators;
- $\boldsymbol{p}_i$ is a vector including the value of profitability indicators;
- $\boldsymbol{g}_i$ is a vector including the value of growth indicators;
- $\boldsymbol{\alpha}$ is a vector of parameters including the intercept and the main effects of control variables;
- $\boldsymbol{\beta}^{(l)}$, $\boldsymbol{\beta}^{(e)}$, $\boldsymbol{\beta}^{(p)}$, $\boldsymbol{\beta}^{(g)}$ are vector of parameters including, respectively, the main effects of liquidity, efficiency, profitability and growth indicators;
- $\boldsymbol{\gamma}^{(l)}$, $\boldsymbol{\gamma}^{(e)}$, $\boldsymbol{\gamma}^{(p)}$, $\boldsymbol{\gamma}^{(g)}$ are vectors of parameters including the interaction effects.

This model formulation allows the default risk associated with: (i) liquidity indicators to differ across industries, (ii) efficiency indicators to differ across technological levels, (iii) profitability indicators to differ across size classes, and (iv) growth indicators to differ across age categories. For example, the odds ratio per unit standard deviation increase of the first liquidity ratio is given by exp ($\boldsymbol{\beta}_1^{(l)}$) for product-centered industries, and by exp ($\boldsymbol{\beta}_1^{(l)} + \boldsymbol{\gamma}_1^{(l)}$) for service-centered industries, where $\boldsymbol{\beta}_1^{(l)}$ and $\boldsymbol{\gamma}_1^{(l)}$ are the first components of parameter vectors $\boldsymbol{\beta}^{(l)}$ and $\boldsymbol{\gamma}^{(l)}$, respectively. As such, the proposed hypotheses can be tested by performing significance tests on $\boldsymbol{\gamma}^{(l)}$, $\boldsymbol{\gamma}^{(e)}$, $\boldsymbol{\gamma}^{(p)}$ and $\boldsymbol{\gamma}^{(g)}$.

As a robustness check, our hypotheses are tested also based on random forests, which constitute a non-parametric approach to prediction based on decision trees. Originally proposed by Breiman (2001), random forests are increasingly applied to corporate default prediction for their ability to handle high-dimensional data, non-linear relationships, and complex interactions (Li *et al.*, 2020, Perboli and Arabnezhad, 2021; Yıldırım *et al.*, 2021). As such, their feature importance measures can provide a more accurate assessment of the predictive relevance of independent variables compared to logistic regression. The most advanced feature importance measure in random forests is permutation importance, which consists in the assessment of the loss in predictive accuracy when the dependent variable is predicted based on random permutations of an independent variable. The more the predictive accuracy decreases, the higher is the importance of the variable. Here, we consider the permutation importance measure proposed by Strobl et al (2007), which is robust when independent variables have different scale of measurement or number of categories. In order to test each hypothesis, which considers a set of indicators and two groups of firms, permutation importance is computed for all indicators altogether (by simultaneously permuting their values) separately for each group of firms.

4. Results

4.1 Logistic regression

Parameter estimation and significance tests for the logistic regression model in equation (1) are performed using R for Statistical Software (R Core Team, 2023). The results are shown in Table 4. In order to ease the interpretation of the estimated model, odds ratios per unit standard deviation increase of indicators involved in each research hypothesis are shown in Table 5.

Tab. 4: Summary of parameter estimation for the logistic regression model in equation (1)

Parameter	Estimate	Std. error	p-value
Intercept	-7.8334	0.2720	0.0000 ***
Region: "north-east" vs. "north-west"	0.0181	0.0350	0.6040
Region: "center" vs. "north-west"	-0.1753	0.0355	0.0000 ***
Region: "south and islands" vs. "north-west"	-0.3088	0.0394	0.0000 ***
Legal form: "consortium" vs. "capital"	-0.6178	0.0763	0.0000 ***
Legal form: "other" vs. "capital"	-0.4560	0.1746	0.0090 **
Debt to assets ratio	1.0564	0.0296	0.0000 ***
Debt to equity ratio	0.2615	0.0132	0.0000 ***
Fixed assets to equity ratio	-0.1561	0.0123	0.0000 ***
Interests to debt ratio	0.8939	0.0129	0.0000 ***
Industry	-0.4030	0.0449	0.0000 ***
Tech	0.0844	0.0306	0.0057 **
Size	0.7312	0.0454	0.0000 ***
Age	3.7698	0.2681	0.0000 ***
Current ratio	-0.0032	0.0471	0.9450
Quick ratio	-1.1610	0.0664	0.0000 ***
Assets to sales ratio	-0.4348	0.0396	0.0000 ***
Inventory to sales ratio	-0.1395	0.0249	0.0000 ***
Receivables to sales ratio	-0.1197	0.0157	0.0000 ***
ROA	0.0877	0.0189	0.0000 ***
ROS	0.0801	0.0186	0.0000 ***
ROE	0.3519	0.0153	0.0000 ***
Assets change	-0.0328	0.1581	0.8356
Sales change	-1.4375	0.3116	0.0000 ***
Income change	-1.1145	0.4322	0.0099 **
Current ratio * *Industry*	-0.9406	0.0770	0.0000 ***
Quick ratio * *Industry*	-0.2067	0.0809	0.0106 *
Asset to sales ratio * *Tech*	0.1733	0.0787	0.0278 *
Inventory to sales ratio * *Tech*	0.1065	0.0448	0.0176 *
Receivables to sales ratio * *Tech*	0.0704	0.0291	0.0154 *
ROA * *Size*	0.0690	0.0326	0.0343 *
ROS * *Size*	0.0902	0.0334	0.0070 **
ROE * *Size*	0.0496	0.0244	0.0422 *
Assets change * *Age*	0.0027	0.1589	0.9864
Sales change * *Age*	0.8411	0.3122	0.0071 **
Income change * *Age*	0.9078	0.4324	0.0358 *

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source: our elaboration

Tab. 5: Odds ratios per unit standard deviation increase implied by the logistic regression model in equation (1)

	Industry	
	"product-centered"	"service-centered"
Current ratio	0.997 (0.909, 1.093)	0.389 (0.337, 0.449)
Quick ratio	0.313 (0.275, 0.357)	0.255 (0.223, 0.290)
	Technological level	
	"low-tech"	"high-tech"
Assets to sales ratio	1.092 (1.052, 1.133)	1.170 (1.104, 1.239)
Inventory to sales ratio	1.083 (1.045, 1.124)	1.186 (1.111, 1.265)
Receivables to sales ratio	1.422 (1.380, 1.465)	1.494 (1.435, 1.556)
	Firm size	
	"small"	"medium/large"
Return on assets (ROA)	0.647 (0.599, 0.700)	0.770 (0.671, 0.883)
Return on sales (ROS)	0.870 (0.828, 0.913)	0.968 (0.899, 1.041)
Return on equity (ROE)	0.887 (0.860, 0.915)	0.952 (0.905, 1.001)
	Firm age	
	≤ 10 years	> 10 years
Assets change	0.968 (0.710, 1.319)	0.970 (0.939, 1.002)
Sales change	0.238 (0.129, 0.437)	0.551 (0.525, 0.578)
Income change	0.328 (0.141, 0.765)	0.813 (0.779, 0.849)

Note: 95% confidence intervals are shown within brackets.

Source: our elaboration

The estimated main effects of current ratio and quick ratio are negative, indicating that, for product-centered industries, higher liquidity is associated with lower default risk, although only the main effect of quick ratio is statistically significant. The estimated interaction terms, both significant and negative, indicate that higher liquidity is associated with a stronger reduction in default risk for service-centered firms than for product-centered ones. Precisely: the odds ratio per standard deviation increase of current ratio is 0.997 (-0.3%) for product-centered firms and 0.389 (-61.1%) for service-centered ones, meaning that the reduction of the default risk is 60.8% higher for the service-centered industry; the odds ratio per standard deviation increase of quick ratio is 0.313 (-68.7%) for product-centered firms and 0.255 (-74.5%) for service-centered ones, meaning that the reduction of the default risk is 5.8% higher for the service-centered industry. Therefore, Hypothesis 1 is supported.

The estimated main effects of assets to sales, inventory to sales, and receivables to sales ratios are significantly positive, indicating that, for firms with low technological level, greater efficiency-reflected in lower values of these indicators-is associated with lower default risk. The estimated interaction terms, all significant and positive, indicate that an improvement of efficiency is associated with a stronger reduction in the default risk for high-tech firms than for low-tech ones. Precisely: the odds ratio per standard deviation decrease of the assets to sales ratio is 1/1.092=0.916 (-8.4%) for low-tech firms and 1/1.170=0.855 (-14.5%) for high-tech ones, meaning that the reduction of the default risk is 6.1% higher for high-tech firms; the odds ratio per standard deviation decrease of the inventory to sales ratio is 1/1.083=0.923 (-7.7%) for low-tech firms and 1/1.186=0.843 (-15.7%) for high-tech firms, meaning that the reduction of the default risk is 8.0% higher for high-tech firms; the odds ratio per standard deviation decrease of the receivables to sales ratio is 1/1.422=0.703 (-29.7%) for low-tech firms and 1/1.494=0.669 (-33.1%) for high-tech firms, meaning that the reduction of the default risk is 3.4% higher for high-tech firms. Therefore, Hypothesis 2 is supported.

The estimated main effects of ROA, ROS and ROE are significantly negative, indicating that, for small firms, higher profitability is associated with lower default risk. The estimated interaction terms, all significant and positive, indicate that an improvement of profitability implies a higher decrease of the default risk for small firms than for medium or large ones. Precisely: the odds ratio per standard deviation increase of ROA is 0.647 (-35.3%) for small firms and 0.770 (-23.0%) for medium and large ones, meaning that the reduction of the default risk is 12.3% higher for small firms; the odds ratio per standard deviation increase of ROS is 0.870 (-13.0%) for small firms and 0.968 (-3.2%) for medium and large ones, meaning that the reduction of the default risk is 9.8% higher for small firms; the odds ratio per standard deviation increase of ROE is 0.887 (-11.3%) for small firms and 0.952 (-4.8%) for medium and large ones, meaning that the reduction of the default risk is 6.5% higher for small firms. Therefore, Hypothesis 3 is supported.

The estimated main effects of assets change, sales change and income change are negative, indicating that, for young firms, growth is associated with lower default risk, although only the impact of change in sales and in income result significantly different from zero. The estimated interaction terms, all positive but significant for sales and income change only, indicate that growth implies a higher decrease of the default risk for young firms than for established ones. Precisely: the odds ratio risk per standard deviation increase of sales change is 0.238 (-76.2%) for young firms and 0.551 (-44.9%) for established ones, equating to a 31.3% reduction of the default risk; the odds ratio risk per standard deviation increase of income change is 0.328 (-67.2%) for young firms and 0.813 (-18.7%) for established ones, equating to a 48.5% reduction of the default risk. Therefore, Hypothesis 4 is supported.

4.2 Random forests

The R package 'party' (Hothorn *et al.* 2024) is used to compute the permutation importance measure proposed by Strobl et al (2007). As a first step, a random forest is constructed with the legal status as dependent variable and all other measures shown in Table 2 as independent variables. For this purpose, we set a number of trees equal to 500 and a number of candidates randomly selected at each split equal to 5, corresponding to the rounded squared root of the number of independent variables as suggested by Breiman (2001). In order to test each hypothesis, which considers a set of indicators and two groups of firms, permutation importance is computed for all indicators altogether (by simultaneously permuting their values) separately for each group of firms. The results are shown in Table 6.

Tab. 6: Hypothesis testing based on permutation importance in random forests. Values are loss in AUC (%) based on 500 random permutations

Hypothesis 1		Loss in AUC (%)
Moderating variable: industry	"product-centered"	2.471 (2.239, 2.698)
Indicators: liquidity	"service-centered"	3.297 (3.139, 3.470)
	(difference)	0.826 (0.506, 1.118)
Hypothesis 2		Loss in AUC (%)
Moderating variable: technological	"low-tech"	1.549 (1.457, 1.709)
level	"high-tech"	1.912 (1.750, 2.077)
Indicators: efficiency	(difference)	0.363 (0.151, 0.574)
Hypothesis 3		Loss in AUC (%)
Moderating variable: firm size	"small"	2.735 (2.639, 2.815)
Indicators: profitability	"medium/large"	2.292 (2.086, 2.483)
	(difference)	-0.443 (-0.678, -0.249)
Hypothesis 4		Loss in AUC (%)
Moderating variable: firm age	<= 10 years	13.236 (7.404, 19.511)
Indicators: growth	> 10 years	2.321 (2.169, 2.490)
	(difference)	-10.915 (-17.291, -5.136)

Note: 95% confidence intervals are shown within brackets.

Source: own elaboration

As shown in Table 6, the loss in AUC after permuting liquidity indicators is higher for service-centered firms than for product-centered firms, with 95% confidence interval for the difference not including value zero and thus indicating significance at 5% level. This finding supports Hypothesis 1. Similarly, the loss in AUC after permuting efficiency indicators is significantly higher for high-tech firms than for low-tech firms, thus supporting Hypothesis 2. The loss in AUC after permuting profitability indicators is significantly higher for small firms than for medium or large firms, therefore Hypothesis 3 is supported. Finally, the permutation importance of growth indicators is significantly higher for young firms than for established firms, providing support to Hypothesis 4.

5. Discussion and implications

This study corroborates the relevance of considering contingent factors-such as industry type, technological level, firm size, and age-when assessing firms' default risk. In this perspective, the study complements prior research, which has highlighted cross-country heterogeneity in vulnerability to financial distress (Igan *et al.*, 2023), by showing that heterogeneity in firm characteristics and the context where the firm is operating, equally shapes the salience of financial indicators. This shift from generalized approaches to default risk to emphasis in firm-level heterogeneity, underscoring that financial signals are not uniformly informative across firms but rather acquire their meaning in relation to the operational, strategic, and institutional contexts in which firms are embedded.

Accordingly, the findings illuminate how firm characteristics modulate the predictive value of financial metrics. In service-oriented firms, the power of liquidity indicators aligns with their operational immediacy and reliance on cash flow rather than tangible assets (Kumar *et al.*, 2018; Xue *et al.*, 2013). In high-technology settings, the heightened sensitivity to efficiency reflects the imperative to translate R&D investments into market outcomes efficiently, given the volatility and competitive intensity of innovation-driven environments (Dagnino *et al.*, 2021). Smaller firms, constrained in access to external capital (Beck and Demirguc-Kunt, 2006), exhibit a stronger dependence on profitability as an internal buffer, while younger firms rely on sustained growth trajectories to signal legitimacy and attract resources in conditions of uncertainty (Ahmed and Safdar, 2017; Brinckmann *et al.*, 2011).

From a methodological point of view, the study combines logistic regression, a traditional statistical model, with random forests, one of the most popular machine learning methods in bankruptcy risk prediction, to explore and validate heterogeneity in predictive relationships. Logistic regression offers a good balance between flexibility and interpretability, while random forests allow to handle high-dimensional data, non-linear relationships, and complex interactions, although at the expense of interpretability likewise other machine learning methods (Magrini, 2025). This integration addresses the growing demand for predictive models that are both transparent and sensitive to contextual variations (Cheraghali and Molnár, 2024).

For practice, these insights invite managers, investors, and policymakers to move beyond generalized risk assessment tools toward approaches attuned to firm-specific conditions. Accordingly, stakeholders can improve decision-making by weighting financial indicators according to firm profiles-for instance, emphasizing liquidity when evaluating service firms, efficiency for high-tech firms, profitability for smaller enterprises, and growth for younger organizations. Such tailoring can improve the allocation of credit, investment, and policy support while mitigating misclassification errors that arise from one-size-fits-all models.

Furthermore, these differentiated sensitivities suggest that managerial priorities should be aligned with the financial dimensions most salient to the firm's structural and competitive context. For managers, this entails not only optimizing the relevant financial ratios but also communicating these dimensions effectively to external evaluators. For investors, incorporating these insights into portfolio strategies may enhance risk-adjusted returns. Policymakers can design more targeted interventions-such as liquidity facilities for service sectors, operational efficiency programs in high-tech industries, profitability-enhancement initiatives for small businesses, or growth-enabling policies for young firms.

6. Limitations and conclusions

In conclusion, this study makes a contribution to the literature on default risk prediction by advocating for context-specific models that account for the heterogeneity among firms. The findings highlight the need for tailored risk assessment tools that can accurately reflect the diverse characteristics of firms, thereby improving risk management practices and decision-making processes.

However, the study is not without its limitations. First, our findings regarding small firms' heightened sensitivity to profitability indicators must be interpreted in light of two caveats. First, the AIDA database covers only incorporated firms, which excludes the large share of unincorporated micro enterprises that may rely more heavily on personal or informal financial resources. Second, our operationalization groups micro and small firms under the same category, potentially masking heterogeneity in their risk profiles. In particular, micro firms, even when incorporated, may have access to informal or owner-based support that weakens the link between profitability and default risk. Future research should aim to disaggregate micro from small firms and extend the analysis to unincorporated businesses to assess the generalizability of our conclusions. Moreover, while the study leverages a rich dataset, it relies heavily on quantitative financial indicators, potentially overlooking qualitative factors such as management quality or market conditions that could also shape default risk (Altman *et al.*, 2010; Altman *et al.*, 2023a; Ciampi, 2015). Future research could also explore the dynamic aspects of default risk by examining how the relationships between financial indicators and default risk evolve over time. Longitudinal studies could shed light on the temporal stability of the identified relationships and help in developing more adaptive and responsive risk models. Moreover, investigating the role of macroeconomic factors such as economic cycles or regulatory changes on default risk could further enhance the predictive power of the models.

While all firms face exposure to default, the degree of vulnerability significantly varies across contexts. Hence, as the economic landscape continues to evolve, future researchers will have the challenge to keep default risk models effective in predicting financial distress, adapting to a greater number of contingencies and to the ever-changing economic landscapes.

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