

Beyond profit maximization: The effect of cooperative governance on insolvency risk in the Brazilian supplementary healthcare industry

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Abstract

Traditional bankruptcy literature has primarily focused on commercial enterprises, often overlooking the unique dynamics of cooperatives and other small organizations. This study addresses this gap by developing a predictive model for insolvency risk within Brazil's supplementary health sector, encompassing both for-profit and not-for-profit healthcare insurers, with a newly curated dataset comprising a total of 684 Brazilian private healthcare medic plan operators in a 10-year span, from 2014 to 2023. For the first time, the financial resilience of cooperatives is quantified, demonstrating that these entities exhibit a significantly lower insolvency risk compared to other organizational forms. This finding is further supported through a propensity score matching analysis. In addition, total debt and administrative expenses were also identified as significant determinants of insolvency risk. From a methodological standpoint, the use of a generalized additive model made it possible to address the limitations of generalized linear models, enabling the

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incorporation of the non-linear relationships between financial and governance variables on the risk of insolvency.

KEYWORDS

bankruptcy, cooperative, forecast, interpretability, machine learning, social enterprise

1 | INTRODUCTION

In the European context, the concept of the social enterprise is closely related to the cooperative movement, sharing some of its principles (Defourny & Nyssens, 2010). However, this concept is not as prominent in Latin America (Gaiger et al., 2019). In fact, there are no legal 'Social Enterprises' in Brazil, and mutuals are unusual (Gaiger et al., 2019).

A concept much more prevalent in the Brazilian context is that of the social economy. The late 20th century's macroeconomic landscape, particularly shifts in capitalist accumulation and its impact on labour, production, global markets and geopolitics, significantly shaped the development of this type of economy (Gaiger et al., 2019). Within this framework, social enterprises encompass a wide array of organizational models, including cooperatives, reciprocal exchange initiatives in commercial networks and a multitude of formal and informal associations. These entities share a common aspect of fostering solidarity-based relationships, voluntary and democratic cooperation to pursue a better quality of life and citizen participation (Bouchard & Chaves, 2022).

As presented by the International Co-operative Alliance (ICA), a cooperative 'is an autonomous association of persons united voluntarily to meet their common economic, social and cultural needs and aspirations through a jointly owned and democratically controlled enterprise' (ICA, 2025). This definition highlights the core values of democratic governance and solidarity shared by cooperatives globally. These values are operationalized through seven key principles: (1) voluntary and open membership; (2) democratic member control; (3) member economic participation; (4) autonomy and independence; (5) provision of education, training and information; (6) cooperation among cooperatives and (7) concern for community. While legal statutes may vary, these principles remain consistent (Hansmann, 2000).

Cooperatives and social enterprises contribute to the promotion of decent work through values that support an alternative economic model aligned with the Sustainable Development Goals (SDGs) and are capable of generating new competitive advantages (Porter & Kramer, 2007, pp. 83–89). Their distinct governance and profit-sharing mechanisms provide insights into business responsibility and its practical implementation (Dam & Scholtens, 2012). Nevertheless, an important question persists regarding cooperative governance: when operating in sectors with strong competition from firms driven primarily by profit maximization, are cooperatives at a disadvantage, facing a greater risk of failure?

Regarding the bankruptcy literature, most of the academic work has concentrated on developed economies, as several studies (Barboza & Altman, 2024; Ozili, 2019) have highlighted the difficulties faced by academics and financial institutions in designing bankruptcy forecast models for developing countries. These challenges stem from underdeveloped financial markets, limited data availability and the lack of comprehensive and standardized credit ratings.

In this context, this article's objective is to develop a model to forecast insolvency in Brazil's supplementary health sector, encompassing both for-profit and not-for-profit healthcare insurers, using a newly curated dataset comprising 684 Brazilian private healthcare medic plan operators observed over a 10-year span (2014–2023) for a total of 6035 observations. By including governance indicators, along with classic financial ratios, we expect to compare the difference in insolvency risk between cooperatives and for-profit enterprises. Our approach relies on bankruptcy forecasting literature, striking a balance between the interpretability of established econometric models and the accuracy of state-of-the-art machine learning techniques.

Our hypotheses are as follows:

Hypothesis 1. *Cooperatives present distinctly anti-cyclical behaviour (Birchall & Ketilson, 2009, pp. 5–9; Zamagni, 2012).*

Hypothesis 2. *Cooperatives are characterized by greater financial soundness than for-profit enterprises, even when offering the same services (Cihák & Hesse, 2007; Forgione & Migliardo, 2018).*

Our study offers a substantial and original contribution to the bankruptcy literature by providing novel empirical evidence concerning cooperative governance on insolvency risk and innovation by using a unique dataset derived from the National Supplementary Health Agency (ANS) in a developing economy.

2 | THEORETICAL BACKGROUND

2.1 | Insolvency forecasting

Emerging in the late 1960s, bankruptcy and insolvency risk analysis are key areas of economic and financial research but still face a challenging landscape due to diverse industry benchmarks and their complex interactions with financial, legal and economic factors (Dasilas & Rigani, 2024; Gholampoor & Asadi, 2024).

Altman (1968) and Beaver (1966) are recognized as the pioneers of modern bankruptcy forecasting, with the influential Z score, utilizing discriminant analysis and financial ratios. Twelve years later, Ohlson (1980) significantly advanced the field by introducing logistic regression (LR) for financial distress forecasting. Since then, the corporate bankruptcy literature has seen exponential growth, accompanied by increasing sophistication in forecasting models.

Machine learning and artificial intelligence have proven more adaptable than traditional logistic and discriminant analysis for assessing insolvency risk (Barboza & Altman, 2024), as financial distress is inherently complex and non-linear (Li et al., 2019), particularly in Latin America (Romero-Barrutieta et al., 2015), limiting the effectiveness of linear techniques.

Developing economies, such as those in Latin America, exhibit unique characteristics that significantly influence bankruptcy risk for privately traded corporations and create challenges for credit risk assessment. High leverage and low profitability, for instance, expose firms in these economies to both endogenous and exogenous liquidity shocks, increasing their probability of bankruptcy. Furthermore, developing bankruptcy forecasting models for private corporations in developing countries presents significant challenges due to the scarcity of data (Charalambakis & Garrett, 2019; Papanas & Spyridou, 2020), as in most developing countries, private firms are not legally obligated to publicly disclose their financial statements, except in regulated markets.

The supplementary health sector in Brazil is the exception: ANS, through ANS' Tabnet System, as part of its transparency policy and in accordance with its institutional purpose of promoting the defence of the public interest in supplementary health care, offers a wide range of query options on relevant data regarding healthcare plan operators, including complete financial statements dating back to March 2000.

The richness and granularity of Tabnet's dataset provide a rare opportunity to conduct robust empirical analyses on the insolvency of healthcare providers, a topic that remains understudied. By leveraging this comprehensive dataset, this study addresses the mentioned gaps, offering one of the first large-scale, data-driven assessments of insolvency risk in the Brazilian supplementary health sector.

Building upon recent developments in bankruptcy research, we highlight a selection of studies that contribute to the themes of this article. These works can be grouped into three primary areas: (i) prediction models for bankruptcy and financial distress, (ii) insolvency risk in cooperatives and nonprofit financial institutions and (iii) financial performance forecasting in relation to governance and social performance indicators.

Regarding bankruptcy prediction models, Gholampoor and Asadi (2024) apply machine learning techniques to predict insolvency in the U.S. healthcare industry using a dataset of 1265 firms and 40 financial ratios. Their findings confirm the superior predictive power of gradient boosting models, with post-tuning accuracy exceeding 90%. Key financial ratios, including return on investment and return on assets, emerge as critical predictors. Similarly, Barboza and Altman (2024) compare LR and random forest (RF) models to predict corporate distress in Latin America, finding RF to be superior, with performance levels remaining stable even during the COVID-19 pandemic. Beauvais et al. (2023) focus on hospital bankruptcies in the United States, employing LR, support vector machines (SVMs) and perceptron neural networks. Their study identifies 18 significant financial and operational variables affecting hospital insolvency risk, filling a gap in predictive models for the healthcare sector. In Europe, Jace et al. (2022) explore bankruptcy prediction in social enterprises using the Bootstrap Mixed Logit model. Unlike the traditional corporate bankruptcy literature, their results indicate that governance-related factors such as board and workforce size influence survival probabilities in social enterprises. de Barros and Beiruth (2016) test Brazilian bankruptcy prediction models in the supplementary health sector, finding that net equity serves as a reliable indicator of insolvency risk for healthcare plan operators, with Altman et al. (1979) demonstrating the highest accuracy.

Focusing on cooperatives and nonprofit financial institutions, multiple studies examine insolvency risks in these specialized sectors. Forgione and Migliardo (2018) analyse small Italian cooperative banks during a financial crisis, emphasizing the importance of bank capital as a predictor of failure. Their findings diverge from for-profit banking models, highlighting that traditional risk factors such as non-performing loans and liquidity are less predictive for cooperatives. Braga et al. (2006) apply the Cox proportional hazards model to Brazilian credit unions, determining that general liquidity, salary expenses and the loan/equity ratio are the most effective indicators of insolvency risk. Naaman et al. (2021) compare risk-taking behaviours between shareholder-owned banks and member-owned credit unions in the United States, revealing that banks tend to assume higher risks, although state regulatory oversight narrows this gap. These findings align with Duncan (2021), who provide a practical framework for small banks and credit unions to conduct risk assessments and strengthen their financial resilience.

Finally, studies examining financial performance forecasting and social performance metrics highlight the interplay between governance, sustainability and financial stability. Chang et al. (2024) investigate how SDGs influence corporate financial performance in the ICT sector,

demonstrating that SDG adoption enhances predictive accuracy for earnings per share. Gulak et al. (2025) focus on health cooperatives, identifying 23 key social performance indicators that should be systematically monitored alongside financial metrics to ensure cooperative sustainability. Their work underscores the importance of transparent communication and member engagement in fostering financial stability.

Building upon the mentioned recent developments in bankruptcy research, we can illustrate the evolving landscape of bankruptcy prediction, cooperative financial stability and the role of governance and sustainability in forecasting financial performance. By integrating insights from diverse methodologies and economic sectors, they provide a robust foundation for refining insolvency prediction models, particularly in the context of health cooperatives and supplementary healthcare providers. However, the comparison of insolvency risk between cooperatives and for-profit enterprises is still scarce, and empirical evidence is rare in the academic literature; thus, our study aims to offer a substantial and original contribution to the bankruptcy literature by providing novel empirical evidence concerning cooperative governance on insolvency risk, drawing upon a state-of-the-art econometric model.

2.2 | Brazilian health system

Brazil's healthcare system is a hybrid model composed of a public subsystem, the Unified Health System (Sistema Único de Saúde [SUS]) and a supplementary private sector. The Unified Health System was established by the 1988 Constitution and guarantees universal, free access to healthcare for all citizens, funded primarily through taxes. SUS provides comprehensive services, including primary, secondary and tertiary care, and forms the backbone of public health in Brazil.

Parallel to SUS, the supplementary health sector offers access to a private network of hospitals, clinics, laboratories and healthcare professionals through healthcare insurance plans regulated by the National Agency of Supplementary Health (Agência Nacional de Saúde Suplementar—ANS) under Law no. 9.656/1998. This sector serves approximately 53 million people, primarily through health plan operators (operadoras de planos de saúde), the subject of this paper. These operators manage and finance access to this network of healthcare services, and their core activities include the following:

1. Selling health insurance plans to individuals or companies;
2. Contracting and managing provider networks (i.e., medical professionals, clinics and hospitals);
3. Processing claims and reimbursing providers.

Operators are classified by legal nature but share a common regulatory framework, which imposes minimum coverage requirements, financial solvency standards and governance rules. This regulatory homogeneity ensures operational consistency across organizational forms, making them directly comparable in terms of business model and financial risk.

Considering sector rules imposed by ANS and data available in ANS's TabNet¹, the main health plan operators are categorized as follows:

¹ <https://www.ans.gov.br/anstabnet/>.

1. Medical cooperatives: Nonprofit entities are organized under cooperative principles, where physicians are members, owners and service providers. The most prominent example is Unimed, the largest medical cooperative system in the world, operating as a federated network of regional cooperatives. Collectively, Unimed holds approximately 38% of the private health market share, serving 20 million people through its network of medical professionals, hospitals and laboratories.
2. Group medicine: Typically, for-profit corporations that manage health plans and often own their own healthcare facilities, such as hospitals and clinics, creating vertically integrated networks. Examples include Hapvida, which is the largest group medicine operator in Brazil with 16% of the market, along with other important firms such as Amil.
3. Self-managed: These operators manage health plans exclusively for a defined group, such as public employees, retirees and dependents of a specific company or professional category. They are nonprofit and do not sell plans to the general public. Self-managed plans are common among public institutions, aiming to provide healthcare benefits as part of employment packages. They represent a small share of the market.
4. Health insurance companies are authorized to operate exclusively in health insurance, offering plans that reimburse medical expenses or provide access to a network of providers. These entities hold approximately 13% of the market, and their largest players are Bradesco Saúde (a part of the Bradesco banking group) and SulAmérica (owned by Rede D'Or, Brazil's largest private hospital group).

Health insurance plans are categorized as individual/family plans and collective plans (primarily corporate). Individual plans are subject to stricter regulatory controls, particularly regarding price adjustments and constitute only 16.7% of the market, while collective plans represent 83.3% of the market and afford greater flexibility in negotiations between operators and contractors.

Unlike hospitals or clinics, which are differentiated by care level (primary, secondary or tertiary), health plan operators are financial and administrative intermediaries. They compete in the same market for the same customers, regardless of legal structure and their exposure to market risk depends on factors such as risk pooling, cost management and governance, rather than on the type of care provided. Their revenue is derived almost exclusively from private contracts. Occasional collaborations with SUS (e.g., elective surgery programmes to reduce SUS waiting lists) are exceptional and do not materially affect operators' financial performance.

2.3 | Cooperative governance in Brazil

To fully grasp the dynamics within the Brazilian supplementary health sector, it is essential to examine the unique organizational and governance structure of cooperatives in Brazil. As in the international scenario, cooperatives are guided by a set of principles based on those established by the ICA. These principles form the conceptual foundation of the cooperative movement and distinguish cooperatives from for-profit and traditional nonprofit entities. The key principles include:

1. Voluntary and open membership: Cooperatives are open to all people able to use their services and willing to accept the responsibilities of membership.

2. Democratic member control: Cooperatives are democratic organizations controlled by their members, who actively participate in setting policies and making decisions. This is often encapsulated in the rule of 'one member, one vote'.
3. Member economic participation: Members contribute equally to, and democratically control, the capital of their cooperative.
4. Autonomy and independence: Cooperatives are autonomous, self-help organizations controlled by their members.
5. Education, training and information: Cooperatives provide education and training for their members and inform the public about the nature and benefits of cooperation.
6. Co-operation among cooperatives: Cooperatives serve their members most effectively and strengthen the cooperative movement by working together.
7. Concern for community: While focusing on member needs, cooperatives work for the sustainable development of their communities.

These principles define an organization whose primary objective is to meet the common needs of its member-owners, rather than to generate profit for shareholders. This fundamental difference in purpose is hypothesized to influence strategic decision-making, risk appetite and long-term stability.

In Brazil, these principles are formalized in a specific legal framework for cooperatives, established by Law no. 5764/1971. This law defines the national policy for cooperativism and institutes the legal regime for cooperative societies. It codifies international principles into Brazilian law, with several distinctive features, including the following:

1. Nature and purpose: Brazilian cooperatives are defined as societies of persons with a distinct legal nature, constituted to provide services to their members, without a profit motive (Art. 3° and 4°).
2. Governance structure: The law mandates a strict governance model rooted in member democracy. The supreme authority is the General Assembly of members (Art. 38). Article 47 stipulates that the administration of the cooperative must be carried out by a Board of Directors or Executive Board, composed exclusively of members elected by the General Assembly.
3. Management: While strategic control rests with the member-elected board, Article 48 allows the administrative bodies to hire technical or commercial managers who are not members. This creates a potential distinction between strategic governance (held by members) and operational management (which may involve hired executives).

This structure is especially relevant to the Brazilian supplementary health sector since health insurance plan cooperatives are a specific type of worker cooperative. In this model, the members are the medical professionals themselves. Therefore, as a direct consequence of Article 47 of Law 5764/71, the governing boards of all cooperative health plan operators in Brazil are, by law, composed exclusively of medical professionals.

Thus, while a cooperative may hire a non-medical CEO for day-to-day operational management (as permitted by Art. 48), the ultimate strategic oversight, approval of major financial decisions, and definition of the organization's ethos reside with the board of directors, which is elected from and by the medical professional members.

However, the broader literature on the relationship between cooperative governance and performance remains inconclusive. As highlighted in the systematic review by Jamaluddin et al. (2023), research on factors such as board size, composition and leadership has yielded

contradictory results, making it difficult to draw definitive conclusions about what constitutes optimal cooperative governance or to ultimately answer questions related to comparative performance to profit-maximizing firms. This ambiguity underscores a significant gap in our understanding of how governance mechanisms translate into tangible outcomes such as financial stability and risk management. Our paper intends to contribute to this debate by providing empirical evidence from the specific context of the Brazilian private health system.

3 | MATERIALS AND METHODS

3.1 | Dataset and variables

We sourced our data directly from the ANS TabNet System, covering the period from 2014 to 2023. This dataset comprises annual accounting data for 684 Brazilian private healthcare plan operators, resulting in an unbalanced panel totalling 6035 operator-year observations after data processing. The raw data required significant preparation, as they were published in a long format and contained numerous missing values. The following steps were taken to construct the final dataset:

1. Annual financial data files were appended row-wise to form a single dataset;
2. The appended data were then reshaped from their original long format to a wide panel format, where each row corresponds to an operator-year and each column represents a specific financial account;
3. Health plan operators lacking a National Registry of Legal Entities (CNPJ) were excluded. We also removed operators reporting zero total assets, zero total liabilities or zero revenue;
4. Missing values for specific accounting items (including revenue from healthcare assistance operations, commercialization expenses, other operating expenses, financial expenses, administrative expenses and equity expenses) were imputed as zero;
5. Finally, operators classified as exclusively odontological plan providers were excluded from the final sample.

To classify health plan operators as financially distressed/insolvent, we followed prior literature and defined distress as the inability to meet financial obligations or having a negative net worth. Thus, for this research, insolvency is defined as (i) negative leverage (i.e., operating income is less than financial expenses) or (ii) negative equity. Specifically, negative leverage indicates that the company is not generating enough operating profit to cover its debt-related costs, forcing reliance on loans or non-operating income to stay afloat. This situation is not sustainable in the long term, especially without a clear strategy for growth or debt reduction. Negative equity is straightforward and typically reflects ongoing operational losses, poor financial management, or over-leveraging.

The selection of independent variables was driven by two key criteria: data availability and their established significance in prior studies (Altman, 1968; Altman et al., 1979, 2017; Barboza et al., 2017; Barboza & Altman, 2024; Braga et al., 2006; Bressan et al., 2011; Forgione & Migliardo, 2018). The variables are defined as follows: Total debt ratio (EndT) measures the proportion of a company's assets financed by debt; current liquidity (LiqC) indicates short-term liquidity, where a ratio above 1 suggests the company can cover its short-term obligations with its short-term assets; net margin (ML) is the percentage of total revenue remaining after all expenses and taxes are paid; administrative expenses ratio (Admin) reflects the weight of administrative costs relative to

TABLE 1 Formulas and definitions for the chosen variables.

#	Name	Formula	Type
1	EndT	$\frac{\text{Total debt}}{\text{Total assets}}$	Financial ratio
2	LiqC	$\frac{\text{Current assets}}{\text{Current liabilities}}$	Financial ratio
3	ML	Net margin	Financial ratio
4	Admin	$\frac{\text{Administrative expenses}}{\text{Total assets}}$	Financial ratio
5	Sinis	$\frac{\text{Assistance expenses}}{\text{Income from monthly fees}}$	Financial ratio
6	ROE	Return on equity	Financial ratio
7	IAT	Revenue/Total assets	Financial ratio
8	Coop	Cooperative	Dummy
9	Auto	Self-managed	Dummy

TABLE 2 Summary statistics of independent variables.

Variable	N	Mean	Min	Pctl. 25	Pctl. 75	Max
EndT	6035	0.5251	0.0000	0.3655	0.6592	4.0779
LiqC	6035	2.8080	0.0000	1.2400	2.5960	317.89
ML	6035	0.0277	−1.9190	0.0025	0.0755	1.0000
Admin	6035	0.1269	−2.5830	0.0941	0.1807	1.0075
Sinis	6035	0.7341	−70.980	0.6781	0.8501	7.0656
ROE	6035	0.0619	−8.7257	0.0091	0.1353	8.3655
IAT	6035	1.8516	−0.0283	1.2554	2.3301	11.5069
Coop	6035	0.4399	—	—	—	—
Auto	6035	0.18	—	—	—	—

the asset base; assistance ratio (Sinis) measures how much of the revenue from members' fees is spent on assistance or claims, a common metric for insurance-like entities; return on equity (ROE) measures profitability relative to shareholders' equity; total revenue to assets (IAT) is a measure that measures how effectively a company uses its assets to generate revenue; Coop is a dummy variable indicating whether the entity is a cooperative (1) or not (0); and Auto is a dummy variable indicating whether the entity is self-managed (1) or not (0), defined as a nonprofit entity that administers private health insurance plans for a closed group of users, typically public employees, linked to one or more companies or professional categories (Table 1).

Table 2 presents the summary statistics of the dependent and independent variables.

3.2 | Study case design

Using the final database, we designed two study cases. In both, the database was split into two samples: training and test. The training sample was used to calibrate the model, while the test sample was used to assess its accuracy. In the first study case, the training sample comprised data

from 2014 to 2019 and the test sample data from 2020. In the second study case, the training sample comprised data from 2014 to 2022, and the test sample comprised data from 2023.

We utilize these two study cases to assess the robustness of the models proposed herein. The first study case forecasts insolvency during a financial and health crisis (COVID-19). The second study case forecasts insolvency for 2023, the most recent year for which financial data were available. The quality of each model is assessed using a set of measures commonly used in financial studies: ROC AUC (Receiver Operating Characteristic - Area Under Curve), accuracy, sensitivity, specificity, balanced accuracy and Type I and II errors.

3.3 | Methodological procedure

Bankruptcy and insolvency forecasting is inherently a classification problem, as the objective is to distinguish between solvent and insolvent firms based on financial and nonfinancial variables. As such, we draw upon a recent literature review on small- and medium-sized enterprises (SMEs) default prediction to support our methodological choices (Cheraghali & Molnár, 2024).

The most widely used method to forecast bankruptcy is LR (Cheraghali & Molnár, 2024). However, authors such as Begley et al. (1996) have argued that traditional methods based on Altman (1968) and Ohlson (1980) became inaccurate, primarily due to their inability to capture non-linear relationships among independent variables (Barboza & Altman, 2024; Khemakhem et al., 2018; Li et al., 2019), which are often present in financially distressed firms. In this context, machine learning methods have emerged as an alternative to the classic logit model, often providing superior predictive accuracy.

While these methods can be highly accurate, their use introduces a critical challenge: interpretability. Many machine learning models operate as 'black boxes', obscuring the underlying internal logic that drives their predictions. This lack of transparency has prompted regulatory scrutiny, such as from the European Union's General Data Protection Regulation (GDPR), which restricts the use of 'black box' models. Under the GDPR, decisions based solely on automated processing are prohibited unless accompanied by meaningful explanations of the reasoning involved (Voigt & von dem Bussche, 2024).

Therefore, we approach this classification problem with a generalized additive model (GAM) to incorporate non-linear effects of the financial and governance variables, addressing the interpretability issues introduced by other ML models while striving to maintain accuracy. We also adopt LR as a baseline model for comparison.

For both LR and GAM, we treat the dataset as pooled observations, as there is evidence that forecasting models can benefit from pooling when there is 'not much heterogeneity in the model parameters' (Mark & Sul, 2012), a condition we assume applies to our sample. This method also follows the preceding literature mentioned in Section 2.1.

3.3.1 | Logistic regression

LR was used as the baseline model, to which the GAM was compared. It is a statistical method used to model the probability that an observation belongs to a particular class. In the case of binary classification, it estimates the probability that Y belongs to Class 1 given a set of independent

variables X via a sigmoid function:

$$p(X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \dots + \beta_n x_n)}} \quad (1)$$

where $p(X)$ is the predicted probability of insolvency, β_0 is the intercept, $\beta_1, \beta_2, \dots, \beta_n$ are the coefficients of the set of independent variables $X = (x_1, x_2, \dots, x_n)$ and e is Euler's number.

As such, LR assumes that the log-odds of the outcome has a linear relationship with the independent variables, so that each x_n contributes additively to the log-odds and the effect of x_n on the log-odds is constant. Although it is the most commonly used model, this linearity assumption may be too restrictive because often the marginal effects of independent variables on bankruptcy are not constant and depend on the specific value that each variable takes. This simplistic assumption can result in poor accuracy and biased insights regarding the contribution of each variable to failure risk.

3.3.2 | Generalized additive models

Introduced by Hastie and Tibshirani (2017), GAMs can be interpreted as an extension of generalized linear models (GLMs). Their main advantage over GLMs is that they allow the introduction of smooth functions of covariates, replacing linear predictors, such as those used in LR. The relationship between the response variable and predictors can be modelled as:

$$g(E[y_i]) = \beta_0 + s_1(x_1) + s_2(x_2) + \dots + s_j(x_j) \quad (2)$$

where $g(\cdot)$ is the logit function and $s_j(\cdot)$ are smooth functions. Each smooth function $s_j(x_j)$ is represented using a basis expansion, and we adopt penalized regression splines for $s_j(\cdot)$:

$$s_j(x_j) = \sum_{k=1}^{m_j} \beta_{jk} B_{jk}(x_j) \quad (3)$$

where $B_{jk}(x_j)$ are basis functions and β_{jk} are coefficients. Then, s_j is penalized to avoid overfitting, given by the integral of its squared second derivative:

$$\int [s_j''(x_j)]^2 dx_j = \beta_j^\top P_j \beta_j \quad (4)$$

where P_j is a penalty matrix derived from the basis.

The model is then estimated by penalized likelihood maximization:

$$l(\beta) - \frac{1}{2} \sum_{j=1}^p \lambda_j \beta_j^\top P_j \beta_j \quad (5)$$

where $l(\beta)$ is the log-likelihood of the GLM and $\lambda_j \geq 0$ are the smoothing parameters.

The λ_j smoothing parameter estimation problem is solved by using the generalized cross-validation (GCV) criterion:

$$V(\lambda) = \frac{n \cdot D(\hat{\beta})}{[n - \gamma(\lambda)]^2} \quad (6)$$

where $D(\hat{\beta}) = -2l(\hat{\beta})$ is the deviance, $\gamma(\lambda) = \text{tr}(A)$ is the effective degrees of freedom, $A = X(X^\top WX + S)^{-1} X^\top W$ is the influence matrix, and W is the GLM weight matrix. The optimal λ is given by iteratively updating λ using the Newton–Raphson method:

$$\lambda^{(k+1)} = \lambda^{(k)} - H^{-1}(\lambda^{(k)}) g(\lambda^{(k)}) \quad (7)$$

where $g(\lambda)$ is the gradient and $H(\lambda)$ is the Hessian.

We implemented the models using the R statistical software package “mgcv” (Wood, 2000) using the *gam()* function.

Finally, it is important to highlight that GAMs retain most of the interpretability of the LR, but their marginal effects can no longer be summarized in a single parameter, as the effect of each predictor on the response variable is no longer linear (Valencia et al., 2019).

3.3.3 | Propensity score matching

Propensity score matching (PSM) was first defined by Rosenbaum and Rubin (1983) as a statistical method typically used in observational studies to estimate the causal effect of a treatment or intervention by mitigating the confounding biases arising from non-random treatment assignment. The core principle is to approximate the conditions of a randomized controlled trial by constructing a sample of control units (non-treated) whose distribution of observed pretreatment covariates is statistically indistinguishable from that of the treated units.

The objective is achieved by reducing the multidimensional vector of covariates into a single scalar: the propensity score. Defined as the probability of treatment assignment conditional on observed baseline covariates, the propensity score serves as a balancing score. Units with similar propensity scores are then matched, allowing for a comparison of outcomes between treated and control units that is less confounded by initial differences. In practice, the propensity score is often estimated via LR (Austin, 2011), which involves regressing the treatment status on a set of observed baseline characteristics.

In this study, the PSM procedure was specifically employed to estimate the differential effect of being a cooperative (the treatment condition) on a set of financial outcome variables. The implementation involved two main steps: first, the estimation of the propensity scores using a RF algorithm; and second, a full matching algorithm with a 0.1 calliper was applied to maximize sample retention while ensuring match quality.

Let $D_i \in \{0, 1\}$ be a binary indicator variable representing the treatment assignment for unit i , where $D_i = 1$ denotes a cooperative (treated unit) and $D_i = 0$ denotes a non-cooperative (control unit).

Let X_i be a vector of observed financial covariates for unit i . The propensity score $p(X_i)$ is defined as the conditional probability that unit i is a cooperative given its observed covariates X_i :

$$p(X_i) = \Pr(D_i = 1 | X_i) \quad (8)$$

Under the framework developed by Rosenbaum and Rubin (1983), a set of assumptions must hold for valid causal inference:

1. Conditional independence (unconfoundedness): Given the propensity score, the potential outcomes are independent of the treatment assignment: $Y(0), Y(1) \perp D \mid p(X)$.
2. Overlap (common support): The propensity score is strictly between 0 and 1 for all values of X : $0 < \Pr(D = 1 \mid X) < 1$.

The estimation of the propensity score is specified as follows:

$$\hat{p}(X_i) = \mathcal{F}_{RF}(X_i) \quad (9)$$

where $\mathcal{F}_{RF}$ represents the RF classifier. Following the estimation of propensity scores $\hat{p}(X_i)$ for all observed firms, treated and control units are matched. We adopt full matching with replacement. This method optimally partitions the sample by minimizing a weighted average of the propensity score distances between all treated and control units within each stratum. The primary advantage of full matching is that the entire sample is retained, maximizing statistical power and reducing the model dependence inherent in simpler matching algorithms such as 1:1 nearest-neighbour.

Furthermore, to ensure match quality and prevent poor matches between units with dissimilar propensity scores, a calliper width of 0.1 standard deviations of the propensity score was imposed. This calliper defines the maximum allowable distance for a valid match. Formally, a control unit j is considered an eligible match for a treated unit i only if:

$$\left| \text{logit}(\hat{p}(X_i)) - \text{logit}(\hat{p}(X_j)) \right| < \epsilon \text{ where } \epsilon = 0.1 \cdot \sigma_{\text{logit}(p)} \quad (10)$$

where $\sigma_{\text{logit}(p)}$ is the standard deviation of the estimated propensity scores on the logit scale.

4 | RESULTS

4.1 | Model quality

Regarding accuracy and validity, Table 3 presents the primary model quality statistics.

The comparative analysis of model performance reveals the consistent superiority of GAM over LR across all metrics, reinforcing its suitability for insolvency prediction. According to Table 3, the COVID-19 period did not significantly impact the accuracy of our forecasts. This indicates that the GAM maintained robust performance in predicting financial distress, even amid the market crashes and economic disruptions caused by the pandemic. Thus, for brevity reasons, we will focus our discussion on the 2023 forecast results.

The GAM achieves an in-sample accuracy of 88.48%, declining only marginally to 83.75% out-of-sample, indicating robust generalization. In contrast, the LR attains 76.01% accuracy in-sample and 74.61% out-of-sample, reflecting its limited flexibility in capturing complex patterns. Sensitivity, a critical metric for detecting true bankruptcy cases, is markedly higher for the GAM (89.33% in-sample, 84.29% out-of-sample) compared to LR (76.94%–74.82%), highlighting its practical utility in minimizing false negatives.

GAM also outperforms LR in its discrimination power, as measured by AUC ROC (0.92 in-sample, 0.90 out-of-sample) presented in Figure 1, significantly exceeding the LR (0.80–0.81) and surpassing benchmarks in econometric bankruptcy forecasting literature (Altman et al., 2017; Fiordelisi & Mare, 2013; Forgione & Migliardo, 2018; Porath, 2006).

TABLE 3 Model quality statistics.

Statistic	2023			
	Logit		GAM	
	In-sample	Out-of-sample	In-sample	Out-of-sample
Accuracy	0.7601	0.7461	0.8848	0.8375
Sensitivity	0.7694	0.7482	0.8933	0.8429
Specificity	0.6803	0.7326	0.8117	0.8023
Balanced accuracy	0.7248	0.7404	0.8525	0.8226
AUC ROC	0.8036	0.8129	0.9175	0.9046
Statistic	Covid-19			
	Logit		GAM	
	In-sample	Out-of-sample	In-sample	Out-of-sample
Accuracy	0.7765	0.8322	0.9047	0.9104
Sensitivity	0.7903	0.8559	0.9184	0.9181
Specificity	0.6555	0.5769	0.7843	0.8269
Balanced accuracy	0.7229	0.7164	0.8514	0.8725
AUC ROC	0.7930	0.8043	0.9164	0.9098

Abbreviation: GAM, generalized additive model.

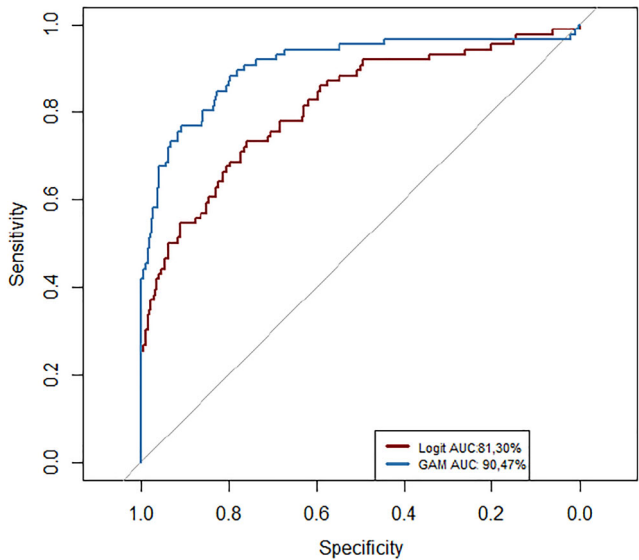


FIGURE 1 Area under the ROC.
[Colour figure can be viewed at
wileyonlinelibrary.com]

The GAM’s ability to model non-linear relationships contributes to robust performance on both the training and test sets, suggesting that it is a superior tool for bankruptcy prediction in our case study. This approach provides strong predictive power without resorting to black-box machine learning techniques, thus retaining model interpretability.

TABLE 4 Regression coefficients.

Variable	2023		Covid-19	
	Estimate logit	Estimate GAM	Estimate logit	Estimate GAM
(Intercept)	−3.521***	−2.6549***	−4.271***	−1.6162
EndT	2.804***	Non-linear***	2.771***	Non-linear***
LiqC	−0.0000	Non-linear***	−0.000	Non-linear***
IAT	−0.1219*	Non-linear***	0.0435	Non-linear*
ML	−1.47***	Non-linear***	−1.2160*	Non-linear***
Admin	3.360***	Non-linear***	4.6750***	Non-linear***
Sinis	−0.1563	Non-linear***	−0.0089*	Non-linear***
ROE	−0.2791	Non-linear***	−0.4246	Non-linear***
Coop	−1.442***	−0.9459***	−1.1240***	−0.3898*
Auto	−0.6264***	−1.1019***	−0.6128**	−1.5484***

Abbreviation: GAM, generalized additive model. *, ** and *** denote statistical significance at the 5%, 1% and 0.1%.

4.2 | Governance insights

As presented in Section 3, we opt for a more direct approach, employing a reduced set of widely used financial ratios due to data reliability concerns. Despite this smaller set of variables, the model's accuracy was robust: the GAM achieved 83.75% out-of-sample accuracy in 2023. This performance is higher than that reported in similar studies that rely on traditional econometric methods. Following the proposed study case design, Table 4 presents the estimated coefficients for the LR and the estimated parameters for the linear components in the GAM, considering both scenarios:

For the LR, each predictor's coefficient represents the change in the log-odds of the outcome for a one-unit increase in that predictor. By exponentiating these coefficients, we obtain the odds ratios (ORs), which provide an intuitive measure of the multiplicative change in the odds of the outcome associated with variations in the predictors. In contrast, within the GAM framework, such a direct log-odds interpretation is only applicable to the 'Coop' and 'Auto' variables, as these were specified as linear terms. The effects of the remaining predictors are captured by non-linear smooth functions and cannot be summarized by a single coefficient.

The 'cooperative governance variable', a binary indicator distinguishing cooperatives (1) from non-cooperatives (0), exhibits a negative and statistically significant coefficient in both the 2023 (−0.9459, $p < 0.001$) and Covid-2020 (−0.3898, $p < 0.05$) models. The corresponding average marginal effect of the 'Coop' variable for 2023 is −0.048, indicating that cooperatives (Coop = 1) have, on average, a 4.8 percentage point lower probability of bankruptcy compared to non-cooperatives (Coop = 0), holding all other variables constant. This finding strongly supports the hypothesis that cooperative structures mitigate insolvency risk, potentially due to shared financial responsibilities and more distinct governance practices.

Indeed, the cooperative governance literature supports this finding (Birchall & Ketilson, 2009, pp. 25; Cihák & Hesse, 2007; Forgione & Migliardo, 2018; Zamagni, 2012), and our results add further evidence that cooperative structures can mitigate operational risk. From an agency theory perspective, Dahlbäck (2019) argues that the cooperative structure can reduce excessive risk-taking because the agent and the principal are largely the same. In addition, considering the non-profit-maximizing nature of cooperatives, one can argue that cooperatives have less incentive to engage in overly risky activities. Birchall and Ketilson (2009) suggest that cooperative banks adhering closely to their cooperative identity have demonstrated greater resilience to eco-

conomic downturns than those that have strayed from their roots. This pattern may extend to supplementary health cooperatives.

Beyond governance mechanisms, organizational characteristics may also explain cooperative resilience. Beaver et al. (2024) suggest that business groups can function as 'shock absorbers', mitigating financial distress at the subsidiary level through internal capital markets and intra-group transactions. Such mechanisms enable the redistribution of resources and risk across affiliated entities, potentially lowering the probability of bankruptcy for individual firms. Similarly, cooperative systems, such as Unimed (a federated network of numerous cooperatives under a common brand and governance framework), leverage solidarity principles and collective governance to achieve comparable outcomes, even though their motivation is not profit maximization but rather member welfare and sustainability. This configuration creates a mechanism for mutual support and resource sharing, allowing financially stronger units to assist weaker ones, thereby reducing the likelihood of individual insolvency.

Moreover, the analogy extends to the role of reputational interdependence. Just as business groups have strong incentives to prevent subsidiary failure to safeguard the group's overall reputation, federated cooperative systems face similar pressures. The collapse of a single cooperative could undermine confidence in the entire network, prompting proactive interventions to maintain stability. Therefore, the lower failure risk observed among cooperatives may also be interpreted as an outcome of group-level coordination and mutual support, echoing the dynamics observed in corporate business groups.

Regarding the non-linear effects of the remaining independent variables, the interpretation is more complex, as the model estimates smooth spline functions rather than fixed linear coefficients. In the context of GAMs, the marginal effect of a continuous predictor variable at a specific point is defined as the instantaneous rate of change of the response (in this case, the log-odds of bankruptcy) with respect to that predictor. This is mathematically represented by the first partial derivative (slope) of the estimated smooth function associated with the predictor. Computing these derivatives allows us to understand how changes in predictor variables influence the response variable across different values. This approach reveals the specific nature of the relationship between each predictor and bankruptcy risk. We now highlight some of the most important findings.

When assessing financial health in the Brazilian supplementary healthcare sector, the assistance ratio is one of the primary KPIs. It quantifies the proportion of premiums used to cover healthcare claims, serving as an indicator of operational efficiency. This metric directly influences premium pricing, solvency requirements, and market stability. Surprisingly, the Assistance Ratio is not a statistically significant predictor of insolvency in the LR; this finding may be due to a non-linear effect. The shape of the smooth function in the GAM (presented in Figure 2) confirms this non-linearity. The model indicates that the assistance ratio is associated with an increased insolvency risk when its value is above 1.25 or below 0.7. Indeed, a high assistance ratio may suggest that a substantial portion of premium revenues is consumed by healthcare claims, potentially undermining the operator's financial stability, while an excessively low ratio might indicate underutilization of services or overly restrictive coverage policies. However, its impact on insolvency risk is modest compared to Total Debt.

The total debt to total assets ratio (EndT) exhibits a positive linear association with bankruptcy risk in the logistic model (2.804 in 2023). In contrast, the non-linear marginal effects from the GAM (presented in Figure 3) suggest that insolvency risk escalates sharply once this ratio exceeds 0.85. This non-linearity implies that the standard linear model underestimates the effect of Total Debt in the interval $0.85 < \text{EndT} < 1.35$ and overestimates its effect when the ratio is outside

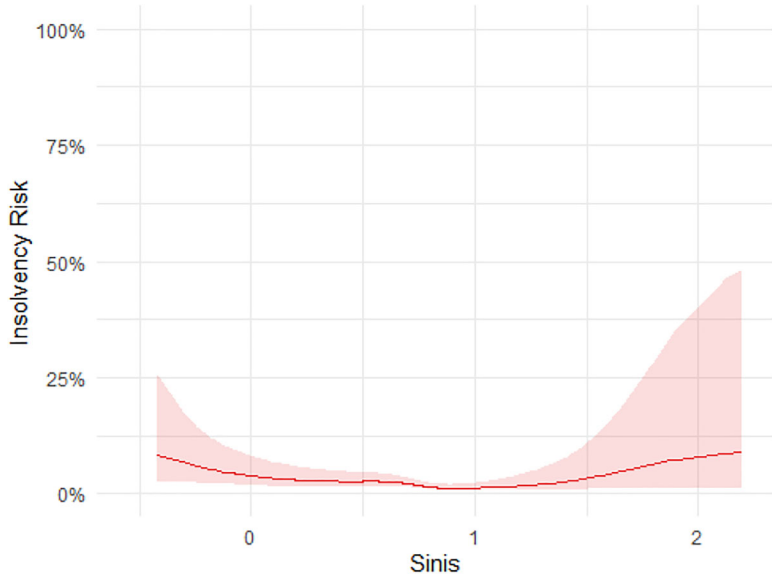


FIGURE 2 Sinistrality's slope of the generalized additive model (GAM) smooth function. [Colour figure can be viewed at wileyonlinelibrary.com]

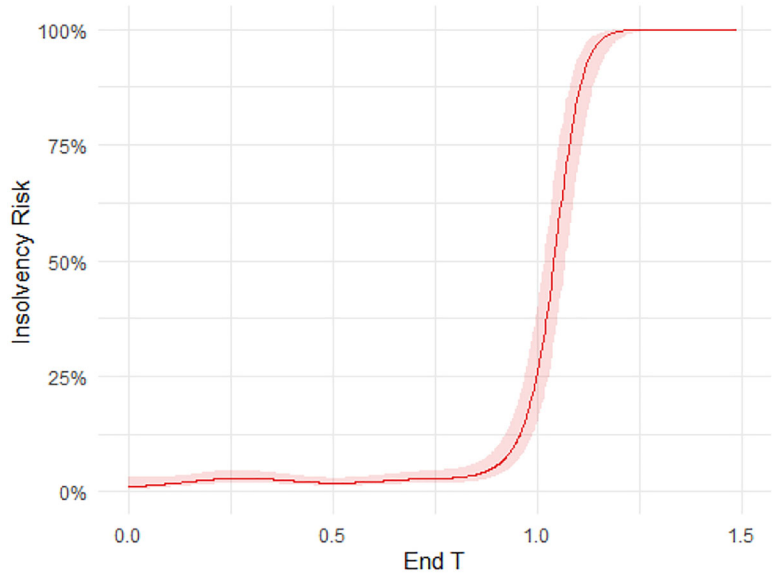


FIGURE 3 Total debt's slope of the generalized additive model (GAM) smooth function. [Colour figure can be viewed at wileyonlinelibrary.com]

this range. Notably, this ratio is not incorporated in the popular set of predictor variables used in Altman's Z score models. However, it is a critical leverage ratio in our study, revealing the proportion of a firm's assets financed by debt. As stated by Reis et al. (2021), Total Debt is the variable that most impacts the ANS's decision to place healthcare operators into a special regime of extrajudicial liquidation.

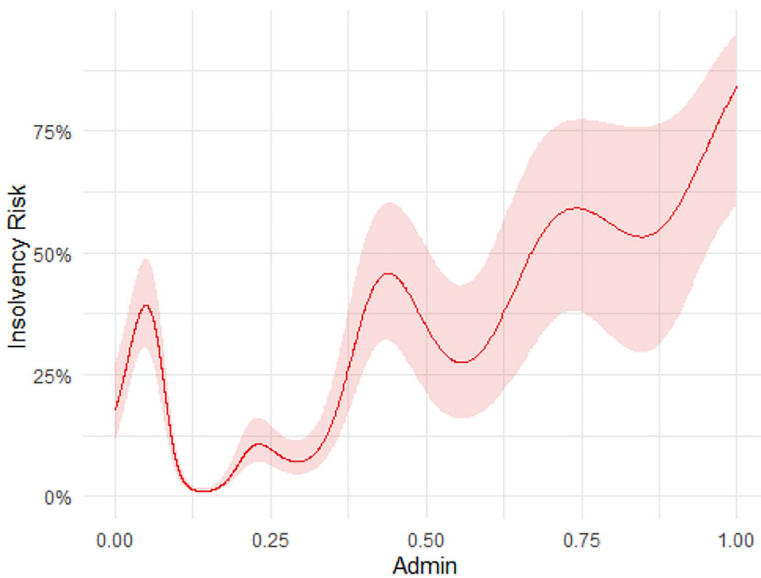


FIGURE 4 Administrative spendings' slope of the generalized additive model (GAM) smooth function. [Colour figure can be viewed at wileyonlinelibrary.com]

Similarly, Admin (administrative expenses over assets) exhibits a positive and statistically significant association with insolvency risk in the logistic model (3.360 in 2023), while its non-linear marginal effects in the GAM suggest a more complex relationship, as presented in Figure 4.

Administrative spending appears to play a paradoxical, although expected, role in insolvency risk for health insurers. Initially, strategic investments in personnel, training and capacity building, along with investments in fraud prevention and regulatory compliance, can plausibly reduce insolvency risk by enhancing operational efficiency, achieving economies of scale, and promoting long-term sustainability. However, beyond an optimal threshold, excessive spending may signal inefficiency or resource misallocation.

Further addressing operational efficiency, herein represented by ML, we find a significant effect on financial sustainability, a finding that echoes Ngumo et al. (2020). Specifically, higher margins appear to improve cash flow, which is in congruence with the findings of Jace et al. (2022), who demonstrate that cash flow negatively affects insolvency risk (Figure 5).

To further explore whether the relationship between financial indicators and insolvency risk differs by organizational form, we extended the GAM to incorporate interaction effects between the cooperative governance variable and continuous financial predictors. Specifically, we employed factor-smooth interactions, which allow the smooth functions of each financial predictor to vary separately for cooperatives and non-cooperatives.

This modelling strategy enables us to capture heterogeneous non-linear effects across organizational forms, rather than assuming a uniform functional relationship for all entities. By estimating separate smooths for each group, we can assess whether cooperatives exhibit different sensitivities to financial stressors compared to their for-profit counterparts. Table 5 shows the estimated coefficients for this interaction model.

While the traditional bankruptcy literature is premised on the model of the profit-maximizing firm, our results reveal a distinct financial risk paradigm for cooperatives. Whereas for-profit insurers are vulnerable to classical market pressures captured by profitability and returns

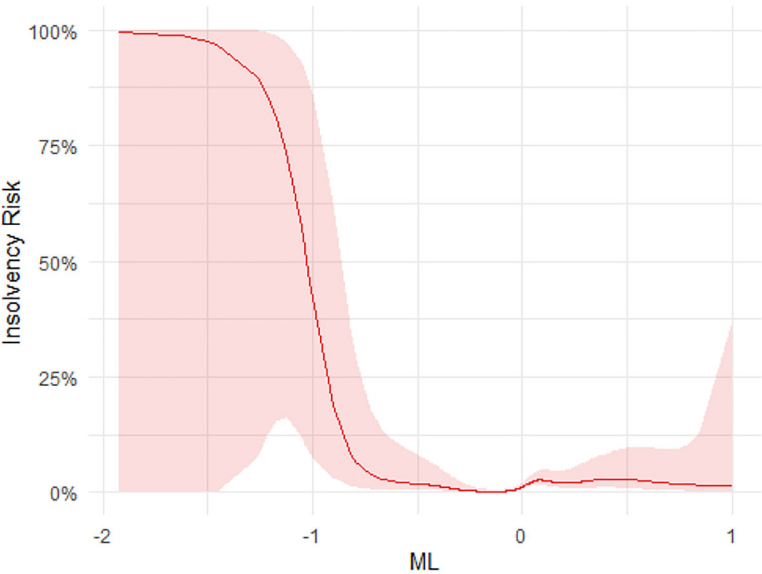


FIGURE 5 Net margin's slope of the generalized additive model (GAM) smooth function. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 5 Estimated coefficients by factor.

Term	Non-coops (estimate/significance)	Coops (estimate/significance)
Parametric terms		
Intercept	−2.8033***	
Coop	6.0623 ^{ns}	
Auto	−1.0689***	
Smooth terms		
EndT	***	ns
IAT	**	*
LiqC	***	ns
ML	***	ns
Admin	***	***
Sinis	ns	***
ROE	***	ns

Abbreviation: ^{ns}, not significant. *, ** and *** denote statistical significance at the 5%, 1% and 0.1%.

(e.g., ML and ROE), cooperatives appear to be governed by a different risk paradigm. Their member-owned, not-for-profit structure seems to insulate them from these specific profitability-based indicators, making their insolvency risk primarily a function of operational efficiency (assistance ratio and administrative expenses).

In the interaction model, which allows the smooth functions of each variable to vary separately for non-cooperatives and cooperative entities, we find that the Coop variable itself is no longer statistically significant. The observed difference in insolvency risk between cooperatives and other entity types is better explained by their differential responses to financial variables rather than by

a simple, constant intercept shift. In other words, organizational form appears to moderate the relationship between financial health and insolvency risk.

The theoretical foundation for understanding cooperative resilience draws from several strands of literature. Agency theory posits that for-profit entities are designed to minimize conflicts between shareholders and managers, with success conventionally measured primarily through financial metrics such as ROE and ML (Ahmed et al., 2024; Baby et al., 2024; Richard et al., 2009; Liu et al., 2013). Conversely, the multitask principal-agent model proposed by Holmstrom and Milgrom (1991) suggests that social enterprises, such as cooperatives, have multiple objectives or goals beyond profit, such as financial education, financial inclusion, member satisfaction or community service. Many of these goals are difficult to quantitatively observe or measure. As noted by Jamaluddin et al. (2023), while financial performance is important for cooperatives, social and environmental factors are also crucial measures of their growth and success. This theoretical distinction leads to the expectation that the financial risk profiles of these organizational forms would differ substantially, although prior empirical research has insufficiently documented these differential pathways to insolvency.

Thus, our findings contribute to both current theory and the cooperative governance literature. For-profit entities are driven by the relatively straightforward and easily observable goals of profit maximization and shareholder value. Their insolvency risk is consequently tied to conventional financial performance metrics, such as ML and ROE. In contrast, cooperatives are driven by member welfare and service provision. Their goal is not to maximize profit for external shareholders but to provide sustainable value for their associates. Therefore, their risk profile is less sensitive to short-term profitability metrics, such as ROE, which is of limited relevance in a structure without external shareholders and more closely aligned with long-term organizational sustainability and operational efficiency.

These findings offer a novel empirical contribution to social enterprise theory (Besley & Ghatak, 2005; 2017) and resonate with empirical research on financial cooperatives (McKillop et al., 2020; van Rijn et al., 2023). We propose that financial resilience (herein represented as the inverse of insolvency risk) can be a measurable outcome of successfully managing the tension between a cooperative's social mission and the market's financial logic. The comparative resilience of the cooperative form suggests that social goals do not necessarily compromise financial viability; in this case, the opposite may be true. In member-oriented organizations, a focus on social value creation can be an element of, rather than a detriment to, financial sustainability.

4.3 | Robustness check

To address potential selection bias and strengthen the causal interpretation of our findings, we conducted a supplementary analysis using PSM. This technique aims to create a more comparable counterfactual by matching cooperative and non-cooperative operators based on their observed financial characteristics, thereby simulating the conditions of a randomized experiment.

The PSM procedure was implemented using an RF algorithm to estimate the propensity scores, a method chosen for its superior ability to capture complex, non-linear relationships between financial covariates and the probability of being cooperative. This estimation was followed by full matching with replacement, which optimally creates matched strata containing at least one treated (cooperative) and one control (non-cooperative) unit, thereby retaining the full sample. A calliper width of 0.1 standard deviations of the logit propensity score was also imposed to ensure match quality. After matching, financial covariates were mostly balanced, as presented in Table 6.

TABLE 6 Covariates after propensity score matching (PSM) balancing.

Variable	Type	SMD	Balance	Var.ratio	Balance	KS.Adj	Balance
Distance	Distance	−0.0001	Balanced	0.9956	Balanced	0.0159	Balanced
EndT	Continuous	0.0612	Balanced	1.5878	Balanced	0.0528	Balanced
LiqC	Contin.	0.0592	Balanced	0.5606	Balanced	0.0546	Balanced
IAT	Continuous	−0.1074	Not balanced	1.0681	Balanced	0.0818	Balanced
ML	Continuous	0.0090	Balanced	0.9703	Balanced	0.0412	Balanced
Admin	Continuous	0.0284	Balanced	1.1730	Balanced	0.0350	Balanced
Sinis	Continuous	−0.0449	Balanced	0.1444	Not balanced	0.0480	Balanced
ROE	Continuous	−0.0395	Balanced	0.8978	Balanced	0.0756	Balanced

Abbreviation SMD, Standardized mean difference.

TABLE 7 Re-estimated coefficients after propensity score matching (PSM) matching.

Variable	2023		
	Estimated Logit	Estimated GAM	PSM Re-estimated GAM
(Intercept)	−3.521***	−2.6549***	−2.423***
EndT	2.804***	Nonlinear***	Nonlinear***
LiqC	0.000	Nonlinear***	Nonlinear***
IAT	−0.1219*	Nonlinear***	Nonlinear
ML	−1.47***	Nonlinear***	Nonlinear***
Admin	3.360***	Nonlinear***	Nonlinear***
Sinis	−0.1563	Nonlinear***	Nonlinear***
ROE	−0.2791	Nonlinear***	Nonlinear***
Coop	−1.442***	−0.9459***	−0.9253***
Auto	−0.6264***	−1.1019***	−1.0040***

Abbreviation: GAM, generalized additive model.

Standardized mean differences were below 0.1 for most variables, indicating that the cooperative and non-cooperative groups were rendered statistically equivalent in their observed baseline financial profiles following matching. The core forecasting model was then re-estimated on this matched sample.

Within the re-estimated model, the Coop variable remains negative and statistically significant ($p < 0.01$). The coefficient of −0.83, while slightly attenuated from the original model, confirms that the significantly diminished insolvency risk for cooperatives is not merely an artifact of their pre-existing financial advantages. The result was consistent across multiple matching algorithms, but the RF propensity score estimation approach yielded the best covariate balance. Table 7 presents the re-estimated coefficients from the matched sample.

The persistence of the Coop variable's significance after matching serves as a robustness check for our initial model. This demonstrates that the protective effect appears intrinsic to the cooperative organizational form, rather than a reflection of cooperatives being, on average, more financially conservative or efficient. This result reinforces the discussion in Section 4.2. By constructing a counterfactual where non-cooperatives are made financially equivalent to cooperatives, we can better isolate the unique contribution of cooperative governance and structure. This finding is aligned with a growing body of academic literature that uses PSM to evaluate the effect

of governance on financial performance (Ali et al., 2021; Alzayed et al., 2023; Ayash & Rastad, 2021; Priestley & VonDohlen, 2024).

Furthermore, the forecasting performance of the model estimated on the matched dataset showed improvement across all metrics in the out-of-sample tests, as detailed in Table 8.

5 | FINAL REMARKS

This study contributes to the literature on insolvency prediction by shifting the focus from traditional commercial enterprises to an underexplored sector: the supplementary health market in Brazil. Employing a GAM framework and using LR as a baseline, this study disentangles both linear and non-linear relationships among financial and governance determinants over a decade-long period.

In line with our hypothesis, our quantitative analyses reveal that cooperative governance exerts a statistically significant mitigating effect on insolvency risk. Specifically, the binary indicator for cooperative structure is associated with a reduction in the probability of insolvency by approximately 4.8 percentage points relative to non-cooperative entities. This finding provides robust empirical support for the contention that the intrinsic characteristics of cooperative governance (such as shared financial responsibilities and prudent risk management practices) yield enhanced financial resilience. This result is consistent with previous studies on this topic (Birchall & Ketilson, 2009; Forgione & Migliardo, 2018, 2007; Hesse & Cihák, 2007; Goddard et al., 2009; Zamagni, 2012).

Furthermore, the study identifies the TDebt, administrative expenses, ML, revenue to total assets and the assistance ratio as critical predictors with pronounced threshold effects. The non-linear association observed for the TDebt indicates a marked escalation in insolvency risk beyond a critical leverage threshold, while a similar non-linear response is observed for administrative expenses when expressed as a proportion of assets. These variables, although often omitted from conventional prediction frameworks such as the Altman Z score, emerge here as vital for articulating the nuanced risk landscape. The non-parametric spline functions estimated via GAM permit a more granular characterization of the instantaneous marginal effects of these financial indicators, thereby delineating complex risk gradients that are obscured by conventional linear assumptions.

From an applied perspective, the findings have substantive implications for policymakers and practitioners. Regulatory bodies, such as the ANS, may leverage these insights to refine risk management protocols and to encourage cooperative governance practices as a means to attenuate insolvency risks. Concurrently, healthcare management professionals are advised to monitor key financial ratios diligently, particularly the total debt and administrative expense thresholds identified in this study, to pre-emptively identify potential distress.

Furthermore, by identifying high-risk cooperatives through the early detection of financial vulnerabilities, the representative entity of cooperatives in Brazil, the OCB System, can tailor its governance programmes and training more strategically. Rather than applying a one-size-fits-all approach, OCB can focus its resources and support on those cooperatives requiring immediate attention. This targeted strategy not only improves the effectiveness of governance initiatives but also ensures that relevant early-warning indicators are monitored and acted upon in a timely manner. The model also empowers cooperatives to enhance financial oversight by engaging their boards more directly. By highlighting key risk factors such as high debt levels or operational inefficiencies, the model prompts boards to make more informed decisions and helps

TABLE 8 Model quality assessment with propensity score matching (PSM) matched sample.

Statistic	2023					
	Logit		GAM		PSM re-estimation GAM	
	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
Accuracy	0.7601	0.7461	0.8848	0.8375	0.8744	0.8545
Sensitivity	0.7694	0.7482	0.8933	0.8429	0.8815	0.8589
Specificity	0.6803	0.7326	0.8117	0.8023	0.8135	0.8256
Balanced Accuracy	0.7248	0.7404	0.8525	0.8226	0.8475	0.8423
AUC ROC	0.8036	0.8129	0.9175	0.9046	0.9087	0.9123

Abbreviation: GAM, generalized additive model.

cooperatives understand how to interpret its outputs and how to apply them in their decision-making processes.

These conclusions, however, are not without limitations. The choice of a pooled modelling approach implies the assumption that the parameter relationships are homogeneous across firms and time periods. While this simplifies the estimation and augments the sample of observations, it may overlook unit-specific or time-varying heterogeneity in the determinants of bankruptcy risk. As such, future studies should consider employing panel data models that explicitly account for this heterogeneity to assess whether the pooled relationships hold uniformly or vary meaningfully across contexts.

Future research should also consider extending the temporal and geographical bounds of this study and systematically compare alternative machine learning algorithms for insolvency prediction. In addition, we contend that the board composition of healthcare insurers may also be an interesting avenue for investigation, especially regarding whether medical professionals are involved in management.

Such endeavours would further elucidate the complex interdependencies influencing financial stability in the healthcare sector and enhance the robustness of predictive modelling in this context.

ACKNOWLEDGEMENTS

The Article Processing Charge for the publication of this research was funded by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) (ROR identifier: 00x0ma614).

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How to cite this article: Victorino, T. O., Nery, A. G., & Rangel, R. L. (2026). Beyond profit maximization: The effect of cooperative governance on insolvency risk in the Brazilian supplementary healthcare industry. *Annals of Public and Cooperative Economics*, 1–27. <https://doi.org/10.1111/apce.70052>