PICCOLA IMPRESA
SMALL BUSINESS

Rivista Piccola Impresa/Small Business

n. 2, anno 2023

Codice ISSN 0394-7947 - ISSNe 2421-5724

RELEVANCE OF THE LEGAL FORM OF COMPANIES FOR BANKRUPTCY PREDICTION

Simone Poli
Università Politecnica delle Marche
s.poli@univpm.it

Marco Giuliani
Università Politecnica delle Marche
m.giuliani@univpm.it

Luca Baccarini
Università Politecnica delle Marche
l.baccarini@pm.univpm.it

Article info

Date of receipt: 18/05/2023
Acceptance date: 30/09/2023

Keywords: *Bankruptcy prediction models, legal form, predictive capacity*

doi: 10.14596/pisb.3787

Abstract

Purpose. *This study aimed to understand whether a general bankruptcy prediction model for small Italian companies having any legal forms has a different predictive capacity than specific bankruptcy prediction models for those having specific legal forms. On the one hand, it focuses on cooperative companies, and on the other, joint-stock and limited-liability companies.*
Design/methodology/approach. *A general bankruptcy prediction model and two specific bankruptcy prediction models (one for cooperative companies and one for joint-stock and limited-liability companies) were constructed and compared regarding predictive capacity.*
Findings. *The overall accuracy levels of the general and specific models were the same, but the percentage of companies correctly predicted to be in crisis out of the total number of companies effectively in crisis (sensitivity) of the latter (in particular, referring to joint-stock and limited-liability companies) was higher than that of the former. Considering the high economic and social costs that can derive from the predictive errors of companies in crisis, specific models should be preferred to the general model.*
Practical and social implications. *This study offers to those who may be interested in evaluating the financial health of a company (stakeholders, such as banks, suppliers, customers, etc., as well as the management and control bodies of the company) bankruptcy prediction models having a high predictive capacity differentiated according to its legal form.*
Originality of the study. *No previous study has verified whether a general bankruptcy prediction model for companies having any legal forms has a different predictive capacity than specific bankruptcy prediction models for companies having specific legal forms. At the same time, in the Italian context, no previous study has proposed a bankruptcy prediction model for cooperative companies.*

1. Introduction

The literature shows that there is a great interest in bankruptcy prediction models (Daubie and Meskens, 2002; Balcaen and Ooghe, 2006; Bellovary et al., 2007; Verikas et al., 2010; Lin et al., 2011; Marques et al., 2013; Sun et al., 2014; do Prado et al., 2016; Chen et al., 2016; Alaka et al., 2018; Veganzones and Severin, 2021). This is mainly due to the awareness of the relevant negative economic and social impacts that bankruptcy can generate.

Nevertheless, the impact of the legal form of companies on the predictive capacity of these models appears to have been overlooked, except for a few studies that do consider them implicitly (Berg, 2007; Amendola et al., 2011; Slefendorfas, 2016; Herman, 2017; Giriuniene et al., 2019; Poli, 2020), i.e. as a sample selection criterion; in others, it is considered explicitly, i.e. as a variable taken into consideration in the construction procedure of the bankruptcy prediction model (Amendola et al., 2013; Camacho-Miñano et al., 2015; Pierri and Caroni, 2017; Papik and Papikova, 2023). However, previous studies have not verified the different predictive capacities of a general model, i.e. built based on, and intended to be applied to, all companies independent of their legal forms, and specific models, i.e. built based on, and intended to be applied to, companies having specific legal forms.

Moving from these considerations, this study aims to understand whether a general bankruptcy prediction model for companies having any legal form has a different predictive capacity than specific bankruptcy prediction models for companies having specific legal forms. Specifically, on the one hand, this study focuses on cooperative companies ('società cooperative'), and on the other, joint-stock (*società per azioni*) and limited-liability companies (*società a responsabilità limitata*). These two groups of companies were chosen to maximise the differences between legal settings. In fact, cooperative companies are mainly characterised by the adoption of cooperative principles and have a mutualistic purpose, while joint-stock companies and limited-liability companies are mainly characterised by the adoption of for-profit principles and have a for-profit purpose. From a practical point of view, this has effects not only on their organisation and management but also on their financial structure and social policies (Mateos-Ronco and López-Mas, 2011)[1].

Considering the research aim, this study can be included among those investigating the different predictive capacities of general (unfocused)

[1] For an analysis of the differences between the legal forms, especially in terms of purposes, it is possible to consult the Italian legal manuals. With reference to cooperative companies, the Legislative Decree n. 6/2003 abolished the 'unlimited liability' cooperative companies. Consequently, since its enforcement, all of them have become 'limited-liability' cooperative companies. With reference to this aspect, therefore, the legal forms considered in this study are homogeneous.

and specific (focused) models. These studies are inspired by the idea that a general model (built based on an overall sample of companies that assume any way of being of a given characteristic, such as economic sector, size, age, etc.) should perform less than a specific model (built based on a sample of companies that assume a specific way of being of a given characteristic, such as a specific economic sector, a specific size, a specific age, etc.) because the latter should reflect the higher level of homogeneity of the companies considered (Varetto, 1999). However, these studies mainly focus on the economic sector of companies (Varetto, 1999; Branciari et al., 2022), neglecting many other characteristics of companies, such as the legal form, considered in this study.

To achieve the research aim, a general model – built based on a sample of companies having different legal forms (cooperative, joint-stock and limited-liability companies) – and specific models – built on the basis of sub-samples of companies having specific legal forms (one for cooperative companies and one for joint-stock and limited-liability companies) – will be constructed and compared in terms of predictive capacity.

The focus of this study is on small Italian companies. This choice depends on the fact that the legal and accounting characteristics of companies can be specific to a country (Korol, 2013) and that small companies are largely prevalent in the Italian economic context and have specific organisational and strategic characteristics (Altman and Sabato, 2007; Ciampi, 2015; Cesaroni and Sentuti, 2016)[2]. In addition, the financial data and ratios

[2] Here, small companies refer to those that prepare financial statements in the short form. According to Italian law, the short form may only be drawn up by companies that, during the first financial year or, following that, for two consecutive financial years, have not exceeded two of the following limits – total assets 4,400,000 €, total revenue from sales and services 8,800,000 € and average number of employees during the financial year 50. Comparing it with the traditional classification criteria (those established at the European Union level), the companies taken into consideration include micro-sized companies (total assets or total revenue from sales and services less than or equal to 2,000,000 €; average number of employees during the financial year less than 10 persons) and exclude companies that could prepare the financial statements in the short form but opt to prepare them in the ordinary form and companies that, although small-sized according to the traditional criteria (total assets or total revenue from sales and services less than or equal to 10,000,000 €; average number of employees during the financial year less than 50 persons), are obliged to prepare the financial statements in the ordinary form (because they exceed the previously mentioned dimensional parameters that the civil law has established for the possibility of preparing financial statements in the short form). Regarding the inclusion of the micro-sized companies, the criterion adopted appears to reflect the most common-sized category of companies in the Italian economic context. Moreover, with respect to the small-sized companies that opt for the preparation of financial statements in the ordinary form, their exclusion appears appropriate because the information base for building the financial ratios would otherwise be uneven. To get an idea of the size and relevance of the phenomenon under investigation, it should be considered that a query made in September 2019 to the AIDA database (in its full configuration) on the financial statements for the financial year 2016 showed that 852,000 deposited financial statements (corresponding to 94% of the total) were prepared in the short form (Poli, 2020).

that can be used for the construction of bankruptcy prediction models for small companies are less numerous and are often proxies for those usually suggested for larger companies (Poli, 2020).

The structure of the paper is as follows. In the next section, an analysis of the state-of-the-art literature and the development of the research hypothesis are presented. Sections 3 and 4 are dedicated, respectively, to the illustration of the research methodology and the presentation and discussion of the results. Finally, a summary of the achieved results together with the implications, limitations and research avenues suggested by this study are highlighted.

2. State of the art and research hypothesis

Previous studies that have considered the legal form can be divided into two groups. Most of the studies fall into the first group.

In the first group of studies, the legal form was considered among the selection criteria of the sample of companies. In other words, the authors of these studies have excluded from the sample compaines having a legal form different from the chosen one (Berg, 2007; Amendola et al., 2011; Slefendorfas, 2016; Herman, 2017; Palazzi et al., 2018; Giriuniene et al., 2019; Poli, 2020). The first group includes the studies proposed by Mateos-Ronco and López-Mas (2011), Dietrich et al. (2005) and Cruz and Sabado (2022). These authors, distinguishing between cooperative companies and traditional companies, have built bankruptcy prediction models using samples of companies composed exclusively of companies belonging to the first category. The models obtained would seem to have a predictive capacity superior to the pre-existing general models (i.e. focused on both for-profit and mutualistic companies) and would suggest the idea that the legal form could have an impact on the predictive capacity of bankruptcy prediction models. In all the mentioned studies, the legal form of the company has been implicitly recognised as relevant. However, the potential effect of the legal form has not been explicitly observed. In addition, the proposed bankruptcy prediction models assume the nature of specific models, i.e. built on the basis of, and intended to be applied to, companies having specific legal forms.

The second group of studies, also numerically limited, instead contemplated the variable 'legal form' among the independent variables of the models. However, they did not arrive at any concordant or conclusive results. Therefore, these studies have verified the impact of the legal form on the predictive capacity of bankruptcy prediction models. In the study by Pierri and Caroni (2017), the variable, although initially contemplated, was excluded in the variable selection phase because it was not statistically significant. In the studies of Amendola et al. (2013), Camacho-Miñano et al. (2015) and Papik and Papikova (2023), the variable was included in the model, but it was not statistically significant. Ptak-Chmielewska (2019) proposed three bankruptcy prediction models obtained by applying three analysis techniques (logistic regression, random forests and neural networks). Among these, only the model obtained through logistic regression contemplated the legal form as an explanatory variable; the other two models did not contemplate the legal form as an explanatory variable because it was not statistically significant. In the study by Ptak-Chmielewska and Matuszyk (2020), the variable was included in the model obtained through the Cox regression, while it was excluded from the model obtained through the random forests. The legal form was identified as a statistically significant variable in the bankruptcy prediction models proposed by Amendola et al. (2015), Lohman and Ohlinger (2017), Ptak-Chmielewska and Matuszyk (2018), Gemar et al. (2019) and Kou et al. (2021).

In all, the literature review did not bring to light studies aiming to verify the different predictive capacities of general models, i.e. built on the basis of, and intended to be applied to, companies having any legal form, and specific models, i.e. built on the basis of and intended to be applied to, companies having specific legal forms.

To contribute to filling this gap, this work aims to test the following null research hypothesis:

H_0: *The specific bankruptcy prediction models (built on the basis of, and intended to be applied to, companies having specific legal forms) do not have different predictive capacities from that of a general bankruptcy prediction model (built on the basis of, and intended to be applied to, companies having any legal form).*

3. Research methodology

The test of the research hypothesis was conducted as follows:

- a 'general' bankruptcy prediction model was built on the basis of an overall sample of companies (mod GEN);
- two 'specific' bankruptcy prediction models were built, one on the basis of the sub-sample of cooperative companies (mod COOP) and one on the basis of the sub-sample of joint-stock and limited-liability companies (mod NO COOP);
- the statistical and substantial significance of the differences between the predictive capacity levels of mod GEN and mod COOP, applied to the sub-sample of cooperative companies, and between the predictive capacity levels of mod GEN and mod NO COOP, applied to the sub-sample of joint-stock and limited-liability companies, was evaluated;

The statistical significance of the differences between the levels of the predictive capacity of the models was evaluated in two different ways.

The first method consisted of the use of the AUC ('Area Under Curve'). As is known, this method is independent of the level of the cut-off used and is insensitive both to the proportions of companies 'in crisis' and 'not in crisis' present in the sample and to the costs of the classification errors of the models. For these reasons, it has been frequently used in previous studies (Chava and Jarrow, 2004; Ravi and Pramodh, 2008; Horta and Camanho, 2013; Pal et al., 2016; Altman et al., 2017; Du Jardin et al., 2017).

The second method consisted of the use of McNemar's test in the version suggested by Trajman and Luiz (2008). As known, once a value has been set for the cut-off, this method makes it possible to evaluate the statistical significance of the differences in terms of 'sensitivity' (percentage of companies correctly predicted to be 'in crisis' out of the total number of companies actually 'in crisis') and 'specificity' (percentage of companies correctly predicted as 'not in crisis' out of the total number of companies actually 'not in crisis') of the models[3].

The construction of the bankruptcy prediction models required the identification of the event that signals the existence of the crisis, the definition of the sample of companies, the choice of the analysis technique and the selection of the variables.

The event signalling the existence of the crisis was identified at the beginning of one of the bankruptcy procedures applicable to the companies on which this work focuses, according to Italian law (Royal Decree n. 267 of March 16, 1942)[4]. The crisis, therefore, has been understood in its legal meaning, as frequently done in the extant studies (Altman, 1968; Altman et al., 1977; Altman and Sametz, 1977; Ohlson, 1980; Dirickx and Van Landeghem, 1994; Ward and Foster, 1997; Daubie and Meskens, 2002; Chari-tou et al., 2004; Ciampi, 2015; Giacosa and Mazzoleni, 2018; Poli, 2020; Branciari et al., 2022). Therefore, a company was considered 'in crisis' if it was affected by the beginning of one of the aforementioned bankruptcy procedures during the

[3] To compare the different levels of 'sensitivity' ('specificity') of the two models, they have been applied to companies 'in crisis' ('not in crisis') and then the different ways of classifying these companies are compared: (a) companies will be classified as 'in crisis' by both models, (b) companies will be classified as 'in crisis' by the general model and 'not in crisis' by the specific model, (c) companies will be classified as 'not in crisis' by the general model and 'in crisis' by the specific model, and companies will be classified as 'not in crisis' by both models (d). The data 'a', 'b', 'c' and 'd' will correspond to the numbers of companies for which the specific classification will be observed. McNemar's test is based on the non-concordant classification numbers ('b' and 'c') and is configured differently according to their total. Further details will be provided later.

[4] The reference is to bankruptcy or forced administrative liquidation for cooperative companies and to bankruptcy or pre-bankruptcy composition for oint-stock and limited-liability companies.

[5] Subsequent years were not considered in order to prevent the analysis from being distorted by the effects of the pandemic.

years 2018 or 2019[5], while it was considered 'not in crisis' in the opposite case.

The sample of companies used was defined in two steps. In the first step, companies 'in crisis' and companies 'not in crisis' were identified based on the selection criteria shown in Tab. 1 and then extracted from the AIDA database (extraction date: June 2022).

Tab. 1 – Criteria for selecting the sample of companies

Companies "in crisis"	Companies "not in crisis"
cooperative companies, joint-stock companies and limited liability companies	=
companies for which the beginning of the bankruptcy procedures was recorded in the years 2018 or 2019	companies for which the beginning of the bankruptcy procedures was not recorded in the years 2018 or 2019
companies not affected by bankruptcy or liquidation or dissolution procedures in previous years	=
companies drafting the financial statements for the second year before the reference years of the "state of health", therefore the years 2016 or 2017	=
companies preparing financial statements in the short form	=
companies having been established for at least three years	=
companies not being innovative start-ups or SMEs according to the Italian law	=
	companies having the size data required by Italian law for the application of the reference bankruptcy procedures
	companies having prepared the financial statements relating to the reference year of the "state of health" and to the one preceding it

In the second step, moving from the extracted data, the companies 'in crisis' were acquired as a whole and combined with an equal number of companies 'not in crisis'. The companies 'not in crisis' were selected using the random selection criterion (Comuzzi, 1995; Ciampi, 2015; Arnis et al., 2018), ensuring that for each legal form, there was an equal number of companies 'in crisis' and companies 'not in crisis'. Therefore, a sample selection strategy aimed at constituting a 'balanced sample' was used (Sun et al., 2014; Veganzones and Severin, 2021). The relative numbers are shown in Tab. 2.

Tab. 2 – Composition of the sample of companies

Legal form	Companies "in crisis"	Companies "not in crisis"	Overall companies
COOP	218	218	436
2018	109	109	218
2019	109	109	218
NO COOP	218	218	436
2018	109	109	218
2019	109	109	218
Total	436	436	872
2018	218	218	436
2019	218	218	436

The sample of companies has been divided into two sub-samples – one (the 'train' sub-sample) consisting of 2/3 of the observations used to estimate the models, and one (the 'test' sub-sample) consisting of 1/3 of the observations used to evaluate the predictive capacity of the models. The division was made on a random basis, making sure that each sub-sample had the same proportion of (1) companies 'in crisis' and companies 'not in crisis', (2) cooperative companies and joint-stock and limited-liability companies and (3) companies by year of bankruptcy.

The analysis technique used was the logistic regression. This choice was made for several reasons. First, in terms of assumptions, logistic regression has fewer constraints than other techniques frequently used to build bankruptcy prediction models (Ohlson, 1980; Zavgren, 1985). Second, among the independent variables, it can include quantitative variables and suitably operationalised qualitative variables (Ohlson, 1980; Keasey and Watson, 1987). Third, it is the most transparent and intelligible technique in terms of results (Jones et al., 2015). Fourth, it makes it possible to directly define the levels of probability of bankruptcy (Giacosa & Mazzoleni, 2018). Finally, it guarantees acceptable performance levels, both in absolute and relative (comparative) terms (Jones et al., 2015). All these reasons have led logistic regression to be one of the most widely used analysis techniques for the construction of bankruptcy prediction models (Ohlson, 1980; Zavgren, 1985; Aziz et al., 1988; Keasey and McGuinness, 1990; Platt and Platt, 1990; Theodossiou, 1991; Salchenberger et al., 1992; Ward, 1994; Laitinen and Laitinen, 1998; McGurr and DeVaney, 1998; Kahya and Theodossiou, 1999; Beynon and Peel, 2001; Neophytou et al., 2001; Westgaard and Wijst, 2001; Foreman, 2002; Brockman and Turtle, 2003; Jackson and Wood, 2013).

Regarding the selection of the variables to be included in the models, in the absence of a universally recognised theory of the business crisis, it is difficult and arbitrary to identify *a priori* the financial data and ratios to be taken into consideration (Du Jardin, 2009)[6]. Consequently, the practice of starting with a large number of financial data and ratios and leaving the selection of those to be included in the models to the most appropriate statistical and econometric techniques has prevailed in the literature (Barontini, 2002). This practice was used in this study. After identifying a large number of financial data and ratios, the variables to be included in the models were selected using the 'stepwise selection method'[7], a technique widely used in previous studies (Veganzones and Severin, 2021).

The starting financial data and ratios were recently suggested by Poli (2020). The author began with the set of ratios traditionally proposed in the existing literature for the analysis of financial statements (Teodori, 2022) and verified which can be built directly or which adaptations they require if the financial statement for analysis is in the short form. Subsequently, the author verified which ratios could generally be built without suffering from a lack of necessary data (some may require the use of financial statement items that are null with a certain recurrence). Therefore, the author defined a set of ratios that can be used in a generalised way to analyse financial statements in a short form. Finally, the author found that this set of ratios was adequate for building effective bankruptcy prediction models. The main strength of the set of ratios suggested by Poli (2020) is represented by the fact that the resulting bankruptcy prediction model can be applied by all subjects interested in evaluating the financial health of a company and can be applied to all companies. Its main weakness is represented by the fact that – compared to the ratios suggested in previous studies when the financial statement in the ordinary form is available – some ratios were not considered, while other ratios were built in terms of proxies. The financial data and ratios are shown in Tab. 3.

Tab. 3 – Financial data and ratios

Financial data and ratios
Total equity-fixed assets margin on assets
Total equity and long-term liabilities-fixed assets margin on assets

[6] This study explores the effectiveness of bankruptcy prediction models based on data consisting either of single items or of ratios constructed on the basis of several items that can be directly drawn from the schedules of the financial statements intended for publication.
[7] The statistical significance of the variables was tested through the likelihood-ratio test, setting a statistical significance level at 1% for the entry of the variable and a statistical significance level at 5% for the exit of the variable.

Total liabilities to assets ratio
Current liabilities to total liabilities ratio
Cash ratio
Cash-current liabilities margin on assets
Acid-test ratio
Cash and receivables-current liabilities margin on assets
Current ratio
Current assets-current liabilities margin on assets
Added value on assets
EBITDA on assets
Operating income on assets
EBIT on assets
EBT on assets
Net income on assets
Total asset turnover ratio
Current asset turnover ratio
Total assets (natural logarithm)
Sales (natural logarithm)

Notes. All financial data and ratios are calculated concerning the financial statements in short form (art. 2345-bis of the Italian Civil Code).

Wishing to construct models with a prediction time horizon of two years, the financial statement data for year n-2 (which corresponds to 2016 or 2017) were used to predict the financial health of companies in year n (which corresponds to 2018 or 2019, respectively)[8].

[8] With reference to the observations included in the train sample, the financial ratios were 'purified' of the outliers. For the financial ratios that can assume values tending to 'less infinite' and/or to 'more infinite', the values lower than the fifth percentile and/or the values higher than the ninety-fifth percentile were considered outliers and were replaced, respectively, with the value corresponding to the fifth percentile and with the value corresponding to the ninety-fifth percentile.

4. Results and discussion

Tab. 4 shows the bankruptcy prediction models obtained by applying the methodology described above.

Tab. 4 – Bankruptcy prediction models

Financial data and ratios	**mod GEN**	**mod COOP**	**mod NO COOP**
Total liabilities to assets ratio	1.79	2.34	3.77
Cash ratio			-1.86
Cash-current liabilities margin on assets	-1.22		
Total assets (natural logarithm)	0.47	0.52	0.30
Constant	-8.84	-9.16	-7.08

Notes. 'mod GEN' was the general model built on the basis of the overall train sample of companies (both cooperative companies and joint-stock and limited-liability companies). 'mod COOP' was the specific model built on the basis of the train sample of cooperative companies. 'mod NO COOP' was the specific model built on the basis of the train sample of joint-stock and limited-liability companies. For each model, the regression coefficients of the variables are reported.

The three models (GEN, COOP and NO COOP) are different for the financial data and ratios included and for the regression coefficients of the variables when the same financial data or ratio is included in more than one model. This is in line with the generality of the studies that, although referring to other characteristics of the companies, have investigated the different predictive capacities of general and specific models (for a recent example referring to the Italian context, focused on the relevance of the economic sector to which companies belong, see Branciari et al., 2022).

Considering the limited number of financial data and ratios that the models include, all are characterised by a high level of 'parsimony'. This makes the models particularly simple to use and, therefore, particularly useful for potential users (Jones et al., 2015).

Considering the financial ratios that they include and the widely shared interpretation of the same (Teodori, 2022), mod GEN and mod NO COOP give importance to the financial structure and liquidity of companies, while mod COOP gives importance only to the financial structure of companies.

It is noteworthy that no model included a profitability ratio. This means that no profitability ratio has an impact on the probability of bankruptcy at the established level of statistical significance (0.01%). Considering that co-operative companies typically have a mutualistic purpose while the other companies typically have a for-profit purpose, the fact that mod COOP excludes a profitability ratio is not surprising (this is in line with Mateos-Ronco and López-Mas, 2011 and Dietrich et al., 2005), while the fact that mod NO COOP also excludes it is surprising (this is in contrast to, for example, the recent study by Poli (2020)).

This result seems to suggest that the different purposes of companies have no relevance to the prediction of bankruptcy or bankruptcy – when it manifests itself in financial statements, in the sense that it can be perceived/predicted on the basis of financial statements – is a unitary phenomenon, mainly of a financial nature.

Tab. 5 shows the AUC values relating to the different models and sub-samples.

Tab. 5 – AUC values

	mod GEN	**mod COOP**	**mod NO COOP**	**chi-squared (p-value)**
test sample COOP	0.89	0.90		0.53 (0.47)
test sample NO COOP	0.86		0.86	0.00 (0.99)
chi-squared (p-value)	0.58 (0.45)			

Notes. 'mod GEN', 'mod COOP' and 'mod NO COOP' have the meaning illustrated in the notes of Tab. 4. The last column/row shows the results of the tests on the differences in the AUC values.

Recalling that the AUC values can vary between 0 (worst predictive capacity) and 1 (best predictive capacity) and using the AUC rating scale proposed by Hosmer Jr. et al. (2013), all models have at least an excellent level of discrimination. Focusing on mod COOP, the fact that this specific model had a high predictive capacity is in line with the research findings of previous studies focusing on other countries (Mateos-Ronco and López-Mas, 2011; Dietrich et al., 2005; Cruz and Sabado, 2022).

The evaluation of the differences between AUC values shows that in no case was there enough evidence to reject the null hypothesis of equality of AUC values. In other words, considering the test sample COOP, mod GEN and mod COOP had statistically equal predictive capacities; as for the test sample NO COOP, mod GEN and mod NO COOP had statistically equal predictive capacities; lastly, when it came to the test sample COOP and the test sample NO COOP, mod GEN had a statistically equal predictive capacity. These results support the research hypothesis that guided this study.

Tab. 6 shows the most important predictive capacity indicators, which are traditionally constructed on the basis of the 'confusion matrix'.

Tab. 6 – Confusion matrix and relative predictive capacity indicators

	mod GEN applied to COOP	mod GEN applied to NO COOP	mod COOP applied to COOP	mod NO COOP applied to NO COOP
Sensitivity	89.19	78.38	90.54	87.84
Specificity	72.97	79.73	72.97	72.97
False positives	23.26	20.55	22.99	23.53
False negatives	12.90	21.33	11.48	14.29
Accuracy	81.08	79.05	81.76	80.41

Notes. 'Sensitivity' is the percentage of companies correctly predicted to be 'in crisis' out of the total number of companies effectively 'in crisis'; it can range from 0 (worst) to 100 (best). 'Specificity' is the percentage of companies correctly predicted as 'not in crisis' out of the total number of companies effectively 'not in crisis'; it can range from 0 (worst) to 100 (best). 'False positives' is the percentage of companies incorrectly predicted to be 'in crisis' out of the total number of companies predicted to be 'in crisis'; it ranges from 0 (best) to 100 (worst). 'False negatives' is the percentage of companies incorrectly predicted to be 'not in crisis' out of the total number of companies predicted to be 'not in crisis'; it ranges from 0 (best) to 100 (worst). 'Accuracy' is the percentage of companies correctly predicted to be 'in crisis' or 'not in crisis' out of the total number of companies; it ranges from 0 (worst) to 100 (best). All indicators were determined assuming a conventional cut-off of 0.50 and were calculated concerning the reference test samples.

Regarding the test sample COOP, the levels of 'accuracy', 'sensitivity' and 'specificity' of mod GEN and mod COOP appeared to be substantially the same. For the test sample NO COOP, the levels of 'accuracy' of mod GEN and mod NO COOP appeared to be substantially the same, but the levels of 'sensitivity' and 'specificity' of mod GEN and mod NO COOP did not appear to be substantially the same (78.38 vs 87.84 and 79.73 vs 72.97, respectively). Concerning the test sample NO COOP, mod GEN was 'more balanced', reporting substantially similar levels of 'sensitivity' and 'specificity', while mod NO COOP appeared to have a more marked capacity to predict companies 'in crisis' ('sensitivity') than companies 'not in crisis' ('specificity').

Tab. 7 and Tab. 8 shows the data for calculating McNemar's test and the respective results of the same for joint-stock companies and limited-liability companies 'in crisis', the first, and 'not in crisis', the second.

Tab. 7 – Joint-stock and limited-liability companies 'in crisis' (evaluation of 'sensitivity')

		mod NO COOP	
		Classified "in crisis"	Classified "not in crisis"
mod GEN	Classified "in crisis"	56	2
	Classified "not in crisis"	9	7
McNemar's test		mid-p-value: 0.0386	

Notes. The two models classify 63 companies in the same way (56 'in crisis' and 7 'not in crisis') and classify 11 companies differently. mod GEN correctly classifies 58 companies, while mod NO COOP correctly classifies 65 companies. Thus, the second model appears to have a higher level of 'sensitivity'. Given the low number of cases classified differently, McNemar's test was conducted with the variant suggested by Fagerland et al. (2013). This reveals that there is enough evidence to reject the null hypothesis of equality of the 'sensitivity' levels.

Tab. 8 – Joint-stock and limited-liability companies 'not in crisis' (evaluation of 'specificity')

		mod NO COOP	
		Classified "in crisis"	Classified "not in crisis"
mod GEN	Classified "in crisis"	13	2
	Classified "not in crisis"	7	52
McNemar's test		mid-p-value: 0.1094	

Notes. The two models classify 65 companies in the same way (13 'in crisis' and 52 'not in crisis') and classify 9 companies differently. The mod GEN correctly classifies 59 companies, while the mod NO COOP correctly classifies 54 companies. Therefore, the first model appears to have a higher level of 'specificity'. Given the low number of cases classified differently, McNemar's test was conducted with the variant suggested by Fagerland et al. (2013). This reveals that there is not enough evidence to reject the null hypothesis of equality of the 'specificity' levels.

McNemar's tests revealed that there was enough evidence to reject the null hypothesis of the equality of 'sensitivity' levels and there was not enough evidence to reject the null hypothesis of the equality of 'specificity' levels.

The in-depth analysis led to the observation that although the two models were substantially similar in terms of overall 'accuracy', the two models were not equally similar in terms of 'sensitivity'.

Considering that the costs of the two types of error ('false negatives' and 'false positives') are generally recognised as not being the same (the former are much higher than the latter) (Veganzones and Severin, 2021: 215), regarding the test sample NO COOP, mod NO COOP could be considered as more 'performing' than mod GEN.

Unlike the previous one, this result does not support – at least partially – the research hypothesis that guides this study. This result is not directly comparable with those of previous studies since, as highlighted in the previous section dedicated to the literature review, no previous study has conducted an investigation similar to the one conducted in this study.

Although the higher predictive capacity of the specific model was limited to mod NO COOP and, with reference to this, to 'sensitivity', it supports the idea that a specific model, built on the basis of a homogeneous sample (in this case, the legal form of the company), is (in some perspective) more performing than a general model, as suggested in the literature (Varetto, 1999).

Focusing the attention on the variables included both in mod GEN and in mod NO COOP (i.e. 'Total liabilities to assets ratio' and 'Total assets (natural logarithm)'), Tab. 9 (Tab. 10) shows that cooperative companies – both those 'in crisis' and those 'not in crisis' – are more indebted (smaller) than the other corresponding companies.

Tab. 9 – Medians of 'Total liabilities to assets ratio' referred to the train sub-samples

Legal forms	Companies "in crisis"	Companies "not in crisis"	Total
COOP	1.14	0.89	0.98
NO COOP	0.96	0.75	0.88
Wilcoxon's test	-5.38***	-3.93***	-5.74***

*Notes. *** means that the level of statistical significance is 0.01%.*

Tab. 10 – Medians of 'Total assets (natural logarithm)' referred to the train sub-samples

Legal forms	Companies "in crisis"	Companies "not in crisis"	Total
COOP	12.96	12.19	12.56
NO COOP	14.25	13.56	13.87
Wilcoxon's test	6.78***	5.68***	8.62***

*Notes. *** means that the level of statistical significance is 0.01%.*

The specific models were able to reflect these heterogeneities more properly and, consequently, were more performing.

The fact that cooperative companies – both those 'in crisis' and those 'not in crisis' – were more indebted than the other corresponding companies suggests that the Italian economic system is inclined to tolerate the higher level of indebtedness of cooperative companies. This could depend on the fact that cooperative companies have a mutualistic purpose or on the peculiar configuration that their financial structures assume. With reference to the latter, it should be remembered that, for Italian cooperatives, shareholder financing (*prestito sociale*) is often a relevant form of financing. A future study could explore if and how this form of financing could impact the probability of bankruptcy in cooperative companies.

From a methodological point of view, the last result suggests the importance of evaluating the predictive capacity of bankruptcy prediction models using different approaches/methods. In fact, if the evaluation had been made only through the AUC values, the important difference that has emerged regarding the 'sensitivity' – that represents one of the dimensions of the predictive capacity of a prediction model – would not have emerged.

5. Conclusions

Focusing on cooperative companies, on the one hand, and joint-stock companies and limited-liability companies, on the other hand, this study aimed to understand whether a general bankruptcy prediction model has a different predictive capacity compared to specific bankruptcy prediction models for companies with specific legal forms.

The research findings have shown that the overall accuracy of specific bankruptcy prediction models (built on the basis of and intended to be applied to companies having specific legal forms) does not appear to be different from that of a general bankruptcy prediction model (built on the basis of and intended to be applied to companies having any legal form). However, the research findings also show that the 'sensitivity', i.e. the predictive capacity of companies 'in crisis', of the former (in particular, that of the bankruptcy prediction model for joint-stock and limited-liability companies) appears to be higher than that of the latter. Therefore, considering that the prediction errors of companies 'in crisis' are associated with high costs and higher than those associated with the prediction errors of companies 'not in crisis', the specific bankruptcy prediction models appear to be preferable. With regard to the aforementioned different predictive capacities, it has emerged that they can be mainly justified by the level of heterogeneity of the two different sub-samples of companies. However, no elements emerged that could directly link the different performance of the models to the different purposes of the studied companies.

From a theoretical perspective, this study contributes to filling the gap in the relevance of the legal form of companies for bankruptcy prediction. The research findings suggest to those wishing to research bankruptcy prediction models to pay adequate attention to the legal form of companies. To improve their predictive capacity, they should build models using samples of companies that are homogeneous in terms of legal form. The research findings also suggest that they evaluate the predictive capacity of bankruptcy prediction models using different approaches/methods.

From a practical perspective, this study offers to those who may be interested in evaluating the financial health of a company (stakeholders such as, for example, banks, suppliers, customers, etc., as well as the management and control bodies of the company) bankruptcy prediction models having a high predictive capacity differentiated according to its legal form. In particular, concerning the model relating to cooperative companies, it should be noted that it is the first model proposed in the literature for such companies in the Italian context.

Focusing attention on the managerial implications of the research findings, the bankruptcy prediction models suggest to the management and control bodies of the company that economic-financial dimensions (represented by the respective financial ratios) should mainly be monitored in order to predict the occurrence of a state of crisis. Specifically, they are the 'Total liabilities to assets ratio' in the case of the cooperative companies and the 'Total liabilities to assets ratio' and the 'Cash ratio' in the case of the joint-stock companies and the limited-liability companies.

In the Italian context, the research findings are particularly relevant considering the recent reform of legislation on business crises (Legislative Decree n. 14/2019), which has given particular importance to the timely prediction of the same (Baldissera, 2019). They provided suggestions regarding the relevance that should be attributed to bankruptcy prediction models within the organizational, administrative and accounting structures that they must establish to facilitate the prompt detection of crises and to promptly undertake appropriate initiatives to comply with the requirements of the new legislation on business crises. From this perspective, if bankruptcy prediction models are adequately used and their results are adequately interpreted as a form of advanced financial statement analysis, they could become part of a suite of management control tools that are useful in promptly detecting states of crisis.

The research findings achieved, however, are not without limitations (Du Jardin, 2010). Barontini (2000: 25) observed that 'the effectiveness of a model [...] depends on the characteristics of the analysis carried out: every methodological choice of the author of the model can significantly influence the performance obtained'. Consequently, the verification of the research hypothesis that guided this study will have to be repeated using different methodological choices. This may represent the first possible future development of the research. At the same time, Veganzones and Severin (2021: 210) noted that 'large samples are needed to obtain more reliable results and robustness, though the size tends to be conditional on the number of failed firms available'. Consequently, the verification of the research hypothesis that guided this study will have to be repeated by expanding the number of companies included in the sample (for example, by expanding the number of years taken into consideration). This may represent a second possible future development of the research.

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