Cooperative credit banks and sustainability

Towards a social credit scoring

Stefano Zedda, Michele Modina, and Carmen Gallucci[1] (***Corresponding Author***)

Abstract

Cooperative Credit Banks (CCBs) play a significant role in fostering social sustainability through lending decisions. In particular, CCBs are interested in supporting socially conscious cooperatives, provided that the credit scoring process classifies them as "credit-worthy". However, existing literature overlooks how cooperatives' balance sheet equilibriums, driven by their social mission rather than profit maximization, impact credit scoring. To bridge this gap, this paper examines the influence of cooperatives' unique balance sheet equilibriums on credit scoring. Specifically, it investigates the potential risk of sub-optimal creditworthiness assessment when CCBs use a "one-size-fits-all" model for cooperatives and non-cooperatives alike. The findings demonstrate that "tailor-made" credit scoring models for cooperatives and non-cooperatives outperform a generic one, enhancing credit classification specificity and sensitivity. These models allow for more effective credit allocation, resulting in improved economic outcomes.

Keywords: *Cooperative Credit Bank (CCB); Sustainability; Cooperatives; Social Credit Scoring.*

1 Corresponding author. Department of Management & Innovation Systems, University of Salerno, Via Giovanni Paolo II, 132 - 84084 - Fisciano (SA), Italy and IPAG Business School 84 Boulevard Saint-Germain - 75006 - Paris, France
cgallucci@unisa.it

1. Introduction

Recent systemic crises and the growing interest in sustainability disrupted the competitive landscape and forced firms to innovate their business models (Ferlito & Faraci, 2022). Since corporate resilience to date implies adopting sustainable innovation (Freeman, 2010), firms must be profitable and responsible from an environmental and social standpoint (Bocken & Short, 2016).

The extant academic literature considers banks as firms operating at the forefront of sustainability that can drive their clients' journey towards a better social and environmental posture (e.g., da Silva Inácio & Delai, 2022). For example, Yip & Bocken (2018) note that banks also factor in sustainability-related hazards when assessing clients' creditworthiness and pricing risks. Similarly, several other scholars have provided evidence that banks reward firms that put efforts into reducing their ecological footprint by applying more convenient lending terms when observing even small commitments towards carbon reduction (e.g., Jung et al., 2018; Eliwa et al., 2021; Raimo et al., 2021). Nevertheless, independent of their ownership and capital structure, banks must be profitable to stay in operation.

However, there is a category of banks, the cooperative credit banks (CCBs), whose primary objective, in addition to achieving economic results that remunerate the risks of banking, is to promote the economic, cultural and social betterment of clients and communities at large (Loubere & Zhang, 2015; Minto, 2016), which extends to their lending decisions. Their very business model revolves around principles like "(...) solidarity, self-help, and equal treatment" (Jovanovíc et al., 2017).

CCBs originated in Europe in the nineteenth century. Their primary role was to support small businesses and mutual organizations by providing them with deposit accounts, credit, and other financial services. Unlike traditional banks, CCBs are specialized in relationship lending and represent the primary funding providers for often financially marginalized households, cooperatives, and SMEs in poorer regions (Wheelock & Wilson, 2011).

In Italy, CCBs are among the prominent players in the local financial system. At the end of 2020, the 248 CCBs and their 4200 branches mostly located in the central-northern and northern-eastern areas of the country represented more than half of the banking sector in Italy and one-fifth of the overall branches. They were responsible for about 7% of the assets under management, but the value becomes higher when considering their type of clients and geographical reference area[2]. Despite the transformations the banking sector underwent, CCBs' role in supporting local economies remains paramount.

Given their social mission and purpose, the business model of CCBs in Italy resembles more that of a stakeholder value bank (STV) rather than that of a shareholder value bank (SHV), whose goal is to maximize returns on the equity invested (Carbó & Williams, 2000). Then, CCBs seek to create value by counterbalancing the interests of a broad set of stakeholders while adopting a long-term view of their business (Casadesus-Masanell & Ricart, 2011; Chesbrough et al., 2011; Casprini, 2015). For them, profit maximization becomes a means to safeguard continuity and growth considering their social goal and mission (Ayadi et al., 2010). In this regard, recent evidence suggests that CCBs in Italy, being STV with strong local relations (Usai & Vannini, 2005), also significantly enhance income per capita, employment, and firms' growth rates (Coccorese & Shaffer, 2021).

The above characteristics make the credit offer of CCBs peculiar (Becchetti et al., 2016). Their size and territorial orientation lead them to develop competitive strategies based on closer relationships with clients and the informational advantages they bring (Baccarani et al., 2013; Caridà et al., 2015; Buffa et al., 2019). In this regard, the extant finance literature suggests that relationship lending reduces information asymmetries between lenders and borrowers, enhancing credit quality (Petersen & Rajan, 1994; Berger & Udell, 1995) and serving otherwise financially marginalized local firms (Coccorese et al., 2016). Furthermore, evidence suggests that CCBs' lower risk tolerance cause them to experience lower earnings volatility and better intertemporal risk management (Ayadi et al. 2010).

However, their business model also exposes them to market dependence (Becchetti et al., 2016) and the risk of regulatory capture due to the inadequate application of the proportionality principle (Schenkel,

[2] Federcasse, 2021

2017; McKillop et al., 2020). Furthermore, investments in financial technologies weigh more on CCBs than on large banking conglomerates (Arner et al., 2017; Ferri, 2017; D'Onza et al., 2021). Besides, CCBs' lending policies may cause poor geographical diversification and scale inefficiencies (Petersen & Rajan, 1994; Berger & Udell, 1995) and excessive institutional dependency (Agostino et al., 2023).

It becomes evident that one of the primary challenges for CCBs is finding the right balance between profit and social orientation. In practical terms, they encounter two technical challenges: selecting clients with adequate creditworthiness within their reference area and accurately predicting potential credit rating changes based on relationship lending data. The ideal solution for CCBs would involve leveraging the available information and implementing suitable technical tools to identify the most lucrative business domestic opportunities across various customer segments.

Among CCBs' customer segments, there is that of cooperatives. According to the International Cooperative Alliance (ICA), cooperatives are *"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"*. Cooperatives are classified based on cooperators' contributions, such as work and production. In worker cooperatives, cooperators receive a salary proportional to their labor along with a share of the end-of-the-year provisional income. Instead, in producer cooperatives, profit sharing depends on cooperators' supplies in terms of production contributions (e.g., the number of grapes given to a wine production cooperative). As in worker cooperatives, a baseline pay is immediately due, while another depends on the end-of-the-year results.

The main difference between traditional firms and cooperatives is that the first pursue profit maximization, and the latter the proportional sharing of the value resulting from individual contributions. Given their specific pursuit and their significant contribution to local development (Matei & Matei, 2012), cooperatives have been the subject of several scholarly enquiries (Chaddad, 2012; Bijman & Hendrikse, 2003; Bijman & Iliopoulos, 2014; Couderc & Marchini, 2011; Figueiredo & Franco, 2018).

One strand of literature focuses on the structure of cooperatives' balance sheets and how their equilibriums differ from traditional firms. Scholars suggest that since cooperatives in case of positive results share the higher income by rising prices or salaries, and in crises, times tend not to lay off cooperators and employees but rather reduce prices or salaries, these policies significantly affect their balance sheets' structure (Delbono & Reggiani, 2013). Caselli et al. (2022) reached a similar conclusion, noting that in crises time cooperatives prefer to be less profitable and to extract a lower value added per worker instead of reducing employment.

CCBs are particularly interested in supporting socially conscious cooperatives, provided that the credit scoring process classifies them as "credit-worthy". The relationship between CCBs and cooperatives warrants special attention for at least two reasons. Firstly, by subsidizing cooperatives striving to meet the social needs of local communities, CCBs can better fulfill their own social mission. Secondly, cooperatives often face challenges in securing credit from traditional banks due to their non-profit orientation. Consequently, CCBs serve as their primary, if not sole, lending references. As with other non-profit-driven firms, cooperatives frequently encounter credit constraints (Aktaș & Barbetta, 2022). Thus, they find it simpler to rely on relationship-oriented banks, especially CCBs, which share their social orientation. Moreover, cooperatives can represent one of CCBs' most profitable customer segments. By appropriately assessing their creditworthiness, CCBs can select the financially sound cooperatives, resulting in lower default rates (Williams, 2007) and reduced credit shifts in their loan portfolio (Mashange et al., 2022) in their loan portfolio. Therefore, it is of outmost relevance for CCBs to conduct thorough evaluations of cooperatives' creditworthiness.

However, existing literature overlooks how cooperatives' balance sheet equilibriums, driven by their social mission rather than profit maximization, impact credit scoring. It is crucial to recognize that cooperatives' financials directly result from their pursuit of a social mission, rather than purely focusing on maximizing profits. This raises an important question: Is there a risk of suboptimal credit quality assessment by CCBs for cooperatives? What are the implications if CCBs employ a "one-size-fits-all" credit scoring model to evaluate the creditworthiness of both cooperatives and non-cooperatives?

To address this research gap, this paper examines the impact of cooperatives' unique balance sheet equilibriums on credit scoring. Specifically, it investigates the potential risk of sub-optimal creditworthiness assessment when CCBs utilize a "one-size-fits-all" model for both cooperatives and non-cooperatives. Drawing from two samples extracted from a comprehensive database of over 74,000 balance sheets, the findings suggest that a "social credit scoring model" tailored to cooperatives results in more informed lending decisions. This specialized model improves the ability to differentiate between defaulted and non-defaulted prospects. Additionally, it enables CCBs to seize opportunities that align with their social mission, thereby avoiding missed chances.

This paper makes three relevant contributions to the literature on credit scoring and, more specifically, to the specific strand of empirical papers dealing with the credit scoring of socially oriented borrowers (Gutiérrez-Nieto et al., 2016; Roy & Shaw, 2022). First, it provides empirical evidence that a credit scoring model tailored to cooperatives outperforms a "one-size-fits-all" model in sensitivity and specificity. Significant improvements can be observed across all model specifications and sample types (i.e., cooperatives and non-cooperatives). Second, it relies on a unique dataset of Italian cooperative firms that includes balance sheet and relationship lending data. This element constitutes a peculiarity of the present paper and a notable contribution to the extant literature on the creditworthiness of cooperatives, which predominantly leans on relationship lending data, but neglects those drawn from financial statements, which are often unavailable (Mashange et al., 2022). Third, our results show that, when employing a tailored credit scoring model, significant shifts can be observed in the statistical significance of the variables under analysis, between cooperatives and non-cooperatives. For example, leverage becomes statistically insignificant when a model specific for cooperatives is built, while credit on sales gains statistical significance, showing that cooperative and non-cooperative firms have different financial and operational characteristics even from the financial ratios point of view.

Furthermore, it is important to highlight that the credit scoring literature emphasizes the significance of firms' activity sectors in achieving accurate prediction models. Studies have demonstrated that models tailored to specific activity sectors outperform generic models (Rikkers and Thibeault, 2011). Building upon this insight, we conducted cluster analyses to examine whether dissimilarities between cooperatives and non-cooperatives surpass the dissimilarities between firms in different activity sectors. The results indicate that the dissimilarities between cooperatives and non-cooperatives are indeed more pronounced, providing an explanation for the superior performance of prediction models specifically designed for each firm category. These findings underscore the importance of tailoring models to the unique characteristics of cooperatives to enhance accuracy and predictive power.

Overall, the findings presented here are of significant practical relevance to CCBs and cooperatives. They can assist the first in not foregoing profitable lending opportunities and the latter in keeping track of those balance sheet equilibriums that can determine a worsening of their credit rating and cost of debt.

The reminder of this paper is structured as follows: section 2 analyzes the research gap and questions, section 3 describes the considered sample and methods, section 4 describes the model and results, section 5 discusses the results significance and implications, and section 6 concludes.

2. Gap and Research questions

The corporate finance and banking literature has paid much attention to default prediction models. Traditional studies have examined various economic and financial aspects of a firm (such as leverage, cost of debt, working capital, asset turnover, and profitability), elaborating on accounting information gathered from their balance sheets (Beaver, 1966; Altman, 1968).

From the bank's point of view, the advantage of using balance sheets to predict the default risk on loans based on a firm's past data is threefold: firstly, they are publicly available, and they are accessible by each bank that has a relationship with the firm; secondly, their content is verified by a third party; and thirdly, they provide a lot of quantitative information that helps to predict the default event at least one year before it occurs.

However, using accounting information alone is not sufficient, since balance sheets are backward-looking, and they cannot promptly signal financial distress to the bank. Banks have access to real-time signals, other than publicly available information, coming from the specific services provided to the firm. Several aspects can distinguish the latter: scope (credit and debit cards, credit lines), depth (relationship length, credit line usage), and form (checking performances, investment portfolio and saving accounts, past loans). Most importantly, the bank can observe this information long before receiving the financial statements of a firm, which might later confirm that the borrower is in financial difficulty (Norden and Weber, 2010). Banks' monitoring and screening efforts would therefore be well repaid as far as this readily available and costless private information is used to produce a superior judgment on borrowers regarding their expected performance in repaying loans.

The consideration of the role of banks in information production has been analyzed in modern research on financial intermediation. For instance, subsequent empirical research on relationship lending has produced evidence that focuses on the benefits of a banking relationship (Foglia et al., 1998; Fiordelisi et al., 2014).

From the technical point of view, the traditional models in credit scoring use financial indicators extracted from balance sheets from defaulted and non-defaulted firms for finding default predictors to classify or to assign a default probability to firms in a given time horizon. Academics in this field propose several techniques: (i) linear discriminant analysis (Beaver, 1966); (ii) multivariate discriminant analysis (Altman, 1968; Altman et al., 1994; Foglia et al., 1998); and (iii) binomial choice models (Altman and Sabato, 2007; Bottazzi et al., 2011). The first two models are based on the a priori assumption that there are two mutually exclusive groups of firms (defaulters and non-defaulters) and that the differences between them can be captured by observing (individually) several financial ratios (Foglia et al., 1998). The more recent logit and probit models refine this same approach, being specifically aimed at the estimation of a probability. Although these analyses differ in the methods adopted and datasets, they primarily identify five groups of accounting indicators as most important in predicting the default probability of firms: leverage, liquidity, profitability, and financial and asset coverage (Altman and Sabato, 2007).

In the last decades, an increasing interest has been observed in improving the prediction power of standard default prediction models (Balios et al., 2016; Grunert et al., 2005; Wang et al., 2023; Yuan et al., 2022). Particularly instructive for this paper is the literature attempting to capture signals to predict financial difficulties through the hard information from the specific bank-firm relationship. This literature studies the informational content of transaction accounts and justifies the need to monitor revolving credit utilization simultaneously with borrowers' default probability (Bergerès et al., 2015). In the same line, the paper by Jiménez et al. (2009a), using the credit register database for Spanish firms, shows that defaulting firms have significantly higher credit line usage rates and line exposure at default values (ratio between actual drawn amount and a fraction of undrawn amount) up to five years before the default event occurs.

To date, scholars mostly agree that default prediction models should incorporate a broader set of variables (Ciampi et al., 2021). In this pursuit of more accurate forecasts, the rising literature on social credit scoring also suggests lenders use tailored approaches to credit scoring when assessing the creditworthiness of socially oriented borrowers (Gutiérrez-Nieto et al., 2016; Roy & Shaw, 2022).

However, despite this rising trend underlying the importance of borrowers other than traditional firms, the extant literature still directs most of its efforts into conventional fields of inquiry.

This paucity of research constitutes a significant gap because the literature on credit scoring models may benefit from analyzing socially oriented borrowers, especially given that they are market entities for which relationship lending data almost make up the sole basis for determining their financial soundness. In this regard, cooperatives can represent a suitable sample of analysis, since their financial statement data are rarely shared (Mashange et al., 2022). This factor, alongside their limited access to equity markets, the need to primarily pursue their social mission, and the subsequent heavy reliance on debt capital to finance inventories and growth, suggests that the evaluation of their creditworthiness should be different from that of traditional firms (Smart et al., 2019). However, how banks score cooperatives in credit assessment processes is still understudied. The main consequence emerging from this rareness of research on the topic is the implicit assumption that, in the absence of valid practical reasons to rely on a "tailor-made" credit scoring model for cooperatives, banks can revert to a "one-size-fits-all" one to assess the creditworthiness of cooperatives and non-cooperatives alike. However, using a "one-size-fits-all" approach may seriously affect cooperatives' access to finance, given that they are, almost by definition, less capitalized, highly leveraged, and less profit-oriented than traditional firms (Mashange et al., 2022).

Specifically, should CCBs base their lending decisions on a "one-size-fits-all" approach to credit scoring, at least three negative consequences are foreseeable.

First, severe induced constraints in the cooperative sector may significantly halt local development. The risk is that the default prediction models built exclusively for for-profit firms may be used to evaluate clients pursuing economic goals alongside social and environmental ones. An unintended consequence of this approach is that market participants like cooperatives (Coccorese & Shaffer, 2021) may suffer credit shortages because their balance sheet equilibriums might have been misinterpreted, ignoring that modest profitability is a direct consequence of their employment concerns (Caselli et al., 2022). This credit shortage issue due to adopting a "one-size-fits-all" credit scoring should be a seriously relevant concern for banks and policymakers. Induced defaults among cooperatives may have significant repercussions on the local economy and cause disruptions across sectors, especially in agriculture (Mashange et al., 2022).

Second, misinterpreting cooperatives' creditworthiness may prevent banks from lending to a category of borrowers that have been found to consistently retain credit ratings, experience only minor shifts in them, and withstand financial crises (Mashange et al., 2022). Corroborating this claim is the existing data on farmer cooperatives: only 2% of them defaulted annually from 1980 to 2012, and the percentage only rose to 5% and 4% in 2004 and 2006 (Williams, 2007).

Third, overlooking cooperatives means not directing sufficient attention to CCBs, their primary debt provider. Together, CCBs and cooperatives have the potential to "make or break" local social development and sustainability proportional to the degree that they manage to fulfill their social mission. Investigating their credit relationship then becomes paramount in light of the broad call to banks to play their part in pursuing socially and environmentally responsible agendas (Avrampou et al., 2019).

Therefore, this paper aims to show what happens if CCBs use a "one-size-fits-all" credit scoring model to assess the creditworthiness of both cooperatives and non-cooperatives. In particular, we set out to answer the following research questions:

RQ1: *Are the default predictors of cooperative and non-cooperative firms significantly different?*

RQ2: *If so, does a tailor-made default prediction model for cooperative firms outperform a generic one?*

RQ3: *Is the distance between cooperatives and non-cooperatives bigger than the distance among different activity sectors?*

For answering to these questions, we conducted an empirical analysis of the Italian context, where both cooperative banks and cooperative enterprises constitute a relevant entrepreneurial phenomenon at the regional and national levels (Cori et al., 2021).

3. Sample, data and method

Cooperatives play a significant role in many countries. In Europe they ”provide more than 4.7 million jobs and have a total annual turnover of 1,005 billion Euros – more than the GDP of Finland, Denmark, Norway and Sweden combined.” … “Banking is the largest sector by cooperative members with more than 43% (60,440,105) of the total number of members in Europe.” [3]

[3] CoopsEurope, 2015.

Italy is among the countries with the larger number of cooperatives[4], they account for 7% of GDP and 7.5% of employees[5], with a specific role for banking: 238 banks, providing for a share on domestic market of 9.2% of deposits, 7% of loans and 12% of mortgages.[6]

We developed our analysis on a unique dataset, referring to a sample of 113 local banks and more than 74.000 balance sheets of Italian firms provided to us exclusively by the IT services company belonging to one of the two Italian cooperative banking groups. The specialty of this dataset is given by the presence of some banking variables, and in particular of the "default" variable, which signals the unregular fulfilling of debts, and which is not publicly available. This variable allows for a prompt evidencing of problems in the bank-firm relationship, while the publicly available data about liquidation or failing can happen even some years later.

The 113 cooperative banks provide loans to micro, small and enterprises located in 100 Italian provinces and operating in 83 different sectors according to the 2-digit Ateco industrial classification. In particular, the enterprises in our sample belong to the following six macro-industries: agriculture, trade, transport and hotels, manufacturing, construction and services. Public administration and financial companies are excluded. Using this dataset, we conducted two types of analysis using two different samples. The first analysis is discriminant and is based on logistic regression by taking all variables together. The second is a clustering analysis based on a previous set of logistic regression developed by single variable.

3.1. Discriminant analysis

In the first analysis, we selected the activity sectors reporting a similar number of cooperative and non-cooperative firms, just filtering for the firms reporting a sales value higher than €100,000 to exclude the too-small cases. A further reduction is due to the unavailability of some values for some variables,

[4] "Italy (39,600), Turkey (33,857), France (22,517) and Spain (20,050) have the largest number of cooperatives in Europe", CoopEurope, 2015.
[5] Ministero delle imprese e del made in Italy, 2022
[6] EACB, 2022

which automatically excludes the cases from the logistic regression. The resulting samples refer to, as classified by the Italian ATECO standards, sector 81, "Cleaning and disinfestation" (see Table 1), including a total of 394 cases, of which 194 cooperatives and 201 non-cooperatives, and sector 01, "Farming of agricultural crops" (see table 3), for a total of 1017 cases, of which 478 cooperatives and 539 non-cooperatives. We tested our hypotheses on each of these two subsets.

Table 1: Sample data for sector 81, "Cleaning and disinfestation"

	Cooperatives	Non-Cooperatives	Total
Not defaulted	182	190	372
Defaulted	11	11	22
TOTAL	**193**	**201**	**394**

Table 2: Average value of the available variables for cooperative and non-cooperative firms of sector 81

Variable	Whole	No coop	Coop
Cash and equivalents on Total assets	6.52	6.49	6.56
Added value on production value	65.03	58.33	72.49
Acid test	858.54	1132.73	547.17
Depreciation and devaluation on costs	9.75	12.96	6.26
Financial autonomy	20.50	18.36	22.88
Net active coverage	19.37	17.44	21.53
Fixed asset coverage	214.08	263.96	158.08
Labor cost on revenues	55.16	45.93	65.34
Labor cost on added value	82.50	78.89	86.48
Labor cost on production value	53.82	45.30	63.22
Credits on Total assets	56.12	55.48	56.85
Current ratio	376.84	297.50	465.39
Short-term payables on Net worth	1178.78	1129.92	1234.22
Total debts on Short-term debts	1280.33	1923.19	549.52
Debts on Net worth	1554.99	1616.23	1486.67
Total debts on Total assets	68.91	73.09	64.26
Tangible assets on shareholders' equity	442.37	513.88	362.04
Tangible assets on Total assets	22.83	22.18	23.54
Short-term debt	50.67	54.21	46.64
Medium and long-term debt	20.94	21.10	20.77
Financial dependence index	94.52	83.09	107.22
Quick ratio	912.60	878.11	950.75
Index of rigidity of assets	29.34	29.00	29.71
EBITDA on revenues	13.43	15.78	10.83
Shareholders' equity on (long-term equity and payables)	57.31	56.99	57.66
Shareholders' equity on equity and inventories	81.82	77.03	87.17
Leverage	2076.92	2159.22	1985.12
Gross operating profitability (EBITDA on production value)	13.03	15.49	10.33
ROA (Return on Asset)	0.64	0.69	0.58
ROE (Return on Equity)	-20.16	-20.78	-19.46
Capital invested rotation	139.15	140.31	137.86
Working capital turnover	2342.08	708.88	4168.62
Inventory turnover	141.39	142.24	140.45
Production value on Revenues	66.84	59.29	75.27
Credit on sales	0.17	0.19	0.15

The variables average value for cooperatives and non-cooperatives for sector 81, reported in Table 2, reports significant differences for some variables, e.g., the "Added value on production value" ratio, averaging 72.49 for cooperatives and 58.33 for non-cooperatives, or "Total debts on Short-term debts" averaging 549.52 for cooperatives, while non-cooperatives report a more than triple value, of around 1923.19.

Table 3: Sample data for sector 01, "Farming of agricultural crops"

	Cooperatives	Non-Cooperatives	Total
Not defaulted	458	508	966
Defaulted	20	31	51
TOTAL	**478**	**539**	**1017**

Table 4: Average value of the available variables for cooperative and non-cooperative firms of sector 01

Variable	Whole	No coop	Coop
Cash and equivalents on Total assets	4.54	4.31	4.80
Added value on production value	34.27	39.62	28.53
Acid test	234.51	205.18	260.97
Depreciation and devaluation on costs	10.08	12.93	6.91
Financial autonomy	26.38	29.91	22.49
Net active coverage	25.80	29.27	21.99
Fixed asset coverage	123.87	137.44	108.93
Labor cost on revenues	23.42	26.82	19.84
Labor cost on added value	61.18	63.01	59.30
Labor cost on production value	19.58	22.28	16.74
Credits on Total assets	25.51	20.37	31.62
Current ratio	150.56	94.97	217.82
Short-term payables on Net worth	815.50	687.08	961.28
Total debts on Short-term debts	3523.50	614.50	6926.98
Debts on Net worth	1434.34	1470.63	1394.47
Total debts on Total assets	71.57	68.37	75.18
Tangible assets on shareholders' equity	709.39	887.73	508.40
Tangible assets on Total assets	47.51	52.90	41.29
Short-term debt	40.03	35.93	44.82
Medium and long-term debt	33.58	33.74	33.40
Financial dependence index	81.30	79.28	83.58
Quick ratio	538.65	205.39	916.41
Index of rigidity of assets	51.90	57.73	45.31
EBITDA on revenues	431.72	839.60	18.27
Shareholders' equity on (long-term equity and payables)	50.08	51.48	48.54
Shareholders' equity on equity and inventories	65.09	66.45	63.59
Leverage	1653.72	1650.38	1657.38
Gross operating profitability (EBITDA on production value)	20.20	26.16	14.10
ROA (Return on Asset)	0.44	0.71	0.13
ROE (Return on Equity)	-11.62	-5.69	-18.12
Capital invested rotation	84.89	63.35	108.58
Working capital turnover	2423.40	319.28	4739.27
Inventory turnover	89.35	67.01	114.53
Production value on Revenues	417.36	777.81	35.30

Also, for sector 01 the variables average value for cooperatives and non-cooperatives, reported in Table 4, reports significant differences for some variables, e.g., the variable "EBITDA on revenues" report an average value of 839.60 for non-cooperatives, while cooperatives just report 18.27. Similarly, the ROA averages 0.71 for non-cooperatives, while cooperatives average just 0.13.

3.2. Cluster analysis

In the cluster analysis, in order to have a larger sample, we considered all business sectors that report a significant number of cooperative (and non-cooperative) enterprises. This allowed us to add to the previous two sectors 01 "Farming of agricultural crops," and 81 " Cleaning and disinfestation", even sectors 41 "Construction of buildings", 43 "Specialized construction work," 47 "Retail", and 52

"Storage and custody", as classified by Italian ATECO standards. We then tested our hypotheses on each business sector, her also filtering out those firms reporting a sales value of more than 100,000 euros to exclude cases that were too small (see Table 5). Due to the different analysis, which is not needing the presence of all values for all variables as preliminary condition for including each case, we have a larger number of cases for sector 81, which reaches a total of 682 cases.

Table 5: Sample data, by sector and firm type

ATECO code	Activity sector	Non Cooperatives	Cooperatives	Total
01	Farming of agricultural crops	539	478	1017
41	Construction of buildings	4530	174	4704
43	Specialized construction works	4129	111	4240
47	Retail	4132	238	4170
52	Storage and custody	486	155	641
81	Cleaning and disinfestation	359	323	682
	TOTAL	**14175**	**1479**	**15454**

Data cleaning

As not all the available variables reported an acceptable value in all cases, we did a double selection process. Firstly, we only kept the variables or which at least 90% of values were present in all sectors both for the cooperatives and for the non-cooperatives firms. Then, we winsorized the values so to bring the 1% outliers to the 99% threshold. Finally, as in Gunnarsson et al. (2021) missing values were imputed using mean replacement.

The second selection was made on the variables significance, just keeping the variables scoring some significance for one sector at least. In this way, we obtained a list of 23 variables, reported in Table 6.

Table 6: Variables and computation

Variable	Computation	Category
Liquidity on total assets	Liquidity / Total Assets	Liquidity
Added value on production value	Added value / Sales	Profitability
Depreciation and devaluation on costs	Depreciation and devaluation / Total Costs	Profitability
Financial autonomy	Equity / (Total Liabilities + Equity)	Capital structure
Net assets coverage	(Equity + Long term liabilities) / Net Assets	Capital structure
Debts on short-term debts	Total Debt / Short-term Debt	Debt management
Debts on Net worth	Total Debt / Net worth	Debt management
Payables to suppliers on Total debt	Payables to Suppliers / Total Debt	Debt management
Degree of indebtedness	Total Debt / (Total Liabilities + Equity)	Debt management
Short-term debt	Short-term Bank Debt / Total Debt	Debt management
Medium and long-term debt	Medium and long-term Bank Debt / Total Debt	Debt management
Financial dependence index	Bank debt / Total Liabilities	Debt management
Quick ratio	(Current Assets – Inventories) / Current Liabilities	Liquidity
Index of assets' rigidity	Fixed Assets / Total Assets	Asset Management
Shareholders' equity on equity and long-term debt	Shareholders' equity / (Equity + Long-term debt)	Capital structure
Shareholders' equity on equity and inventories	Shareholders' equity / Equity + Inventories	Capital structure
Leverage	Total Assets / Equity	Capital structure
ROA	EBIT / Total Assets	Profitability
ROE	Net income/ Shareholders' equity	Profitability
Invested Capital turnover	Sales / Invested Capital	Asset Management
Working capital turnover	Sales / Working capital	Asset Management
Total Asset Turnover	Sales / Total Assets	Asset Management
Added value on sales	Added value / Sales	Profitability

4. Model and Results

4.1. Discriminant analysis

This paragraph shows the results of the logistic regression for the two sectors examined: Sector 81 "Cleaning and disinfestation" and Sector 01 "Farming of agricultural crops", as to say, the two sectors in which the number of cooperatives and non-cooperatives is very close (see table 5), allowing for a balanced analysis.

Sector 81 "cleaning and disinfestation"

When considering the whole sample (Table 7), with no distinction among cooperative and non-cooperative firms, the pseudo R^2 reports a good fitting, near 40%, and all the selected variables are statistically significant at 10% at least (just excluding credit on sales)[7].

Table 7: Results of logistic regressions for sector 81, "Cleaning and disinfestation"

	Model					
	Indistinct		**Specific for Coop**		**Specific for non-Coop**	
Violation share	.0625515	***	0.220141	***	.0462543	**
Financial coverage	-.0019497	*	-0.025025	*	-.0014895	
Degree of indebtedness	.0637105	**	0.124173	**	.1069205	*
Tangible assets on Total assets	-.0406617	**	-0.055697	*	-.1138106	**
Short-term debt	-.0324088	**	0.001320		-.0593018	**
Financial dependence	.0057095	***	0.011122	**	-.0327643	
Leverage	.0000252	*	-0.000002		.0000475	
Invested Capital turnover	-.0204102	***	-0.036266	**	-.044177	**
Credit on sales	.8015494		-9.177278	**	3.438448	
_cons	-4.377132	**	-7.835287	*	-.8004922	
Pseudo R^2	**0.3948**		**0.5347**		**0.5685**	

In terms of classification, results show a significantly lower quality: just 5 out of 22 defaults are correctly classified, reporting a sensitivity of 22.73% (see Table 8). A more detailed classification can be evidenced by separately considering the classification values for cooperative and non-cooperative firms. In fact, for the first group, the general model correctly classified just 1 out of 11 defaults, reporting a sensitivity as low as 9.09%. Some better result is obtained for the non-cooperative firms, for which the correct classification of defaults is obtained in 4 out of 11 cases, reporting a sensitivity of 36.36%. Instead, when the scoring model is tuned separately for cooperative and non-cooperative firms, results show higher performances. Firstly, for non-cooperative firms, the pseudo R^2 scores a significant

[7] A control variable test on each of the subsequent logit models estimations, reported the non-significance of sales volume, so, of the firms' dimension.

improvement, reaching 56.85%. Secondly, the variables' significance and coefficients report pretty different results, e.g., the "Short-term debt" variable is no more significant for cooperative firms, and changes its coefficient from the -0.032 value in the general model, to a -0.059 value for the non-cooperative model. Similarly, "Leverage" and "Credit on sales" report clear differences in significance and coefficients.

Passing to the classification correctness (Table 8), the output of the specific model for non-cooperative firms reports a significant improvement, raising the correct classification of defaults to 5 out of 11, thus scoring a sensitivity of 45.45%. When considering the performances of the cooperative firms' tuned model, we can see an even more significant improvement. The pseudo R^2 here also reports a significant improvement, reaching 53.47%. Regarding the variables' coefficients and significance, the values estimated for the cooperative firms are quite different both from the non-cooperatives model and the general model, evidencing the importance of the separate model estimation and supporting a positive answer to our RQ1. Here also, the correct classification goes significantly up, reporting the correctness of 7 out of 11 defaults (and 181 out of 182 non-defaults), scoring a sensitivity of 63.64%. This result, coupled with the similar improvement reported for the non-cooperatives subsample, supports a positive answer to our RQ2.

Table 8: Classification correctness for sector 81, "Cleaning and disinfestation"

	Model				
	Indistinct	**Undistincted on Coop**	**Undistincted on Non-Coop**	**Specific for Coop**	**Specific for non-Coop**
Sensitivity	22.73%	9.09%	36.36%	63.64%	45.45%
Specificity	99.19%	99.45%	98.95%	99.45%	99.47%
Positive predictive value	62.50%	50.00%	66.67%	87.50%	83.33%
Negative predictive value	95.60%	94.76%	96.41%	97.84%	96.92%

Sector 01 "Farming of agricultural crops"

Similar results can be obtained for the 1171 firms of sector 01 "Farming of agricultural crops". Here also (see Table 9), the specificity is very high, while the sensitivity is quite low, just reporting a 5,88%. If we split this sensitivity among cooperatives and non-cooperatives, the cooperatives report a 10%, and the non-cooperatives report the lowest score, as low as 2.38%. Instead, when tuning the two models separately, the cooperatives-tuned model reports an encouraging 25%, while the non-cooperatives-tuned model still reports a low score, around 9,7%, but clearly higher than the previous 2.38%.

Table 9: Classification correctness for sector 01, "farming of agricultural crops"

	Model				
	Indistinct	**Undistincted on Coop**	**Undistincted on Non-Coop**	**Specific for Coop**	**Specific for non-Coop**
Sensitivity	5.88%	10.00%	2.38%	25.00%	9.68%
Specificity	99.69%	99.59%	99.35%	99.34%	99.61%
Positive predictive value	50.00%	50.00%	20.00%	62.50%	60.00%
Negative predictive value	95.25%	96.46%	93.73%	96.81%	94.76%

When considering the variable's coefficient and significance (see Table 10), the "general" model reports some significance for all the 10 considered variables, while the two specific ones show a higher selection of variables, reporting some significance for 6 variables in the case of the cooperative, and just 4 variables in the non-cooperatives case. Interestingly, for cooperatives the "violation share" variable, which measures the percent value of credit above the granted value, is just significant for cooperatives, while for non-cooperatives the significant variable measures the number of months per year in which the credit used was above the granted value. Turnover is only significant for non-cooperatives, but at the highest level. More, the two variables reporting a statistical significance in both specific models, namely "Credit line usage" and "Added value on production value" report different coefficients.

Table 10: Results of logistic regressions for sector 01, "farming o agricultural crops"

	Model					
	Indistinct		**Specific for Coop**		**Specific for non-Coop**	
Credit line usage	.0337591	***	.0567716	***	.0211914	**
Violation share	-.0349125	***	-.0586751	***	-.0200677	
Violation months	.2010752	***	.129311		.239377	***
Added value on production value	-.0252786	***	-.0473316	**	-.0221532	**
Short-term payables on Net worth	-.0003933	*	-.0008233	*	-.0002648	
Payables to suppliers on Net worth	.0136468	*	.0281519	**	.0067508	
Shareholders' equity on equity and payables	-.0167514	**	-.0324448	**	-.0081001	
ROA (Return on Asset)	-.036248	*	-.0418845		-.0341927	
ROE (Return on Equity)	-.0026848	*	-.004897		-.0036856	
Turnover	-.0077048	**	-.0023592		-.0167585	***
_cons	-3.904667	***	-5.126614	***	-3.142557	***
Pseudo R^2	0.2894		0.4142		0.2663	

4.2. Cluster analysis

Another way for verifying if the sector differences are stronger or weaker than the cooperative/non-cooperative activity, relies on the cluster analysis.

For measuring the dissimilarities among the different cases, and performing the cluster analysis, a set of indicators is needed. In this analysis, our aim is to verify if the cooperative firms credit scoring is differently affected by financial ratios. Thus, we verified which is the estimated significance and coefficient of the available variables. While the typical values for comparing the variables significance for credit scoring are obtained by a logistic regression on all the considered variables, as we did in the previous analysis, when considering a larger number of activity sectors, the limited number of defaults and of cooperatives in each sector does not allow for a regression on all the 23 considered variables. Thus, we performed one logistic regression for each considered variable. The estimation results are reported in Appendix 1 and 2.

Based on each variable coefficient, significance (in terms of its z-values), and R^2, the cluster analysis performs subsequent splitting of the considered set. At each turn, the algorithm computes the distances among each observation, then splitting the groups into subgroups, each of them including the most similar cases. The analysis results can be either visualized as data, reporting each group composition, or by a dendogram, a tree-like representation in which the top is for the whole group which, going down the chart, recursively splits into smaller and smaller groups, up to three single cases. The same dendogram can be read in an opposite perspective, in which single cases are recursively grouped based on their nearness, so to eventually end in a single group.

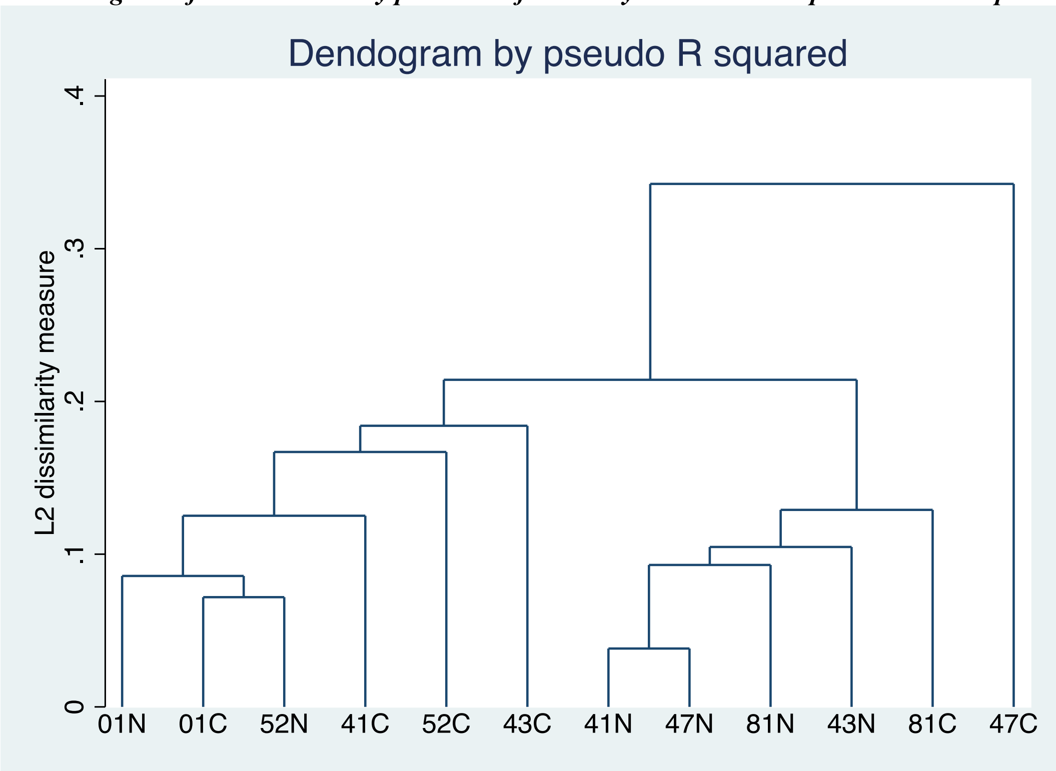
We performed three cluster analyses, for verifying if the sector differences report larger or smaller "dissimilarity measures" from the cooperative/non-cooperative attitude, so to answer to our RQ3. Each cluster analysis refers to one parameter of the previous estimation, namely: coefficients, z-values and determination coefficient (pseudo R^2). In the following figures, the resulting dendograms are reported.

The first dendogram (Figure 1) is based on the discriminant regressions determination coefficient, or pseudo R^2. The figure shows that the grouping of most similar cases (bottom-up look) always reports groupings of different sectors at the lowest level, adding the correspondent cooperative/non-cooperative at some higher level, thus evidencing that the dissimilarities are higher for the cooperative or non-cooperative attitude than for sector activity.

Looking at the same picture from the opposite point of view (top-down) the dendogram evidences that the first splitting is of the cooperatives of sector 47 on the one side, and all the rest on the other side.

Then, the second splitting is more balanced, selecting 6 entities on one side and 5 on the other. Within this second splitting, a clear characterization is in the groups' composition: in the left group, four out of six are cooperatives, while in the right one four out of five are non-cooperatives.

Figure 1: Dendogram of dissimilarities by pseudo R2 for activity sectors and cooperative/non-cooperative



Similar results are obtained when computing the dissimilarities by the estimated coefficient values (Figure 2). In this dendogram, the first splitting leaves three cooperatives sectors on the right side, and all the rest on the left side. The second splitting just excludes the cooperatives of sector 47 from the main group, and the third splitting groups four non-cooperatives out of five entities on the one side, and two non-cooperatives and one cooperative on the other side.

Figure 2: Dendogram of dissimilarities by coefficients for activity sectors and cooperative/non-cooperative

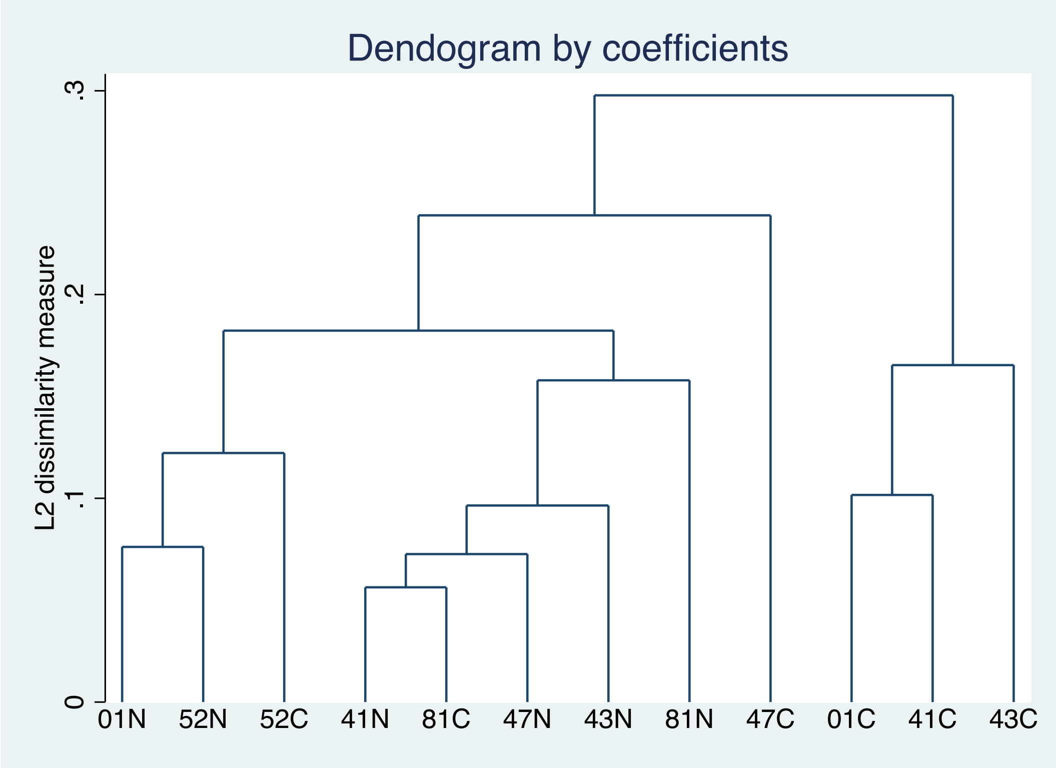
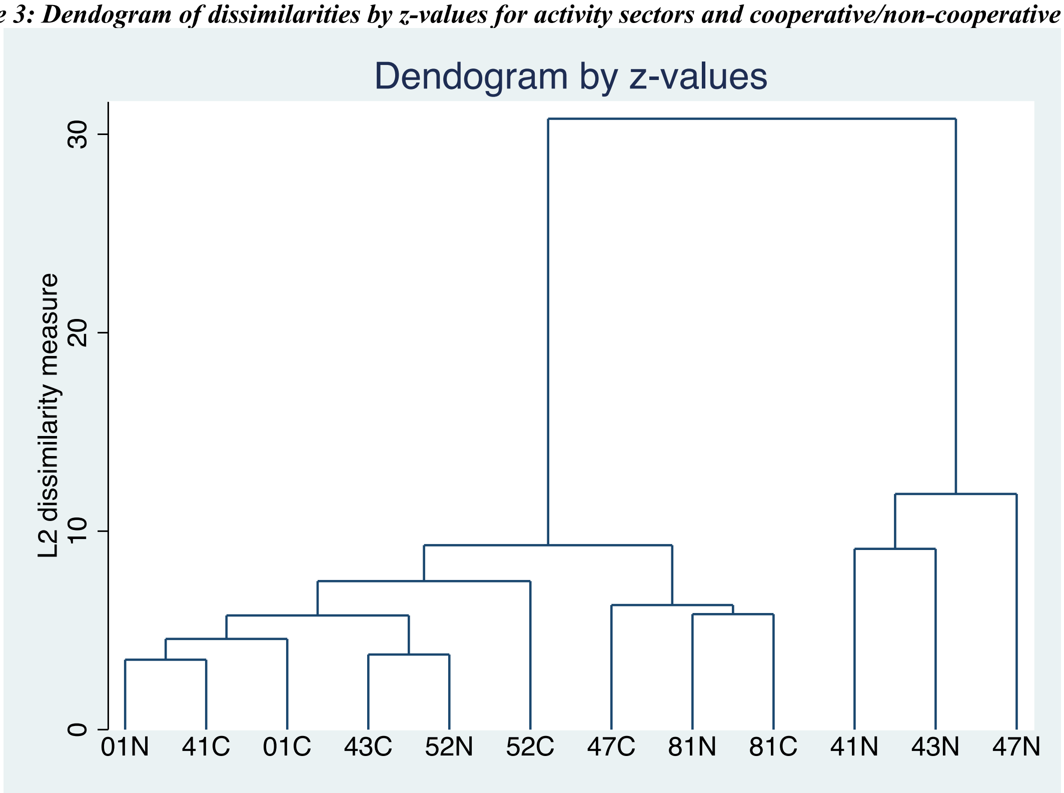
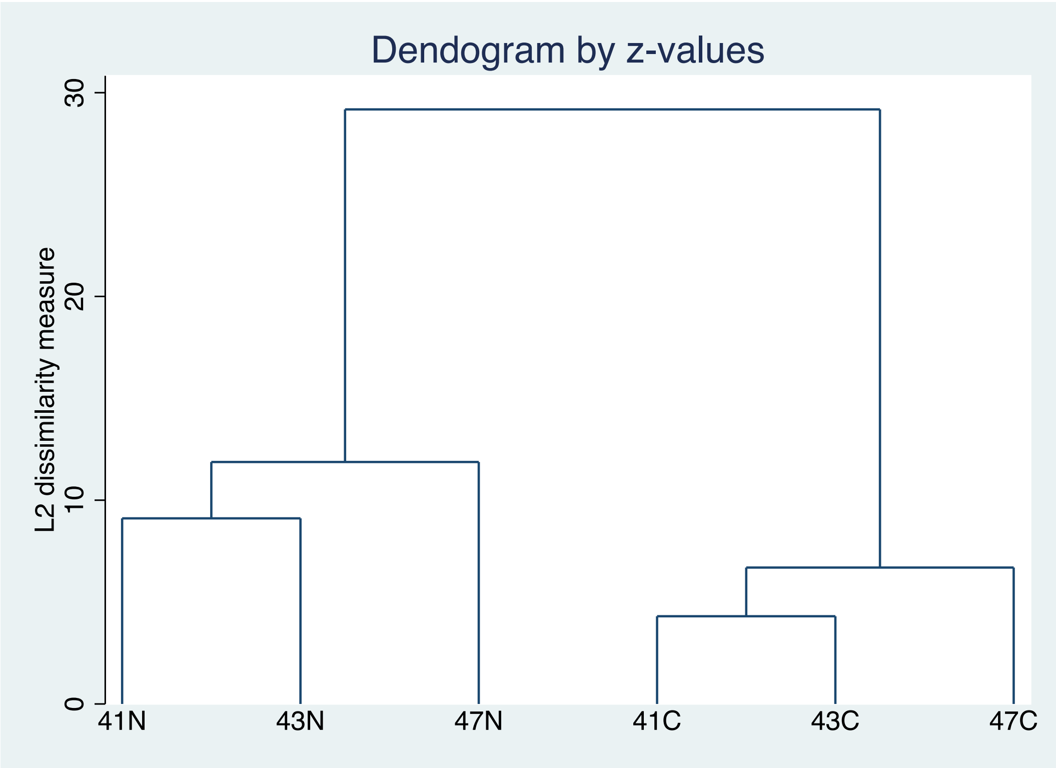


Figure 3: Dendogram of dissimilarities by z-values for activity sectors and cooperative/non-cooperative



The third dendogram (Figure 3), performed on z-values, so on the variables significance, show a first splitting which groups three non-cooperative sectors on the right and all the others on the other side, and setting more splitting just at a low level (around 10) of dissimilarity. If we just consider more similar activities, the ones starting with 4, we obtain the dendogram reported in figure 4, which clearly show that, for these activity sectors, the main difference is among cooperatives and non-cooperatives (dissimilarities around 30), overcoming by far the residual splitting, among activity sectors, set ad dissimilarity levels around 10, supporting the positive answer to our RQ3.

Figure 4: Dendogram of dissimilarities by z-values for housing related activity sectors and cooperative/non-cooperative



5. Discussion and implications

Our evidence provides empirical support to justify the development and adoption on behalf of CCBs of "tailor-made" credit scoring models for cooperatives and non-cooperatives.

This finding corroborates Gutiérrez-Nieto et al. (2016), who warned scholars proposing credit scoring methodologies not to overlook that the entrepreneurship spectrum ranges from solely profit-driven ventures to exclusively socially driven ones and encompasses everything in the middle. These varying degrees of social orientation should constitute a relevant element of sample differentiation.

On the methodological front, this paper makes explicit the side effects inherent in the shortsighted use of credit scoring models to assess the creditworthiness of cooperatives. A "one-size-fits-all" approach to credit scoring and the exclusive reliance on balance sheet data at the expense of relationship lending data determines significant procyclical effects in credit supply shortage (Ferri, 2012), a critical occurrence for cooperatives who primarily rely on debt to finance their growth and inventories (Mashange et al., 2022).

Characterizing the results obtained is another peculiar pattern: the statistical significance of predictors and their main effect change between the "one-size-fits-all" and the "tailored" credit scoring models and among "tailored" models.

One example of the observed differences between groups is that the amount of short-term debt is statistically significant at the 5% level and negatively affects the likelihood of default in the generic model. While the same pattern can be observed in the non-cooperative sample, although the coefficient's magnitude is more marked, the short-term debt variable becomes statistically insignificant, and its coefficient is positive in the cooperative sample. Something similar happens in the case of the financial dependence ratio: in the undifferentiated model, the coefficient is positive and statistically significant at the 1% level. Yet, it becomes statistically insignificant in the non-cooperatives sample and eventually negative and statistically significant at the 5% level in the "Farming of agricultural crops" sample. Notably, the leverage ratio completely loses explanatory power in the "tailored" model, while remaining only statistically significant in the "one-size-fits-all" model. Last, the coefficient of sales made "on credit" is statistically insignificant in the undifferentiated model, but strongly negative and statistically significant at the 5% level in the cooperative-specific one.

These findings corroborate the nascent literature examining the balance sheet equilibriums of cooperatives. For example, the gain in statistical significance observed relative to credit on sales when comparing the "tailored" model to the "untailored" model may be due to the prominent role these financial management decisions play in the cooperative sector, traditionally prone to experience external financing constraints. Credit on sales determines much of the success or failure of cooperatives.

On the one side, they are forced to distribute equity among members (Mashange et al., 2022). On the other, cooperatives heavily rely on debt because the nature of their businesses prevents them from accessing capital markets (Martínez-Victoria & Maté-Sanchez-Val, 2022). However, once the maximum debt capacity has been reached, the companies are obliged to revert to accounts payable and receivable policies to subsidize their operations. In this regard, Mashange & Briggeman (2022) provide empirical support to the claim that cooperatives place great emphasis on accounts receivable management. In their dataset spanning from 1996 to 2019, they find that only 8% of cooperatives' accounts receivables are 30 days past due, signaling that they are monitored regularly. These considerations would also explain the insignificance of leverage as a default predictor: It is in the very nature of cooperatives to be financially leveraged (Mashange et al., 2022), so this element no longer acts as a discriminating factor. A similar argument can be made regarding the irrelevance of short-term debt. Since much of cooperatives' financial operations revolve around accounts payable and receivable (Mashange & Briggeman, 2022), and given that bank debt is predominantly used to finance growth and inventories (Mashange et al., 2022), its predictive role, once considering the other covariates, becomes irrelevant.

The "Farming of agricultural crops" sample displays different default predictors, most of which have been discussed in the exiguous literature examining balance sheet equilibriums and relationship lending in farming cooperatives (e.g., Martínez-Victoria & Maté-Sanchez-Val, 2022; Mashange & Briggeman, 2022; Mashange et al., 2022). Here the difference between cooperatives and non-cooperatives becomes even clearer. The statistical significance of the predictors tied to cooperatives' accounts payable strongly indicates the relevance of such balance sheet items in this sector (Mashange & Briggeman, 2022).

The adoption of a " one-size-fits-all" approach has important consequences on the bank's front. In a banking firm, the credit process is efficient when the bank manages to minimize type I error and type II error (Altman, 1980). A type I error occurs when a lender rejects a loan application even though the applicant would have been able to repay the loan. This error is also known as a "false positive." In other words, the lender has mistakenly classified a creditworthy borrower as a risky borrower. The type I error produces negative effects on the bank's income statement as it misses business opportunities. More specifically, the type I error reduces the bank's interest margin due to lower interest charged on loans. A Type II error occurs when a lender approves a loan application even though the applicant would not be able to repay the loan. This error is also known as a "false negative." In other words, the lender has mistakenly classified a risky borrower as a creditworthy borrower. Type II error can lead to loan defaults, which can result in financial losses for the lender and negative impacts on the borrower's credit score. Therefore, it's important for lenders to carefully evaluate loan applications to minimize the risk of both types of errors.

This circumstance assumes growing value in the financing of cooperatives. The bank's limited ability to identify the characteristics of social enterprises due to the failure to adopt a tailor-made creditworthiness assessment system produces two unwanted effects. On the one hand, the bank, especially if a CCB, could limit the social impact of lending on the territory if access to credit for cooperative enterprises were made difficult and, in particular, if financing was denied to deserving ones. On the other hand, the adoption of a "one-size fits all" approach could favor the financing of unworthy cooperatives with subsequent negative effects on the bank's capital adequacy, on the quality of its assets and on its earning capacity which would be eroded from credit losses.

Cooperatives are unique business entities that differ from traditional businesses in their organizational structure and decision-making processes. As a consequence, evaluating the creditworthiness of cooperatives can be challenging for lenders. Our work demonstrates how relying only on balance sheet data can make it difficult to accurately assess their financial health and repayment capacity, as shown by the cluster analysis dendograms, which proof that the dissimilarities among cooperatives and non-cooperatives are larger than the dissimilarities computed among different activity sectors, well known and considered by banks.

In this context, lenders may face a higher risk of making Type I errors, where they may reject creditworthy cooperative loan applications due to inadequate evaluation methods or incomplete information. On the other hand, they may also make Type II errors, where they may approve risky cooperative loan applications due to an overestimation of the cooperative's financial capacity.

In this sense, our results proof that the main improvement are in the sensitivity and positive prediction value, as to say, on the higher share of correct estimation of defaults, as to say, on the reduction of type II errors, the most impacting ones.

In more general terms, our results suggest that banks should develop specialized assessment models, and processes tailored to the unique characteristics of cooperatives, to minimize the risk of these errors. This could include incorporating non-financial factors such as governance structures, decision-making processes, and social impact metrics into the credit evaluation process.

In this perspective, fintech can play a significant role in helping cooperative credit banks elevate the sustainability of the areas they operate in by building social credit scoring systems when assessing the creditworthiness of cooperative enterprises. A well-designed social credit scoring system can promote sustainable business practices and encourage responsible lending.

For example, fintech can leverage non-traditional data sources, such as social media activity and utility payment history, to build a more tailored credit profile of enterprises. This data can help identify sustainable business practices and responsible financial behavior. At the same time, fintech can help banks to include ESG factors in credit scoring algorithms, rewarding enterprises, both cooperatives and non-cooperatives, that demonstrate commitment to environmental sustainability, social responsibility, and sound corporate governance. This can help incentivize bank customers to adopt sustainable practices and align their interests with the long-term well-being of the community.

By integrating advanced analytics and alternative data sources, a "tailored" credit scoring models can become more accurate and better aligned with the long-term well-being of the community and the environment.

6. Conclusions

In this analysis, we tested whether the cooperative form induces significant effects on the firm's balance sheet to limit the effectiveness of credit scoring models. We investigated our hypotheses on the two activity sectors in which the number of cooperative firms was significant and similar to that of non-cooperative firms.

Our evidence shows that the significant variables as default predictors for cooperative and non-cooperative firms are significantly different in both sectors. This is evidenced both by the different significance of variables and by different estimated coefficients when the variables are significant in both models.

Results also highlight that a unique model, making no distinction between cooperative and non-cooperative firms, is always worst performing than the two separate tunings. Therefore, a separate calibration of scoring models for cooperative and non-cooperative firms may improve the scoring performance, enhancing the specific characteristics of the two types of firms.

Cooperative and non-cooperative firms have different financial and operational characteristics, which affect the way they are evaluated. For example, cooperative firms have a stronger focus on maintaining the financial stability of the firm, while non-cooperative firms focus more on maximizing profits. These differences may be captured by different financial ratios, which may be more relevant for one type of firm than the other, so that a separate calibration of the models may improve their performance.

The significance of our findings underlines that the use of unspecific scoring models by the banks can result in both a lower credit risk control and a possible credit rationing for cooperatives, while more accurate modeling can avoid these effects. In the context of cooperative lending, type I and type II errors have meanings that go beyond those of traditional lending. A type I error would occur when a lender rejects a loan application from a creditworthy borrower, while type II error would occur when a lender approves a loan application from a borrower that is unable to repay the loan. Both errors produce a cascading effect on the bank's balance sheet, impacting its ability to generate revenue, maintain adequate capital and liquidity, and meet regulatory requirements.

However, type I errors in cooperative lending can result in more than just missed opportunities for a cooperative to obtain necessary funding. Cooperatives are often founded with a social or community-oriented purpose, and rejection of a loan application can have wider social and economic impacts on the cooperative's members and the community it serves. This can impact the cooperative's ability to achieve its mission and have a negative impact on the local economy. Type II errors in cooperative lending can also have additional implications beyond financial losses for the lender. Cooperative lending is often based on social collateral and trust among members, and a loan default can have broader social implications beyond the financial impact. It can erode trust and social cohesion within the cooperative and damage the cooperative's reputation within the community. This can make it more difficult for the cooperative to access financing in the future and achieve its social and economic goals. Therefore, especially in the context of cooperative lending, it is important to have robust tailor-made lending processes in place to minimize the risk of both types of errors and avoid implications that could harm the bank's ability to serve the community and area in which it operates.

Adopting a "one-size-fits-all" credit score model for cooperatives and non-cooperatives may affect the lending policies of a cooperative credit bank (CCB) in several ways. First, it may not accurately capture the risk profile of these firms and it may not take into account relevant factors that could affect their creditworthiness. This could lead to either over - or under - estimating the creditworthiness of these firms, which in turn could lead to either too much or too little credit being extended to them. Second, a "one-size-fits-all" model may not take into account the unique ownership structure and governance model of cooperatives, which may affect their risk profile and the way they operate.

While a "one-size-fits-all" model may be simpler and easier to implement, it may not provide the best results for cooperative banks. Fintech can help cooperative credit banks in building social credit scoring systems that incentivize sustainable practices, promote transparency and trust, and enhance the long-term sustainability not only of the bank, but also of its community and the area it serves.

The results of our analysis are obtained just looking at the Italian case, where cooperatives have a significant role and tradition. It both constitutes a strong point and a limitation of its significance.

It is a strong point as it refers to a uniform area, affected by the same market constraints and challenges, ruled by the same laws and financed by the same banking system. This single country approach is strictly in line with the credit scoring stylized facts, which clearly reports that credit scoring models must be tuned to single countries, industries, and firms' dimensions.

At the same time, just focusing on one country limits its evidence to the considered country. But, as the cooperative firms and cooperative banks' role is significant also in other countries, we suspect that similar results can be found in other countries, in which, as in Italy, cooperative banks are historically prevalent and influential, have a long tradition and are deeply rooted in local communities, providing financial services to individuals, households and enterprises, especially in local areas.

Although the importance of cooperative banks may vary from country to country, certain characteristics are commonly associated with them. These include the priority role of financial inclusion and social objectives coupled with the financial sustainability, a strong focus on relationship banking, a commitment to member-driven decision-making, and a cooperative governance structure.

We believe that our analyses could possibly be extended to countries such as Germany (Cooperative Financial Network Germany – BVR, Raiffesenbank, REWE), Spain (Cajas Rurales), France (Crédit Agricole, BPCE, Crédit Mutuel) and the Netherlands (Rabobank), where cooperative banks play a significant role in the banking system, and we hope further research could analyze in a similar way the cooperative banks' role and cooperative firms' specificities, so to possibly confirm (or not) and extend (or not) the results we showed for Italy.

References

Agostino, M., Ruberto, S. & Trivieri, F. (2023). The role of local institutions in cooperative banks' efficiency. The case of Italy. *International Review of Economics & Finance*, 84, 84-103.

Aktaş, K., & Barbetta, G. P. (2022). The effect of giving credit to social enterprises: Evidence from Italy. *Italian Economic Journal*, 1-29.

Alaka, H. A., Oyedele, L. O., Owolabi, H. A., Kumar, V., Ajayi, S. O., Akinade, O. O., & Bilal, M. (2018). Systematic review of bankruptcy prediction models: Towards a framework for tool selection. *Expert Systems with Applications*, 94, 164-184.

Altman, E.I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance* 23(4), 589–609.

Altman, E. I., 1980. Commercial bank lending: process, credit scoring, and costs of errors in lending. *Journal of Financial and Quantitative Analysis* 15(4), 813-832.

Altman, E.I., Marco, G., Varetto, F., 1994. Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience). *Journal of Banking and Finance* 18(3), 505–529.

Altman, E.I., Sabato, G., 2007. Modelling credit risk for SMEs: Evidence from the US market. *Abacus* 43(3), 332–357.

Arner, D. W., Barberis, J., & Buckey, R. P. (2016). FinTech, RegTech, and the reconceptualization of financial regulation. *Northwestern Journal of International Business and Law*, 37(1), 371-413.

Avrampou, A., Skouloudis, A., Iliopoulos, G., & Khan, N. (2019). Advancing the sustainable development goals: Evidence from leading European banks. *Sustainable Development*, 27(4), 743-757.

Ayadi, R., Llewellyn, D. T., Schmidt, R. H., Arbak, E., & De Groen, W. P. (2010). Investigating diversity in the banking sector in Europe: Key developments, performance and role of cooperative banks. *CEPS Paperbacks*.

Baccarani, C., Golinelli, G. M., & Rullani, E. (2013). *Le BCC banche di territorio. Il mutualismo per la costruzione del futuro*. Cedam.

Balios, D., Thomadakis, S.& Tsipouri, L. (2016). Credit rating model development: An ordered analysis based on accounting data. *Research in International Business and Finance*, 38, 122-136.

Beaver, W.H., 1966. Financial ratios as predictors of failure. *Journal of Accounting Research*, 7–111.

Becchetti, L., Ciciretti, R., & Paolantonio, A. (2016). The cooperative bank difference before and after the global financial crisis. *Journal of International Money and Finance*, 69, 224-246.

Berger, A. N., & Udell, G. F. (1995). Relationship lending and lines of credit in small firm finance. *Journal of Business*, 68(3), 351-381.

Bergerès, A.S., d'Astous, P., Dionne, G., 2015. Is there any dependence between consumer credit line utilization and default probability on a term loan? Evidence from bank-customer data. Journal of Empirical Finance 33, 276–286.

Bhimani, A., Gulamhussen, M.A., Lopes, S.D.R., 2010. Accounting and non-accounting determinants of default: An analysis of privately-held firms. *Journal of Accounting and Public Policy* 29(6), 517–532.

Bijman, J., Hendrikse, G., 2003. Cooperatives in chains: institutional restructuring in the Dutch fruit and vegetable industry. ERIM Report Series Research in Management.

Bijman, J., Iliopoulos, C., 2014. Farmers' cooperatives in the EU: policies, strategies, and organization. Ann. Public Coop. Econ. 85 (4), 497–508.

Bocken, N. M., & Short, S. W. (2016). Towards a sufficiency-driven business model: Experiences and opportunities. *Environmental Innovation and Societal Transitions*, 18, 41-61.

Bottazzi, G., Grazzi, M., Secchi, A., Tamagni, F., 2011. Financial and economic determinants of firm default. *Journal of Evolutionary Economics* 21(3), 373–406.

Boyd, J.H., Prescott, E.C., 1986. Financial intermediary-coalitions. *Journal of Economic Theory* 38(2), 211–232.

Brealey, R., Leland, H.E., Pyle, D.H., 1977. Informational asymmetries, financial structure, and financial intermediation. *The Journal of Finance* 32(2), 371–387.

Buffa, F., Franch, M., Martini, U., & Tamanini, A. (2019). Scelte strategiche e pratiche ambientali nelle Pmi alberghiere. Verso un nuovo modello di business sostenibile. *Sinergie Italian Journal of Management*, 37(1), 85-106.

Burke, B.J., Piekielek, J., 2011. Cooperatives, politics, and development in rural Paraguay. Hum. Organ. 70 (4), 355–365;

Carbó, S., Williams, J. (2000). *Stakeholder Value in European Savings Banks. In: Schuster, L. (eds) Shareholder Value Management in Banks*. Palgrave Macmillan, London.

Caridà, A., Colurcio, M., & Melia, M. (2015). Designing a collaborative business model for SMEs. *Sinergie Italian Journal of Management*, 33, 233-253.

Caselli, G., Costa, M., & Delbono, F. (2022). What do cooperative firms maximize, if at all? Evidence from Emilia-Romagna in the pre-Covid decade. Ann Public Coop Econ, 93, 821–847.

Casprini, E. (2015). Business model innovation: a typology. *Sinergie Italian Journal of Management*, 33, 181-197.

Chaddad, F., 2012. Advancing the theory of the cooperative organization: the cooperative as a true hybrid. Ann. Public Coop. Econ. 83 (4), 445–461.

Chesbrough, H., Minin, A. D., & Piccaluga, A. (2011). Percorsi di innovazione nei modelli di business. In *Nuovi modelli di business e creazione di valore: la Scienza dei Servizi* (pp. 73-94). Springer.

Ciampi, F., 2015. Corporate governance characteristics and default prediction modeling for small enterprises. An empirical analysis of Italian firms. *Journal of Business Research* 68(5), 1012–1025.

Ciampi, F., Giannozzi, A., Marzi, G., & Altman, E. I. (2021). Rethinking SME default prediction: a systematic literature review and future perspectives. *Scientometrics*, 126(3), 2141-2188.

Coccorese, P., & Shaffer, S. (2021). Cooperative banks and local economic growth. *Regional Studies*, 55(2), 307-321.

Coccorese, P., Ferri, G., Lacitignola, P., & Lopez, J. (2016). Market structure, outer versus inner competition: The case of Italy's credit coop banks. *International Review of Economics*, 63(3), 259-279.

CoopsEurope, (2015). The Power of Cooperation – Cooperatives Europe Key Figures 2015. Available at: https://coopseurope.coop/wp-content/uploads/2016/04/The-power-of-Cooperation-Cooperatives-Europe-key-statistics-2015.pdf, accessed on October 6, 2023.

Couderc, J.-P., Marchini, A., 2011. Governance, commercial strategies and performances of wine cooperatives: an analysis of Italian and French wine producing regions. Int. J. Wine Bus. Res. 23 (3), 235–257.

D'Onza, G., Formisano, V., Landi, A. & Modina, M. (2021), Il credito cooperativo: modello di business, governance e sostenibilità, *AIDEA Position Paper*, 1-24.

Dainelli, F., Giunta, F., Cipollini, F., 2013. Determinants of SME credit worthiness under Basel rules: The value of credit history information. *PSL Quarterly Review* 66(264), 21–47.

da Silva Inácio, L. & Delai, I. (2022). Sustainable banking: a systematic review of concepts and measurements. *Environment, Development and Sustainability*, 24, 1-39.

Delbono, F., & Reggiani, C. (2013). Cooperative firms and the crisis: evidence from some Italian mixed oligopolies. Annals of Public and Cooperative Economics, 84, 383–397.

Diamond, D.W., 1984. Financial intermediation and delegated monitoring. *The Review of Economic Studies* 51(3), 393–414.

Dierkes, M., Erner, C., Langer, T., Norden, L., 2013. Business credit information sharing and default risk of private firms. *Journal of Banking and Finance* 37(8), 2867–2878.

EACB (2022). EUROPEAN ASSOCIATION OF CO-OPERATIVE BANKS, The Co-operative difference : Sustainability, Proximity, Governance, KEY STATISTICS as of 31-12-21 (Financial Indicators). Available at: https://v3.globalcube.net/clients/eacb/content/medias/key_figures/20221014_hg_luce_eacb_key_statistics_2021.pdf (accessed 6 October 2023)

Eliwa, Y., Aboud, A., & Saleh, A. (2021). ESG practices and the cost of debt: Evidence from EU countries. *Critical Perspectives on Accounting*, 79, 102097.

Ferlito, R. & Faraci, R. (2022). Business model innovation for sustainability: a new framework. *Innovation & Management Review*, 19(3), 222-236.

Ferri, G. (2017). The evolution of banking regulation in the post-crisis period: cooperative and savings banks' perspective. In: *Institutional Diversity in Banking* (pp. 1-31). Palgrave Macmillan.

Ferri G. (2012). Credit Cooperatives: Challenges and Opportunities in the New Global Scenario. *Euricse Working Paper*, 031(12). https://euricse.eu/wp-content/uploads/2015/03/1334309723_n2044.pdf

Figueiredo V., Franco M., (2018). Wine cooperatives as a form of social entrepreneurship: Empirical evidence about their impact on society, Land Use Policy 79 812–821.

Fiordelisi, F., Monferrà, S., Sampagnaro, G., 2014. Relationship lending and credit quality. *Journal of Financial Services Research* 46(3), 295–315.

Foglia, A., Laviola, S., Reedtz, P.M., 1998. Multiple banking relationships and the fragility of corporate borrowers. *Journal of Banking and Finance* 22(10), 1441–1456.

Freeman, R. E. (2010). *Strategic Management: A stakeholder approach*. Cambridge University Press.

Ghauri, S., Jackson, E. L., Marinova, D. & Mohammadi, H. (2022). Agricultural co-operatives for managing natural capital to achieve UN Sustainable Development Goals 12–15: A conceptual framework. *Journal of Co-operative Organization and Management*, 10(2), 100188.

Grunert, J., Norden, L., Weber, M., 2005. The role of non-financial factors in internal credit ratings. *Journal of Banking and Finance* 29(2), 509–531.

Gutiérrez-Nieto, B., Serrano-Cinca, C., & Camón-Cala, J. (2016). A credit score system for socially responsible lending. *Journal of Business Ethics*, 133(4), 691-701.

Jiménez, G., Lopez, J.A., Saurina, J., 2009a. Calibrating exposure at default for corporate credit lines. *Journal of Risk Management in Financial Institutions* 2(2), 121–129.

Jiménez, G., Lopez, J.A., Saurina, J., 2009b. Empirical analysis of corporate credit lines. *Review of Financial Studies* 22(12), 5069–5098.

Jovanovíc, T., Arnold, C. & Voigt, K.-I. (2017). Cooperative banks in need of transition: The influence of Basel III on the business model of German cooperative credit institutions. *Journal of Co-operative Organization and Management*, 5, 39-47.

Jung, J., Herbohn, K., & Clarkson, P. (2018). Carbon risk, carbon risk awareness and the cost of debt financing. *Journal of Business Ethics*, 150(4), 1151-1171.

Loubere, N. & Zhang, H. X. (2015). Co-operative financial institutions and local development in China. *Journal of Co-operative Organization and Management*, 3, 32-39.

Martínez-Victoria, M. & Maté-Sanchez-Val, M. (2022), Determinants of trade credit financing: a dynamic analysis comparing agri-food cooperatives and non-cooperatives. *Agricultural Finance Review*, 82(5), 890-913.

Mashange, G. & Briggeman, B. C. (2022). Assessing the financial condition and accounts receivable risk among US farmer cooperatives. *Agricultural Finance Review*, 82(2), 344-358.

Mashange, G., Featherstone, A. M., Briggeman, B. C. (2022). Evaluating changes in credit rating quality of U.S. farmer cooperatives. *Journal of Co-operative Organization and Management*, 10, 100153.

Matei, L., Matei, A., 2012. The social enterprise and the social entrepreneurship – instruments of local development. A comparative study for Romania. Procedia – Soc. Behav. Sci. 62, 1066–1071.

McKillop, D., French, D., Quinn, B., Sobiech, A. L., & Wilson, J. O. (2020). Cooperative financial institutions: A review of the literature. *International Review of Financial Analysis*, 71, 101520.

Mester, L.J., Nakamura, L.I., Renault, M., 2007. Transactions accounts and loan monitoring. *Review of Financial Studies* 20(3), 529–556.

Metz, C.E., 1978. Basic principles of ROC analysis. Seminars in Nuclear Medicine 8, 283–298.

Ministero delle imprese e del made in Italy, (2022). Descrizione del mondo cooperativo italiano, novembre 2022, available at: https://www.mimit.gov.it/images/stories/documenti/Descrizione_del_Mondo_cooperativo_Italiano_-_Novembre_2022.pdf (accessed on October 6, 2023).

Minto, A. (2016). The spirit of the law over its letter: The role of culture and social norms in shielding cooperative banks from systemic shocks. *Law and Financial Markets Review*, 10(1), 16-26.

Nakamura, L., 1993. Commercial bank information: Implications for the structure of banking. In Klausner, M., White, L.J. (Eds.), Structural Change in Banking. Business One/Irwin, Homewood, IL.

Norden, L., Weber, M., 2010. Credit line usage, checking account activity, and default risk of bank borrowers. *Review of Financial Studies* 23(10), 3665–3699.

Omiccioli, M., Carmignani, A., 2007. Costs and benefits of creditor concentration: An empirical approach. Working Paper No, 645, Bank of Italy Temi di Discussione.

Petersen, M. A., & Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *The Journal of Finance*, 49(1), 3-37.

Puri, M., Rocholl, J., Steffen, S., 2016. What do a million observations have to say about loan defaults? Opening the black box of relationships. Available at SSRN: https://ssrn.com/abstract=1572673 or http://dx.doi.org/10.2139/ssrn.1572673. Accessed on 10th October 2016.

Raimo, N., Caragnano, A., Zito, M., Vitolla, F., & Mariani, M. (2021). Extending the benefits of ESG disclosure: The effect on the cost of debt financing. *Corporate Social Responsibility and Environmental Management*, 28(4), 1412-1421.

Ricart, J., & Casadesus-Masanell, R. (2011). How to design a winning business model. *Harvard Business Review*, 89(1-2), 100-107.

Rikkers, F., & Thibeault, A. E. (2011). Default prediction of small and medium-sized enterprises with industry effects. International Journal of Banking, Accounting and Finance, 3(2–3), 207–231.

Roy, P. K. & Shaw, K. (2022). Developing a multi-criteria sustainable credit score system using fuzzy BWM and fuzzy TOPSIS. *Environment, Development and Sustainability*, 24, 5368–5399.

Schenkel, A. (2017). Proportionality of Banking Regulation - Evidence from Germany. *European Association of Cooperative Banks*.

Shin, K.S., Lee, T.S., Kim, H.J., 2005. An application of support vector machines in bankruptcy prediction model. *Expert Systems with Applications* 28(1), 127–135.

Shin, K.S., Lee, Y.J., 2002. A genetic algorithm application in bankruptcy prediction modeling. *Expert Systems with Applications* 23(3), 321–328.

Smart, N., Briggeman, B. C., Tack, J., & Perry, E. (2019). Sustainable growth rates of farmer cooperatives. *Agribusiness: An International Journal*, 35(4), 1-14.

Strahan, P. E. (1999). Borrower risk and the price and nonprice terms of bank loans. FRB of New York staff report, (90).

Tinoco, M.H., Wilson, N., 2013. Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. *International Review of Financial Analysis* 30, 394–419.

Usai, S., & Vannini, M. (2005). Banking structure and regional economic growth: lessons from Italy. The *Annals of Regional Science*, 39(4), 691-714.

Wang, D., Chen, Z., Florescu, I. & Wen, B. (2023). A sparsity algorithm for finding optimal counterfactual explanations: Application to corporate credit rating. *Research in International Business and Finance*, 64, 101869.

Welch, B.L., 1947. The generalization of 'student's' problem when several different population variances are involved. *Biometrika* 34, 28–35

Wheelock, D. C., & Wilson, P. W. (2011). Are credit unions too small?. *Review of Economics and Statistics*, 93(4), 1343-1359.

Williams, R. C. (2007). *The cooperative movement: Globalization from below*. Ashgate Publishing.

Yip, A. W., & Bocken, N. M. (2018). Sustainable business model archetypes for the banking industry. *Journal of Cleaner Production*, 174, 150-169.

Yuan, K., Chi, G. Zhou, Y. & Yin, H. (2022). A novel two-stage hybrid default prediction model with k-means clustering and support vector domain description. *Research in International Business and Finance*, 59, 101536.

Appendix 1: logistic regressions by single variables, used as inputs for dendograms

Table 11: Results of single variable logistic regressions for sector 01 "Farming of agricultural crops"

	Non-coop			Coop		
	Coef.	Sign.	Pseudo R^2	Coef.	Sign.	Pseudo R^2
Immediate liquidity on total assets	-0.12851		0.0243	-0.24793	**	0.0534
Added value on production value	-0.00596		0.0019	-0.01018		0.0041
Depreciation and devaluation on costs	0.01624		0.0082	-0.00600		0.0003
Financial autonomy	-0.01146		0.0083	-0.02913	*	0.0204
Net assets coverage	-0.01195		0.0089	-0.02683		0.0178
Debts on short-term debts	-0.00010		0.0011	-0.00025		0.0049
Debts on Net worth	-0.00003		0.0010	0.00001		0.0001
Payables to suppliers on Total debt	-0.01755	*	0.0173	0.00406		0.0014
Degree of indebtedness	0.01384	*	0.0137	0.02897	*	0.0247
Short-term debt	0.00276		0.0007	-0.00766		0.0049
Medium and long-term debt	0.00651		0.0041	0.01569	*	0.0195
Financial dependence index	0.00104		0.0002	0.00295		0.0015
Quick ratio	-0.00930	**	0.0420	-0.00158		0.0148
Index of assets' rigidity	0.00426		0.0018	0.00808		0.0044
Shareholders' equity on equity and long-term debt	-0.01209	**	0.0185	-0.02847	***	0.0618
Shareholders' equity on equity and inventories	-0.01324	**	0.0202	-0.01096		0.0120
Leverage	-0.00003		0.0009	0.00000		0.0000
ROA	-0.09412	**	0.0293	-0.14925	***	0.0475
ROE	-0.00534	**	0.0138	-0.00607	*	0.0160
Invested Capital turnover	-0.01017	**	0.0296	-0.00325		0.0069
Working capital turnover	-0.00477	**	0.0410	-0.00211		0.0221
Sales on Total Assets	-0.01374	**	0.0456	-0.00262		0.0049
Added value on sales	-0.00054		0.0001	-0.00541		0.0030

The results reported in Table 11 show that for agriculture firms, the roles of shareholders equity, return and turnover are the most significant ones. But even more evidently, it shows that cooperatives and non-cooperative firms report significantly different results. Already the first variable shows this difference, reporting different coefficients (-0.248 for cooperatives vs. -0.128 for non-cooperatives), different significance of the coefficient (95% vs. less than 90%) and different determination coefficient (5.34% vs. 2.43). Looking at the big picture, the results are of different significance of variables, and, even when the variable is significant for both groups, coefficients are different, e.g. ROA reports a -0.14925 coefficient for cooperatives and -0.09412 for non-cooperatives.

Table 12: Results of single variables logistic regressions for sector 41 "Construction of buildings"

	Non-coop			Coop		
	Coef.	Sign.	Pseudo R^2	Coef.	Sign.	Pseudo R^2
Immediate liquidity on total assets	-0.08868	***	0.0206	-0.22100	**	0.0926
Added value on production value	0.00048		0.0000	-0.00650		0.0048
Depreciation and devaluation on costs	-0.02200	***	0.0034	-0.06215		0.0023
Financial autonomy	-0.04427	***	0.0457	-0.02546	*	0.0265
Net assets coverage	-0.04424	***	0.0456	-0.02546	*	0.0265
Debts on short-term debts	0.00000		0.0000	-0.00103		0.0249
Debts on Net worth	0.00004	***	0.0125	0.00000		0.0002
Payables to suppliers on Total debt	-0.00437	**	0.0015	-0.01967	*	0.0339
Degree of indebtedness	0.04421	***	0.0572	0.02324	*	0.0285
Short-term debt	0.00772	***	0.0069	0.00282		0.0010
Medium and long-term debt	0.00331	**	0.0014	0.00746		0.0072
Financial dependence index	0.00582	***	0.0096	0.00646		0.0049
Quick ratio	-0.00018	**	0.0035	-0.00749	*	0.0509
Index of assets' rigidity	-0.00945	***	0.0056	-0.00361		0.0008
Shareholders' equity on equity and long-term debt	-0.00897	***	0.0134	-0.02636	***	0.0931
Shareholders' equity on equity and inventories	-0.01143	***	0.0164	-0.01897	**	0.0486

Leverage	0.00004	***	0.0123	0.00000		0.0002
ROA	-0.06418	***	0.0166	-0.07610		0.0148
ROE	-0.00214	***	0.0084	-0.00360	*	0.0206
Invested Capital turnover	-0.00400	***	0.0086	-0.00707	*	0.0272
Working capital turnover	-0.00044	***	0.0030	-0.00284		0.0202
Sales on Total Assets	-0.00480	***	0.0119	-0.00742	*	0.0280
Added value on sales	0.00004		0.0000	-0.00690		0.0116

The results reported in Table 12 show that for construction firms, almost all variables report a statistical significance for non-cooperatives, while just around half of the variables report some significance for cooperatives. Here also, the coefficients are clearly different, e.g. the first variable, immediate liquidity on total assets, report a coefficient of -0.221 for cooperatives, and less than half of it, -0.08868 for non-cooperatives. Passing to the determination coefficients, the highest results are for “Immediate liquidity on total assets”, “Shareholders' equity on equity and long-term payables”.

Table 13: Results of single variable logistic regressions for sector 43 “Specialized construction works”

	Non-coop			Coop		
	Coef.	Sign.	Pseudo R^2	Coef.	Sign.	Pseudo R^2
Immediate liquidity on total assets	-0.06862	***	0.0224	-0.14805		0.0601
Added value on production value	0.00241		0.0003	-0.00238		0.0003
Depreciation and devaluation on costs	-0.02957		0.0013	-0.12595		0.0146
Financial autonomy	-0.07808	***	0.0842	-0.01556		0.0058
Net assets coverage	-0.07829	***	0.0798	-0.01519		0.0056
Debts on short-term debts	0.00000		0.0000	-0.00213		0.0121
Debts on Net worth	0.00023	***	0.0491	-0.00008		0.0028
Payables to suppliers on Total debt	-0.01250	***	0.0088	-0.03008		0.0395
Degree of indebtedness	0.06289	***	0.0996	0.02205		0.0166
Short-term debt	0.00549	**	0.0024	0.00382		0.0012
Medium and long-term debt	0.01409	***	0.0169	-0.00034		0.0000
Financial dependence index	0.00262	***	0.0085	-0.00278		0.0033
Quick ratio	-0.00077	**	0.0072	-0.00553		0.0246
Index of assets’ rigidity	-0.00629	*	0.0019	0.00576		0.0015
Shareholders' equity on equity and long-term debt	-0.01860	***	0.0431	-0.01227		0.0211
Shareholders' equity on equity and inventories	-0.01804	***	0.0382	-0.01147		0.0189
Leverage	0.00019	***	0.0435	-0.00009		0.0040
ROA	-0.07008	***	0.0264	-0.12647	***	0.1519
ROE	-0.00471	***	0.0161	-0.00335		0.0093
Invested Capital turnover	-0.00484	***	0.0093	-0.00787		0.0284
Working capital turnover	-0.00005		0.0003	-0.00472		0.0389
Sales on Total Assets	-0.00443	***	0.0077	-0.01114		0.0490
Added value on sales	0.00363		0.0009	-0.01286		0.0113

The results for Specialized construction works, reported in Table 13, show that for this sector many variables of all categories play a significant role in predicting defaults for non-cooperatives, while just the return on assets reports a significant result for cooperatives. This result is not easily understandable, as typically cooperatives don’t have a profit target, and as the return on equity is instead non-significant. From the determination coefficient point of view, instead, apart from the ROA which report a 15,19% determination coefficient, all turnover and liquidity indexes report determination coefficients higher than 2%, while non-cooperatives mainly report the highest determination coefficients for indebtedness related indexes.

Table 14: Results of single variable logistic regressions for sector 47 "Retail"

	Non-coop			Coop		
	Coef.	Sign.	Pseudo R^2	Coef.	Sign.	Pseudo R^2
Immediate liquidity on total assets	-0.06622	***	0.0243	-0.02783		0.0065
Added value on production value	0.00478		0.0006	0.01719		0.0063
Depreciation and devaluation on costs	0.04279	**	0.0030	0.10929	*	0.0360
Financial autonomy	-0.04058	***	0.0319	-0.08940	**	0.1183
Net assets coverage	-0.04258	***	0.0314	-0.08762	**	0.1105
Debts on short-term debts	0.00014		0.0008	-0.00005		0.0003
Debts on Net worth	0.00014	***	0.0178	0.00020	*	0.0343
Payables to suppliers on Total debt	-0.00873	***	0.0052	-0.03087		0.0340
Degree of indebtedness	0.03804	***	0.0552	0.08646	***	0.2638
Short-term debt	0.00824	***	0.0053	0.00952		0.0073
Medium and long-term debt	0.00763	***	0.0053	0.02142		0.0380
Financial dependence index	0.01289	***	0.0225	0.02088	***	0.1107
Quick ratio	-0.00022		0.0030	-0.00391		0.0401
Index of assets' rigidity	-0.00267		0.0005	0.00942		0.0054
Shareholders' equity on equity and long-term debt	-0.01165	***	0.0174	-0.02053		0.0343
Shareholders' equity on equity and inventories	-0.01750	***	0.0197	-0.00933		0.0079
Leverage	0.00013	***	0.0167	0.00012		0.0172
ROA	-0.04732	***	0.0228	-0.08296	**	0.0610
ROE	-0.00299	***	0.0165	-0.00499	**	0.0701
Invested Capital turnover	-0.00513	***	0.0265	-0.00047		0.0001
Working capital turnover	-0.00151	***	0.0148	-0.00199		0.0235
Sales on Total Assets	-0.00487	***	0.0255	-0.00590		0.0142
Added value on sales	0.00593	*	0.0014	-0.03519		0.0146

The retail firms, whose results are reported in Table 14, show very low significance for the added value related variables, while indebtedness show higher role in default prediction. Here also, quite often the cooperatives report higher coefficients, around double the value reported for non-cooperatives, e.g. the ROE estimated coefficient is of -0.0022 for non-cooperatives and of -0.00499 for cooperatives, net assets coverage coefficient is of -0-04058 for non-coop and of -0.08762 for coops. With reference to the determination coefficient, the degree of indebtedness reports a huge 26,38%, but also the financial dependence index, financial autonomy and net assets coverage report values higher than 10% for cooperatives, while for non-cooperatives the highest value is the 3.19% of financial autonomy.

Table 15: Results of single variable logistic regressions for sector 52 "Storage and custody"

	Non-coop			Coop		
	Coef.	Sign.	Pseudo R^2	Coef.	Sign.	Pseudo R^2
Immediate liquidity on total assets	-0.10724	*	0.0371	-0.06251		0.0283
Added value on production value	-0.00769		0.0055	0.00383		0.0012
Depreciation and devaluation on costs	-0.02523		0.0049	0.03388		0.0138
Financial autonomy	-0.01280		0.0067	0.00440		0.0005
Net assets coverage	-0.01196		0.0058	-0.00316		0.0002
Debts on short-term debts	-0.00079		0.0052	0.00009		0.0005
Debts on Net worth	-0.00004		0.0006	-0.00018		0.0175
Payables to suppliers on Total debt	-0.00728		0.0042	-0.01150		0.0108
Degree of indebtedness	0.03003	***	0.0433	0.01463		0.0168
Short-term debt	0.01049		0.0103	-0.00127		0.0002
Medium and long-term debt	0.00370		0.0010	0.01395		0.0188

Financial dependence index	-0.00036		0.0003	0.00552	*	0.0639
Quick ratio	-0.00402		0.0216	-0.00026		0.0024
Index of assets' rigidity	-0.00360		0.0013	-0.00394		0.0009
Shareholders' equity on equity and long-term debt	-0.01375	**	0.0237	-0.00869		0.0114
Shareholders' equity on equity and inventories	-0.00235		0.0002	0.03592		0.0109
Leverage	-0.00004		0.0008	-0.00017		0.0183
ROA	-0.04266		0.0102	-0.01102		0.0015
ROE	0.00031		0.0000	0.00633		0.0118
Invested Capital turnover	-0.00148		0.0028	-0.00916	**	0.0828
Working capital turnover	0.00000		0.0000	0.00020	*	0.0287
Sales on Total Assets	-0.00150		0.0031	-0.00891	**	0.0806
Added value on sales	-0.00731		0.0060	0.00653		0.0034

The Storage and custody sector results, reported in Table 15, show that for this sector the variables reporting some significance are a limited number for both groups, and different for cooperatives and non-cooperatives, namely turnover related and financial dependence for cooperatives, and liquidity, indebtedness and shareholders' equity on equity and long-term debt for non-cooperatives.

About the determination coefficient, invested capital turnover, sales on total assets and financial dependence index report a value higher than 6% for cooperatives, while just the degree of indebtedness report a value higher than 4% for non-cooperatives.

Table 16: Results of single variable logistic regressions for sector 81 "Cleaning and disinfestation"

	Non-coop			Coop		
	Coef.	Sign.	Pseudo R^2	Coef.	Sign.	Pseudo R^2
Immediate liquidity on total assets	-0.03004		0.0067	-0.08593		0.0275
Added value on production value	-0.01858	*	0.0240	-0.01626		0.0103
Depreciation and devaluation on costs	-0.10373		0.0151	0.00262		0.0000
Financial autonomy	-0.04962	**	0.0408	-0.05000	**	0.0506
Net assets coverage	-0.04749	*	0.0362	-0.04672	**	0.0422
Debts on short-term debts	-0.00017		0.0030	-0.00076		0.0062
Debts on Net worth	0.00019	***	0.0473	0.00010		0.0120
Payables to suppliers on Total debt	-0.01330		0.0076	0.00190		0.0002
Degree of indebtedness	0.03754	***	0.0533	0.04676	***	0.1033
Short-term debt	0.00741		0.0043	0.01504		0.0154
Medium and long-term debt	0.02108	**	0.0305	0.01953	*	0.0193
Financial dependence index	0.00240		0.0048	0.00514	***	0.0546
Quick ratio	-0.00198		0.0102	-0.00614	*	0.0447
Index of assets' rigidity	-0.00297		0.0005	-0.02038		0.0175
Shareholders' equity on equity and long-term debt	-0.01583	**	0.0324	-0.02504	***	0.0657
Shareholders' equity on equity and inventories	-0.02332	***	0.0689	-0.01664	*	0.0197
Leverage	0.00018	***	0.0444	0.00008		0.0081
ROA	-0.02451		0.0079	-0.02938		0.0053
ROE	-0.00326	*	0.0189	-0.00102		0.0012
Invested Capital turnover	-0.00837	*	0.0246	-0.00072		0.0003
Working capital turnover	-0.00001		0.0000	0.00016	**	0.0303
Sales on Total Assets	-0.00863	*	0.0261	-0.00027		0.0001
Added value on sales	-0.01839	*	0.0244	-0.01382		0.0074

The results reported in Table 16 show that the cleaning and disinfestation firms report the highest significance of coefficients for Shareholders' equity on equity and inventories, leverage, degree of indebtedness and debts on net worth for non-cooperatives, while cooperatives highest significance variables are “Shareholders' equity on equity and long-term debt”, “Financial dependence” and “Degree of indebtedness”. Differently from some previous sector, some variable report very similar coefficients for both groups (e.g. “Financial autonomy” and “Net assets coverage”). Within this sector, the determination coefficient reports its higher values for the “Degree of indebtedness”, reaching 10% for cooperatives and 5.33% for non-cooperatives.

Appendix 2: Analysis of the comparative results of logistic regressions by single variables, for cooperatives and non-cooperatives

The results reported above evidenced that all the considered sectors report significant differences among cooperatives and non-cooperatives. It raises a question: is there any common effect of cooperatives on all sectors? As to say, is the cooperative activity changing in a typical way the balance sheets equilibriums?

For trying to answer this question, we compared the estimation results of cooperative and non-cooperative firms by broad financial ratios categories, grouping them into five groups, for evidencing the main effects of returns, margins, assets’ structure, debt structure and capitalization. For these categories we considered three values, namely coefficients, z-value, and determination coefficient (pseudo R^2). Tables 9 to 14 report these results.

Table 17: Average value of coefficients for each index category, for cooperatives and non-cooperatives

Index	Non-cooperatives	Cooperatives
Liquidity	-0.042	-0.068
Profitability	-0.017	-0.021
Capital structure	-0.021	-0.019
Debt management	0.007	0.006
Assets management	-0.004	-0.003

The estimates in Table 17 report that liquidity measures have a higher impact in determining the expectation of a default or no default in cooperatives, while for the other index categories the effects are similar for cooperatives and non-cooperatives. This high effect of liquidity can be considered jointly with the lower significance of variables for cooperatives, in so signaling that, in the lack of economic or financial structure determinants, the liquidity buffer provides a significant cushion against the credit default.

Table 18: Average value of coefficients for each index category, by sector and coop/no coop

Index	01N	01C	41N	41C	43N	43C	47N	47C	52N	52C	81N	81C
Liquidity	-0.069	-0.125	-0.044	-0.114	-0.035	-0.077	-0.033	-0.016	-0.056	-0.031	-0.016	-0.046
Profitability	-0.018	-0.035	-0.018	-0.031	-0.020	-0.054	0.001	0.001	-0.017	0.008	-0.034	-0.012
Capital structure	-0.010	-0.019	-0.022	-0.019	-0.039	-0.011	-0.022	-0.041	-0.008	0.006	-0.027	-0.028
Debt management	0.001	0.006	0.008	0.003	0.010	-0.001	0.008	0.015	0.005	0.003	0.008	0.013
Assets management	-0.006	0.000	-0.005	-0.005	-0.004	-0.004	-0.004	0.000	-0.002	-0.005	-0.005	-0.005

When considering the same indices categories by activity sector, the higher impact on cooperatives of liquidity is confirmed for sectors 01, 41, 43 and 81, while sectors 47 and 52 report a lower value for the same index. The other categories lower difference on average reported in table 17 is explained in table 18 by highly different effects on different sectors, as in the case of capital structure, higher for non-cooperatives in sector 43, higher for cooperatives in sector 47 and 01, and similar in the other sectors.

Table 19: Average z-value for each index category, for cooperatives and non-cooperatives

Index	Non-cooperatives	Cooperatives
Liquidity	-2.73	-1.28
Profitability	-1.79	-0.73
Capital structure	-3.10	-1.15
Debt management	2.41	0.60
Assets management	-2.43	-0.62

Table 19 reports the average z-value for each index category, showing that cooperatives always score a lower significance (on average) of the correspondent variables. This is particularly evident for debt management and for assets management, on both categories the z-value for non-cooperatives is around four times the correspondent value for cooperatives.

Table 20: Average z-value for each index category, by sector and coop/no coop

Index	01N	01C	41N	41C	43N	43C	47N	47C	52N	52C	81N	81C
Liquidity	-2.0	-1.4	-4.5	-2.0	-3.9	-1.1	-3.5	-0.7	-1.6	-0.8	-0.8	-1.6
Profitability	-0.8	-1.3	-3.2	-1.1	-2.6	-1.1	-1.7	-0.6	-0.9	0.5	-1.6	-0.7
Capital structure	-1.5	-1.5	-5.6	-1.8	-5.5	-0.8	-3.8	-1.0	-1.0	-0.2	-1.3	-1.6
Debt management	0.1	0.5	4.3	0.1	4.6	-0.2	4.0	1.3	0.3	0.4	1.1	1.6
Assets management	-1.6	-0.6	-4.5	-1.3	-2.7	-0.9	-4.4	-0.4	-0.5	-0.8	-0.9	0.2

When considering the z-value by activity sectors (see Table 20), we can see that no cooperative report any value higher than 2 (in absolute value), while non-cooperatives reach a 5.6. More, in some sector

(41, 43, and 47) almost all categories report, for the non-cooperatives, a z-value higher than 2.5 (in absolute value). The lower z-values for cooperatives, coupled with the above mentioned higher values of coefficients for the same kind of firms, signals a higher variability of the correspondent financial indexes.

Table 21: Average value of the pseudo R2 for each index category, for cooperatives and non-cooperatives

Index	Non-cooperatives	Cooperatives
Liquidity	0.019	0.037
Profitability	0.010	0.019
Capital structure	0.029	0.029
Debt management	0.015	0.025
Assets management	0.012	0.020

Table 21 reports the average pseudo R-squared for each index category, evidencing general higher values for cooperatives, in particular for liquidity, and debt management, but also for profitability and assets management. Capital structure, instead, reports high values for both firm kinds.

Table 22: Average value of the pseudo R^2 for each index category, by sector and coop/no coop

Index	01N	01C	41N	41C	43N	43C	47N	47C	52N	52C	81N	81C
Liquidity	0.033	0.034	0.012	0.072	0.015	0.042	0.014	0.023	0.029	0.015	0.008	0.036
Profitability	0.011	0.014	0.006	0.011	0.009	0.037	0.009	0.038	0.005	0.006	0.018	0.005
Capital structure	0.011	0.022	0.027	0.039	0.058	0.011	0.023	0.058	0.007	0.008	0.045	0.037
Debt management	0.005	0.008	0.013	0.014	0.026	0.011	0.016	0.070	0.009	0.018	0.022	0.030
Assets management	0.030	0.010	0.007	0.019	0.005	0.029	0.017	0.011	0.002	0.048	0.013	0.012

The analysis of pseudo R-squared by activity sector (Table 22) confirms that in the largest part of cases cooperatives report higher values for the determination coefficient.