Utility of fuzzy set Qualitative Comparative Analysis (fsQCA) methodology to identify causal relations conducting to cooperative failure

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ABSTRACT: This study focuses on the search for the causes, or combination of circumstances, that lead to business failure processes. There is renewed interest in this subject due to the adverse consequences that the recent economic crisis has caused in the business world. A fuzzy set Qualitative Comparative Analysis (fsQCA) is thus carried out to identify the combination of financial ratios that points to situations of financial difficulty. The study centres on the cooperative sector, represented by a sample of 56 companies holding this legal status, belonging to various different productive sectors. The results obtained, and confirmed through a number of different robustness tests, reveal the presence of sufficient conditions comprising combinations of variables reflecting high indebtedness, low liquidity, low solvency and small firm size, representing a scenario that would be sufficient for an entity to face business continuity problems. Thanks to its ability to identify combinations of variables that warn of business failure, as well as its ease of interpretability, the fsQCA technique can be extremely useful for business management and the identification of business failure situations.

KEYWORDS: Business failure, cooperatives, prediction models, fuzzy sets, fsQCA.

ECONLIT DESCRIPTORS: C100, M200, M400.

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RESUMEN: Este estudio se centra en la búsqueda de las causas, o combinaciones de circunstancias, que generan procesos de fracaso empresarial, un interés que se ha visto reactivado por las consecuencias negativas que la reciente crisis económica ha causado en el tejido empresarial. Para ello se ha procedido a realizar un análisis comparativo cualitativo basado en conjuntos difusos o fsQCA *(fuzzy set Qualitative Comparative Analysis)* que ha permitido identificar la combinación de ratios financieras que informan de situaciones de dificultad financiera. El estudio se ha aplicado a entidades del sector cooperativo, representado en una muestra de 56 empresas de esta naturaleza jurídica pertenecientes a varios sectores productivos. Los resultados que se han obtenido, ratificados con diferentes pruebas de robustez, muestran la presencia de las condiciones suficientes en forma de combinaciones de diversas variables indicativas alto endeudamiento, baja liquidez, baja solvencia y de un tamaño empresarial reducido como representativas de un escenario suficiente para que una entidad pudiera tener problemas de continuidad. La identificación de las combinaciones de variables que pueden informar del fracaso de la entidad y, además, su sencilla interpretabilidad confiere a la técnica fsQCA una gran utilidad para la gestión de la empresa y la identificación de situaciones que pueden abocarla a su fracaso.

PALABRAS CLAVE: Fracaso empresarial, cooperativas, modelos de predicción, conjuntos difusos.

Resumen extendido

Utilidad de la metodología del análisis comparativo cualitativo de conjuntos fuzzy (fsQCA) para identificar los factores determinantes del fracaso en las sociedades cooperativas

El estudio de las causas que favorecen el desarrollo de los procesos de insolvencia y su concreción en modelos eficaces, precisos, estables y capaces de anticipar situaciones de insolvencias es una cuestión de enorme interés para numerosos los agentes económicos, especialmente para los gestores empresariales.

A pesar de que cada sector económico presenta unas características especiales se ha advertido que una vez sobreviene la crisis, originada por diversas causas, sus consecuencias y resultados en la generalidad de las empresas suelen ser comunes. Por ello, este estudio buscará los factores que pueden conducir a situaciones de dificultad financiera de una manera generalizada desvinculándolos, en la medida de lo posible, de las singularidades de una determinada coyuntura o sector económico concreto.

Tradicionalmente el interés de los investigadores se ha centrado en desarrollo de nuevos modelos buscando mejoras en eficacia, precisión y estabilidad respecto a los ya existentes identificando en la mayoría de los casos los factores más relevantes para predecir las situaciones de inestabilidad financiera. En un breve recorrido doctrinal se puede apreciar como la reciente aplicación de técnicas que incluyen clasificadores no lineales, como redes neuronales y las técnicas de aprendizaje estadístico como *AdaBoost* y bosques aleatorios han superado en eficacia predictiva a las técnicas consideradas tradicionales como el análisis discriminante, *logit* o *probit*.

El estudio realizado comienza con una revisión de la literatura destacando las aportaciones más relevantes relacionadas con el objeto específico del trabajo. Posteriormente, se describe la muestra de estudio y los ratios y variables utilizados. A continuación, se detalla el método estadístico empleado y, por último, se presentan los resultados de la investigación junto a las principales conclusiones y líneas futuras de trabajo.

Las cooperativas, con una relevante tradición e implantación en diversos sectores económicos de nuestro país, son sociedades de carácter social que pretenden facilitar a sus socios bienes o servicios a menor precio o retribuirles mejor sus prestaciones. Para ello cuentan con una regulación peculiar diferente de otros tipos de sociedades. Este hecho nos ha obligado a matizar algunos ratios utilizados habitualmente en el análisis financiero y estadístico, principalmente en los de endeudamiento y rentabilidad.

Este trabajo sigue la teoría de conjuntos denominada análisis comparativo cualitativo basado en conjuntos difusos o *fsQCA* (*fuzzy set qualitative comparative analysis,* en inglés). Esta metodología establece relaciones causales a partir de la identificación de las condiciones o combinación de condiciones (variables independientes) que son suficientes para que se presente un determinado resultado (variable dependiente). Este método intenta descubrir las combinaciones más simples de condiciones que producen un determinado resultado. De este modo, *fsQCA* permite la exploración de recorridos complejos que configuran la presencia de un cierto resultado.

El enfoque basado en la teoría de conjuntos es diferente de los métodos convencionales, con una orientación hacia las variables, en el sentido de que no desagrega de un modo independiente las características de las observaciones y, en su lugar, agrupa las observaciones o los casos como combinaciones causales o configuraciones. Esta metodología es más apropiada cuando el resultado proviene de iteraciones complejas, porque *fsQCA* ayuda al investigador a encontrar patrones o configuraciones en las condiciones de los casos estudiados y a que las variables cobren un mayor sentido.

En este trabajo se pretende encontrar la combinación de factores que identifican y pueden conducir a una empresa a una situación de dificultad financiera. Para ello se realiza un análisis comparativo cualitativo basado en conjuntos difusos o *fsQCA* (fuzzy set qualitative compartive analysis) sobre una muestra de datos financieros de empresas cooperativas españolas fracasadas en el año 2015.

Tras una revisión de los contenidos de los estudios orientados a la elaboración de modelos que tratan de anticipar escenarios de fracaso empresarial se puede constatar que son muy escasos los que se sirven de *fsQCA* e inexistentes los que aplican la técnica al sector cooperativo. Con ello contribuimos a superar esta ausencia en la literatura empresarial.

El objetivo de este trabajo ha sido pues encontrar la combinación de variables financieras capaz de predecir la situación de fracaso empresarial de una empresa cooperativa. Para ello, y como se ha señalado, se ha recurrido al algoritmo *fsQCA*, una metodología basada en la teoría de conjuntos que ha permitido identificar las combinaciones de variables que mejor identifican un escenario de dificultad financiera de una entidad. Asimismo, se ha añadido información complementaria indicando también el escenario de ausencia de dicha dificultad o éxito de la sociedad cooperativa.

La muestra seleccionada para este trabajo se ha configurado con empresas cooperativas españolas de diversos sectores, excepto del financiero y seguros. La revisión de la literatura nos ha permitido verificar el carácter pionero de este estudio en cuanto a la aplicación de esta técnica al campo del fracaso empresarial en el sector cooperativo.

Como hemos indicado las cooperativas son sociedades en nuestro tejido empresarial que presentan unas características singulares de marcado carácter social, tanto desde una perspectiva normativa como de funcionamiento, que las hace diferentes del resto de sociedades. Las relaciones de estas sociedades con los trabajadores, la remuneración del capital aportado y la manera de repartir los resultados las configuran como entidades con un profundo carácter, sin olvidar también su vertiente mercantil.

Los resultados derivados del estudio haciendo uso de la metodología *fsQCA* indican la relevancia conjunta de las combinaciones de variables indicativas de alto endeudamiento (*END.2*), baja liquidez (*LIQ.2*), baja solvencia (*SOLVLP.1*) y un tamaño empresarial reducido (*LOGTA*), como representativas de un escenario suficiente para que una entidad pudiera tener problemas de continuidad.

Por otro lado, se ha obtenido que una combinación de variables de una alta rentabilidad (*REN.1*), un bajo endeudamiento (*END.2, END.3, END.4,* Y *END.5*) y una alta solvencia (*SOLVLP.1*), representaría una configuración causal suficiente para no entrar en una situación de fracaso.

Finalmente se ha evidenciado, tras un análisis de robustez, que la combinación causal identificada que conduce al fracaso resulta coherente y no contradictoria. De ese modo se ha comprobado la ausencia de relaciones causales paradójicas o contradictorias.

Los resultados obtenidos son afines con la evidencia empírica, por lo que entendemos que la metodología aplicada es plenamente válida para alcanzar los objetivos perseguidos, que no son otros que la detección de relaciones causales que expliquen el fracaso empresarial en empresas en el ámbito del sector de las sociedades cooperativas.

Finalmente, dada la novedad y bondad de la metodología se considera interesante seguir aplicándola en estudios de fracaso empresarial en pymes, en general y por sectores de actividad, tanto a nivel nacional como europeo. Por otro lado, dado que sobre las cooperativas no se han hecho demasiados estudios de fracaso, parece interesante seguir profundizando en el mismo por diferentes sectores de actividad.

1. Introduction

The study of the causes that that can lead to insolvency processes and the subsequent specification of effective, accurate, stable models capable of predicting such situations is a matter of great interest to all economic agents, especially business managers.

Despite the specific characteristics of each economic sector, it has been observed that the outbreak of a crisis, stemming from various causes, tends to have similar consequences and outcomes for most companies. Therefore, this study seeks to identify the factors that can lead to situations of financial difficulty. It takes a generalized approach, to the extent possible disconnecting said factors from the characteristic features of a particular economic situation or sector.

Researchers have traditionally tended to focus their attention on developing new models, in an attempt achieve improvements in efficiency, accuracy and stability compared to existing ones, with most identifying the key factors for predicting situations of financial instability. Briefly surveying the field, it can be seen how the recent application of techniques that include nonlinear classifiers such as neural networks, and statistical learning techniques such as AdaBoost and random forests, have surpassed traditional techniques such as discriminant analysis and logit or probit models in terms of predictive power.

This study seeks to determine the combination of factors that can lead a company to financial difficulty, and that can be used to detect such a situation. To that end, a fuzzy set qualitative comparative analysis (fsQCA) is performed on a sample of financial data from Spanish cooperative companies that failed in 2015.

A review of the studies aimed at developing models to predict business failure scenarios reveals that very few of them use fsQCA, and there are none that apply the technique to the cooperative sector. Hence, this study contributes to addressing this gap in the business literature.

Cooperatives have a strong tradition in Spain, where they are involved in various different economic sectors. They are socially-oriented companies aimed at providing their members with goods or services at a lower price, or paying them better for their services. As such, they are governed by specific regulation that differs from that applicable to other types of companies (Carreras, 2011). There is thus a need for some minor clarifications regarding the ratios commonly used in financial and statistical analyses, mainly those of indebtedness and profitability (Pozuelo et al., 2012). We dedicate a few lines to these clarifications when we present the explanatory variables of the possible models.

The paper begins with a review of the literature, highlighting the most relevant contributions related to the specific subject of this study. The study sample, the ratios and the variables used are then described. Next, the statistical method used is detailed and, lastly, the results of the research are presented together with the main conclusions and future lines of research.

2. Background

Since the very first studies on business failure in the early twentieth century, researchers have focused their efforts on identifying models that include the indicators with the greatest power to predict situations of financial difficulty, or simply to distinguish healthy companies from failed ones. Moving on from the traditional models based on information from certain ratios (Fitzpatrick, 1932), this line of research turned towards econometric models grounded on univariate and multivariate discriminant analyses (Beaver, 1966; Altman, 1968) and probability analyses that incorporate conditional logit and probit models (Ohlson, 1980; Zmijewski, 1984; Keasey and Watson, 1987).

In recent years, this line of research has been enriched by the incorporation of techniques based on artificial intelligence, particularly machine learning. These include techniques that rely on neural networks, which are based on a system of neurons aggregated in different layers that perform certain calculations or tasks depending on the architecture of the connections used. Various studies have used this methodology (Bell et al., 1990; Tam, 1991; Tam and Kiang, 1992; Odomwilson and Sharda 1992; Fletcher and Gross, 1993; Wilson and Sharda, 1994; Boritz and Kennedy, 1995; Zhang et al., 1999; Ravi, P. and Ravi, V., 2007; López and Pastor, 2015; Popescu et al. 2017; and Jayanthi et al*.* 2017, among others), demonstrating its advantages over other, more traditional statistical techniques for predicting failure.

The adoption of deep learning, part of the family of machine learning methods, represented a clear step forward from neural network models. By adding more layers through which the sample data is processed, it became possible to perform more complex operations and obtain much more reliable results when dealing with a large amount of data. A notable study in this regard is that by Chaudhuri and Ghosh (2017), who achieve models with a high predictive power, outperforming previous models developed using other methods.

A recent addition is the boosting method, characterized by the use of combinations of individual decision trees into classifiers, yielding models with a high predictive power. This algorithm helps to identify the most relevant variables, and also makes it possible to more reliably detect companies in financial difficulties. This method has been used in various studies on business failure, both internationally (Kim and Kang, 2010; Kim and Upneja, 2014); Wang *et al.* (2014); Kim et al*.,* 2015; Zieba et al.. (2016) and nationally (Díaz et al., 2004; Alfaro et al*.,* 2008; Momparler et al., 2016; Pozuelo et al.., 2018; Climent et al., 2019; Carmona et al.*.,* 2019) demonstrating its utility and high predictive power.

The boosting method has evolved, and new algorithms have recently emerged which improve results, such as AdaBoost (Alfaro et al., 2008; Cortés et al., 2008), FS-Boosting (Wang et al., 2014), GBM (Kim et al., 2015; Zieba et al., 2016; Momparler et al., 2016, and Pozuelo et al., 2018) and XGBoost (Zieba et al., 2016; Climent et al., 2018 and Carmona et al., 2018, Romero et al., 2021).

Another novel technology that has been used in recent years is the fsQCA algorithm. In other areas of knowledge, fsQCA has proved capable of identifying the combination of variables that best explains a certain outcome. The study by Roig-Tierno et al. (2017) contains a review of the research using this method. Lassala et al. (2016a and 2016b) have applied this algorithm in economics research, specifically in the field of consultancy and financial advice, noting in both studies that fsQCA generates an improvement in explanatory power compared to other methodologies. The studies by Momparler *et al.* (2020) and Bustos et al. (2020) focus on predicting bank failure. Both studies reach similar conclusions, highlighting that the fsQCA method satisfactorily identifies the necessary and sufficient conditions that can lead to bank failure.

As pointed out above, our study addresses the failure of cooperatives, a field that has traditionally been understudied in the scientific literature, despite the relevant role played by these entities in our economic fabric. Only Vargas (2010), Iturrioz (2010) and Iturrioz and Martín (2013) analyse cooperatives' arrangements with creditors, but without providing a predictive model of their failure.

Pozuelo et al. (2012) carry out a study employing statistical techniques to estimate predictive models. Marí et al. (2014) qualitatively analyse the determinants of failure using the Delphi method, while Masa et al. (2016) measure the predictive power of a partial least squares structural equation model applied to business failure.

In any case, we have identified a lack of studies applying the fsQCA method to explore insolvency among cooperatives. This fact, together with the overall dearth of studies on the failure of cooperatives, constitutes a key justification for the use of fsQCA in the present study; we aim to confirm its usefulness in identifying the combinations of variables that have the highest predictive power of the failure of cooperatives.

3. The concept of business failure used in the empirical analysis

Failure is equated to the legal definition of insolvency according to Insolvency Law 22/2003, under which a cooperative company shall be considered failed if it has filed for insolvency and shall otherwise be considered healthy.

4. Sample selection and sources of data on companies

The financial database *SABI* (*Sistema de Análisis de Balances Ibéricos*) was used in the process of selecting the different samples of companies.

The selection of companies to form part of the study sample was limited to non-financial cooperatives that failed in 2015 according to the chosen definition of failure; 2015 is a year free of extraordinary circumstantial factors and not too far back in time. The application of this selection criterion yielded only 74 companies that had filed for insolvency in the year in question.

One filter was then applied to the 74 resulting companies to eliminated newly created companies (up to three years old) and those that did not provide complete accounting data for at least three years prior to the date of failure.

Following these selection and filtering processes, the number of firms remaining in the study sample was eventually reduced to a total of 56 failed cooperatives.

In order to complete the study sample and to be able to apply certain statistical classification tools, we used a pairing technique whereby each failed businesses was associated with a healthy firm that had the same characteristics. Said healthy firm was randomly selected from among those of a similar size measured in terms of volume of assets and operating in the same economic sector established by the NACE (National Classification of Economic Activities), at the four-digit level where possible and if not at the three-digit level. Through this process, another 56 companies were incorporated into the sample, such that it eventually comprised 112 cooperatives, half of which were healthy and the other half of which had failed.

The sectoral grouping has been carried out by categories according to the sections of the N.A.C.E. (National Classification of Economic Activities) of 2009 trying to homogenize the different activities, which has allowed us to distinguish 9 basic groups. The summary of the sectoral distribution resulting from the sample is shown in Table 1, where the specific weight of each sectoral category can be seen.

Table 1. Distribution of the sample by industries

CATEGORIES (Basic Groups)	SECTIONS NACE 2009	ACTIVITIES OF THE COMPANY GROUP	COMPANIES	%
0	A	Agriculture, livestock, forestry and fishing	12 + 12	21,42
1	B	Extractive industries	4 + 4	7,14
2	C	Manufacturing industry	13 + 13	23,21
4	G	Wholesale and Retail; repair of motor vehicles and motorcycles	9 + 9	16,07
5	H I J	Transport and storage Hostelry Information and communications	5 + 5	8,92
6	L M	Real estate activities Professional, scientific and technical activities	3 + 3	5,35
7	N O	Administrative activities and auxiliary services Public administration and defense; compulsory social security	2 + 2	3,57
8	P Q R	Education Health and social service activities Artistic, recreational and entertainment activities	6 + 6	10,71
9	S T U	Other services employers of domestic staff; producers of goods and services for own use Activities of extraterritorial organizations and bodies	2 + 2	3,57
TOTAL COMPANIES (failed and not-failed)			56 + 56	100,00

Source: Authors' own creation.

To complete the characteristics of the sample, we show in Table 2 the different groups of companies, classified according to size. In this case, to distinguish the different company sizes, we have based on the classification offered by the European Union in Annex I of Regulation (EU) No. 651/2014 of the Commission, taking as a reference the volume of assets.

Table 2. Size of the considered companies

	N.	%	Volume of Assets (Thousands of €) (*)
Microenterprises	24 + 24	42,85	Less than 2.000
Small	23 + 23	41,07	From 2.000 to 10.000
Medium	5 + 5	8,92	From 10.000 to 43.000
Large	0	0,00	More than 43.000
Total companies (Failed and not- failed)	56 + 56	100,00	

Source: Authors' own creation.
(*) Regulation (EU) No. 651/2014 of the Commission (Annex 1).

5. Selection and definition of explanatory variables

A key element in the development of business failure prediction models is deciding which independent variables to include; in our case, they are mostly economic and financial ratios. The first difficulty when embarking on this stage of the study is the lack of a general theory to guide the selection process. This represents a major limitation when modelling business failure[1]. This study attempts to tie in the experiences reported by other authors with the proposed objectives. Therefore, we select the ratios for the analysis on the basis of the following considerations:

1. Traditionally used ratios in the accounting literature.
2. Frequency of use in previous studies.
3. Ease of calculation and definition based on available accounting information.

Since our objective is to formulate business failure prediction models, we focus on the variables that, in principle, provide information about the solvency and profitability aspects of the firm, without overlooking the influence of indebtedness. In addition to these categories, we include turnover, activity and asset structure.

Taking into account the uniqueness of the companies with which we are working, we make a few qualifications regarding some of the chosen ratios, specifically the indebtedness and profitability ones, for reasons that we will explain below.

1. An interesting study which provides a guide to incorporating ratios based on an economic/financial model of business solvency is that by Dieguez et al. (2006). Readers can also consult Pozuelo et al. (2010) and Labatut et al. (2009).

A characteristic that differentiates cooperatives from capitalist companies is that they are open associations, meaning their share capital varies, while respecting the statutory minimum - rising when members join and dropping when they leave.

It has traditionally been established that a cooperative's capital[2] forms part of its equity and would only be constituted as a debt when a cooperative member leaves. However, the adaptation of accounting standards to the 2007 General Accounting Plan (PGC by its initials in Spanish) and to the International Financial Reporting Standards (IFRS) through Order EHA/3360/2010 establishes that, in general, the contributions of members and other stakeholders to cooperatives should be classified as a liability as the cooperative does not have an unconditional right to refuse to return such contributions. Thus, we can establish that there are two types of members in a cooperative: owner members and creditor members. The statutory amendments provided in the legislation were to allow the Governing Board the possibility of agreeing on the conversion of the contributions with the right to reimbursement in the event of withdrawal, into contributions that could be unconditionally refused by said governing body. For this reason, we have considered it appropriate to maintain the amount of equity that appears in the database used to compile the study sample.

Regarding profitability and given its direct relationship with the outcome, we make the following clarifications in relation to its measurement in the type of company under study here:

There are two types of accounting profit in the cooperative enterprise:

1. That generated by transactions with members (surplus).
2. That generated by transactions with non-member third parties and extraordinary transactions.

Since the 2011 financial year, the calculation of cooperatives' accounting profit has been governed by practically the same standards as other companies and is the same as the cooperative surplus. This is important when using databases to analyse cooperatives, as we do, since most of their data is presented in formats similar to those of other companies. As such, they do not reflect the fact that cooperatives used to be different in this regard and that the result of the profit and loss account is not the same as the cooperative surplus appearing in the equity on the balance sheet.

Regarding the profitability ratios, we should not forget that in cooperatives, maximum profitability for members will probably be achieved by securing good prices for cooperative products and services. In the case of associated work cooperatives, part of the profitability obtained by the worker members is received via the salary for the work carried out in the cooperative society. Within the category of profitability, we have considered mixed ratios comprising different ratios of profit and indebtedness. We also include in the profitability category some ratios based on cash flow in its traditional sense of resources generated; that is, earnings + depreciation + provisions.

Our study makes use of the information contained in cooperatives' financial statements, transforming it into ratios, which will allow us to precisely establish their financial situation

2. For further consideration of debt and equity in cooperatives, see Martin et al. (2007) and Bretos et al. (2018).

and make comparisons between the different companies and different financial periods. In addition to the classic ratios used in this type of study, the variable size is included, measured as the total amount of the company's assets. The use of the variable size, measured in different ways, is very common in business failure studies. In some studies, such as those by Back (2005) and Turetsky and McEwen (2001), it is expressed as the natural logarithm of total assets. Other authors, such as Calvo and García (2006), go with the criterion established by the European Commission (1996), while some, such as Honjo (2000), have opted to use the number of firm employees as a measure of size.

For operational reasons, different sources of information -such as those of a qualitative nature- have not been used.

Table 3 lists the ratios initially considered, divided into categories:

Table 3. Ratios used in the empirical analysis

Key	Profitability
PROF. 1	Operating income / assets
PROF. 2	Net income / equity
PROF. 3	Cash flow resources generated / net income
PROF. 4	Cash flow resources generated / equity
PROF. 5	Cash flow resources generated / assets

Key	Financial structure
DEBT. 1	Liabilities / equity
DEBT. 2	Financial expenses / liabilities
DEBT. 3	Financial expenses / sales
DEBT. 4	Non-current liabilities / equity
DEBT. 5	Current liabilities / equity

Key	Activity
ACT. 1	Value added / sales
ACT. 2	Net income / value added

Key	Turnover
TURN. 1	Sales / assets

Key	Solvency (liquidity)
LIQ. 1	Current assets / current liabilities
LIQ. 2	Current assets less stock / current liabilities
LIQ. 3	Available assets / current liabilities

Key	Long-term solvency
LT SOLV 1	Assets / liabilities

Key	Economic structure
ES. 1	Current assets / assets

Key	Other variables
TA	TOTAL ASSETS

Source: Authors' own creation.

All items included in the ratios have been sourced from the balance sheet and profit and loss account of the companies that make up the different samples.

6. Methodology

In this study, we follow the set-theoretic method developed by Ragin (1987, 2000, 2008); namely, fsQCA. This method establishes causal relationships by identifying the conditions or combination of conditions (independent variables) that are sufficient for the presence of a certain outcome (dependent variable). As Vis (2012) reports, this method seeks to discover the simplest combinations of conditions that produce a certain outcome. Thus, fsQCA allows the researcher to explore the complex paths leading to the presence of a certain outcome.

Fiss (2011) points out that the set-theoretic approach differs from conventional, variable-based approaches in that it does not disaggregate cases into independent characteristics of the observations but rather groups observations or cases into causal combinations or configurations. Hsu, Woodside and Marshall (2013) argue that this method is more appropriate when the outcome arises from complex iterations, because fsQCA helps the researcher to find patterns or configurations in the condition variables for the cases under study and make sense of them. Thinking in terms of alternative mechanisms points to the fact that different causal recipes may be related to a certain outcome (or dependent variable); as such, this is a better approach than developing a theory based on the impact caused by independent variables (Woodside and Marshall, 2013). The purpose of an ordinary least squares regression is to confirm whether, in a sample of cases, a given variable has a significant effect, positive or negative, on a dependent variable. This effect is considered net of the effect of the other variables involved. A regression provides the magnitude and direction of the effect of a given variable, but in isolation, without considering the rest of the model variables. However, fsQCA does not consider the independent effect of a variable; on the contrary, it takes into account the combined effect of the different variables. Its purpose is to identify the conditions (variables) that are responsible for the presence of a certain outcome or response, by seeking combinations or causal configurations (Elliot, 2013). This method thus offers important advantages over traditional statistical techniques such as regression-based analysis.

The fsQCA method is used to analyse in detail how a causal condition or set of conditions can be determinants of the existence of a given outcome, providing explanations for complex causal relationships (Ragin, 2000, 2008). Cases or observations are composed of combinations of causal conditions and an outcome or response value.

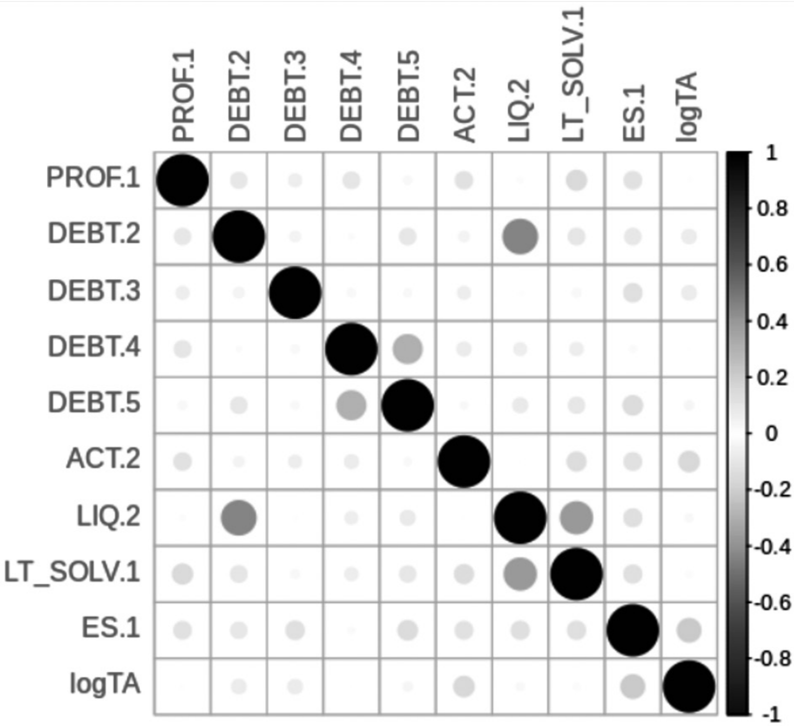
To apply the fsQCA method, the considered variables have to be transformed into values that indicate the degree of set membership. This allows the researcher to explore which combinations of these sets can determine the presence of the set that generates the outcome. According to Longest and Vaisey (2008), this approach can be used to identify which combination or combinations of conditions (the equivalent of independent variables in an ordinary regression) could lead to an outcome (the equivalent of the dependent variable in an ordinary regression). It thus yields a number of different combinations, called configurations or causal recipes, which enable the presence of the outcome under study. The present study is aimed at identifying the combinations of financial ratios that form the subset of cooperatives in a situation of insolvency. In other words, the aim is to determine the conditions or causal configurations that may lead to insolvency.

As pointed out by Schneider and Wagemann (2010), the fsQCA method seeks to extract patterns revealing the association between observations, in order to identify the existence of possible causal relationships. It is important to clarify that the identified causal relationships must be interpreted through the mathematical laws of Boolean algebra.

7. Results

The analysis started out with a total of 18 financial ratios and variables, as indicated above. Before proceeding with the study, the Pearson correlation matrix was used to check that there were no strong correlations among variables. Variables with a correlation greater than 0.5 were eliminated from the study, leaving the following variables in the analysis: PROF.1, DEBT.2, DEBT.3, DEBT.4, DEBT.5, ACT.2, LIQ.2, LTSOLV.1, ES.1 and TA. Therefore, these 10 conditions or antecedents will be used to identify the causal recipes that lead to the outcome of a high likelihood of failure in cooperatives. Figure 1 is a correlogram depicting the correlations between the conditions retained in the analysis, where it can be seen that the values of these correlations are very low.

Figure 1. Correlogram of financial variables considered as conditions



Notes: logTA is the logarithm of TA (total assets).

The other variables are detailed in Table 3.

The application of the fsQCA method first requires the calibration of the variables to convert them into conditions or antecedents of the outcome variable. This calibration process is carried out in order to assign variables a degree of set membership. It is similar to the normalization or typification of the source data on a variable (Woodside, 2013). It consists of expressing the degree of membership in a set and requires the use of three reference values: full membership in the set (1.0), full non-membership in the set (0.0), and a value of maximum ambiguity, where the observation or case is neither inside nor outside the set (0.5). In our study, we use a percentile-based approach to calibrate the continuous variables and transform them to fuzzy sets (Lassala et al., 2016a, Lassala et al., 2016b and Carmona et al., 2016). Thus, the 20th, 50th and 80th percentiles have been taken as the three abovementioned reference values to transform the continuous variables into fuzzy sets.

All models have been fitted using version 3.6.1 of the R statistical package (R Core Team, 2019) and the fsQCA analysis has been carried out using version 3.2 of the QCA package (Dusa, 2019).

Analysis of the conditions leading to the failure of cooperatives

As Fiss (2011) notes, qualitative comparative analysis seeks to identify the conditions that are sufficient to lead to the presence of a given outcome. To do so, it is necessary to extract from the information the combinations of attributes that are sufficient for achieving the outcome.

A condition is sufficient when it always leads to the achievement of an outcome; that is, observations or cases that are found to be sufficient also correspond with the outcome. In other words, a condition is sufficient when it constitutes a subset of the outcome set. To identify this relationship of sufficiency, we have to generate a truth table. This involves identifying all possible combinations of the different causal conditions (one row for each of the combinations) that can lead to the desired outcome. That is, the truth table consists of all possible logical combinations that can be formed from the conditions (Fiss, 2011). Thus, observations or cases are assigned to the logical combination with a degree of membership above 0.5. Boolean algebra is then used to analyse the results, which usually entails logical reduction or simplification by means of the Quine-McCluskey algorithm (Fiss, 2007). For a number *n* of conditions, the truth table would have a total of 2^n rows. As we have 10 conditions in our study, the total number of possible causal combinations that could be an antecedent of the desired outcome is 1024.

As noted by Hsu et al. (2013), to assess the strength of the causal relationships identified with the fsQCA method, two indicators are typically used: consistency and coverage. In the sufficiency relationship, consistency represents the proportion of observations or cases in which a causal condition or configuration and the desired outcome are both present relative to the total number of cases in which said causal condition or configuration occurs (Dusa, 2019). In other words, consistency quantifies the extent to which observations or cases with a similar causal configuration correspond with the desired outcome. On the other hand, in terms of sufficiency, coverage provides a measure of how much of the desired outcome is explained by a causal configuration or condition; that is, it indicates the empirical relevance of the causal solution. It is the degree to which the cases or observations belong to a given configuration and to the desired outcome relative to all the cases that give rise to the outcome. The higher the coverage, the more important the condition. When a causal configuration covers 100% of the desired outcome, it is said that in addition to being sufficient it is necessary. Relating these measures to traditional statistics, consistency can be seen as equivalent to Pearson's correlation coefficient *r*, and coverage would be analogous to the coefficient of determination *R2* (Hsu et al., 2013).

Table 4 shows the results of the analysis of the sufficiency of the conditions that may lead to the failure of a cooperative society, presenting reasonable and acceptable values of consistency (0.829) and coverage (0.441). The solution shows only one model; that is, according to the available data, a single causal configuration has been identified that is sufficient to achieve the desired outcome, which is a high likelihood of a cooperative entering into insolvency proceedings. Thus, a situation of high indebtedness (DEBT2), low liquidity (liq.2), low solvency (ltsolv.1) and small size (logta) represents the scenario that would be sufficient for a cooperative to have problems of continuity.

Table 4. Analysis of the sufficiency of the conditions for the failure of a cooperative

Solution: DEBT.2*liq.2*ltsolv.1*logta → FAILURE

	Consistency	Coverage
DEBT.2*liq.2*ltsolv.1*logta	0.829	0.441
Minimum total	0.829	0.441

Notes:
Sample size = 112.
Lowercase letters indicate the absence of the condition and capital letters indicate the presence.
logta: logarithm of total assets. The rest of the variables are defined in Table 3.

In terms of notation, capital letters have been used to indicate the presence of a certain condition and lowercase letters to indicate the negation or absence of the condition.

To complete the analysis, we have also applied the fsQCA method to the opposite outcome, that is, the likelihood of non-failure of a cooperative. To do so, the values of the expected outcome variable first have to be inverted as 1 indicates the condition of a failed cooperative and 0 one that has not failed. The Boolean algebra operation *1 – set of failed companies* has been used to obtain the negation of failed companies, which can alternatively be referred to as the non-failed companies. Table 5 presents the results of the fsQCA based on the conditions considered in our study for failure but now taken as determinants of the opposite outcome; that is, the non-failure or success of the cooperative. Therefore, sufficient conditions for a cooperative not failing are high profitability (PROF.1), low indebtedness (debt.2, debt.3, debt.4, and debt.5) and high solvency (LTSOLV.1), in line with the conditions identified above as sufficient for the entity to face problems of survival.

Table 5. Analysis of the sufficiency of the conditions for the success of a cooperative

Solution: PROF.1*debt.2*debt.3*debt.4*debt.5*LTSOLV.1 → NO FAILURE

	Consistency	Coverage
PROF.1*debt.2*debt.3*debt.4*debt.5*LTSOLV.1	0.755	0.351
Minimum total	0.755	0.351

Notes:
Sample size = 112.
Lowercase letters indicate the absence of the condition and capital letters indicate the presence.
logta: logarithm of total assets. The rest of the variables are defined in Table 3.

On the other hand, it should be emphasized that the analysis with the fsQCA method produces three different solutions: the complex, the intermediate and the parsimonious. The causal configurations containing these solutions may differ from one another, however, they are consistent with Boolean logic and never contain contradictory information (Ragin, 2008).

The complex solution does not incorporate any assumption on the basis of which to simplify the results, so the causal configurations obtained are very complicated and difficult to interpret, especially when there is a large number of causal antecedents or conditions. The parsimonious solution reduces the causal configurations to their minimum expression; and these include only the so-called prime implicants, which cannot be left out of any of the solutions derived from the truth table. The fsQCA algorithms automatically make a series of decisions about logical remainders, without considering theoretical arguments that support such automatic decisions. Ragin (2008) advises against the use of such severe simplification criteria and therefore against computing and reporting the parsimonious solution in fsQCA.

On the other hand, the intermediate solution is obtained by selectively considering assumptions that help reduce the complexity of the causal phenomena. These assumptions relate only to scenarios that are consistent with theoretical knowledge or empirical evidence. The use of this solution is strongly dependent on the researcher having a clear understanding of the relationships between the conditions and the expected outcome, based on their theoretical knowledge or proven empirical evidence.

We have opted to include the intermediate solution in our study, as shown in Tables 4 and 5. We hold this solution to be the most appropriate because it does not entail the shortcomings of the simplified solution or the difficulties involved in attempting to interpret the more complex solution. Table 6 shows the expected relationships between the causal conditions and the likelihood of a cooperative entering into insolvency proceedings.

Table 6. Expected relationships between causal conditions and likelihood of failure

Condition	Expected sign
PROF1	Negative
END2	Positive
END3	Positive
END4	Positive
END5	Positive
ACT2	Negative
LIQ2	Negative
LTSOLV1	Negative
ES1	Uncertain
TOTAL ASSETS	Uncertain

Notes: The variables are defined in Table 3.

Robustness analysis

As Dusa and Alrik (2013) point out, a situation could occur in which a causal condition or configuration is sufficient to produce both the expected outcome and the negation of it, which would be contradictory or a seemingly paradoxical relationship. It is therefore very important to check that this possible contradiction does not arise. To that end, a new algorithm is applied to the solution for failure obtained with the fsQCA algorithm, but this time it is applied to the negation of the expected outcome; that is, the absence of a high likelihood of a cooperative failing. Table 7 reveals very low consistency and coverage values for the negation of the outcome, meaning that the aforementioned contradictory or paradoxical relationship would not apply here.

Table 7. Analysis of the sufficiency solution for the negation of cooperative failure

Solution: DEBT.2*liq.2*ltsolv.1*logta → failure

	Consistency	Coverage
DEBT.2*liq.2*ltsolv.1*logta	0.271	0.052
Minimum total	0.271	0.052

Notes:
Sample size = 112.
Lowercase letters indicate the absence of the condition and capital letters indicate the presence.
logta: logarithm of total assets. The rest of the variables are defined in Table 3.

Dusa and Alrik (2013) also refer to another possible problem that may arise when a causal condition or configuration and its negation are both sufficient to produce the same desired outcome. Table 8 shows that the negation of the causal configuration obtained for the failure of a cooperative would not also give rise to the presence of a high likelihood of failure in cooperatives; indeed, it can be seen that the consistency and coverage values are very low. It is thus confirmed that this possible contradiction is not present in the solution obtained.

Table 8. Analysis of the sufficiency solution for the negation of the causal configuration for failure

Solution: negation (DEBT.2*liq.2*ltsolv.1*logta) → FAILURE

	Consistency	Coverage
negation (DEBT.2*liq.2*ltsolv.1*logta)	0.270	0.011
Minimum total	0.270	0.011

Notes:
Sample size = 112.
Lowercase letters indicate the absence of the condition and capital letters indicate the presence.
logta: logarithm of total assets. The rest of the variables are defined in Table 3.

8. Conclusions

The aim of this study has been to find the combination of financial variables that can predict the business failure of a cooperative company. To do so, the fsQCA algorithm has been applied; this set-theoretic method makes it possible to identify the combinations of variables that best detect a scenario of financial difficulties for the entity. The analysis also incorporates additional information reflecting a scenario in which there is an absence of such difficulties, that is, the success of the cooperative.

The objective is not predictive and, on the contrary, the purpose is to identify which causal combinations would be decisive for expecting that a cooperative that fulfilled one of them would find itself in a situation of high risk of failure.

The sample selected for this study comprises Spanish cooperative companies from various sectors, except the financial and insurance industries. However, it must be considered that the limited size of the sample might influence the obtained results and conclusions.

The review of the literature allowed us to confirm the novelty of this study in terms of the application of this technique to the field of business failure in cooperatives.

Within the business world, cooperatives have unique socially-oriented characteristics -from both a regulatory and operational perspective- which set them apart from other companies. Without overlooking their commercial side, cooperatives' relations with their employees, return on the capital provided and way of distributing profits represent profound differences.

The results from the analysis using the fsQCA method point to the joint relevance of the combinations of variables reflecting high indebtedness (*DEBT.2*), low liquidity (*LIQ.2*), low solvency (*LTSOLV.1*) and small size (*LOGTA*), representing a sufficient scenario for an entity to face problems of continuity.

On the other hand, the analysis has shown that a combination of the variables high profitability (*PROF.1*), low indebtedness *(DEBT.2, DEBT.3, DEBT.4,* and *DEBT.5*) and high solvency (*LTSOLV.1)* represents a causal configuration that would be sufficient for a cooperative not to enter into a business failure situation.

Lastly, a robustness analysis has confirmed that the identified causal combination that leads to failure is not contradictory, demonstrating the absence of paradoxical or contradictory causal relationships.

Given that the results obtained are consistent with the empirical evidence, we consider the methodology applied to be entirely valid for the research objectives established; namely, to identify causal relationships that can explain business failure in companies in the cooperative sector.

Finally, given the novelty and appropriateness of the methodology, we believe it would be interesting to apply it in future studies focusing on business failure in SMEs, in general and broken down by sectors of activity, at both the national and European level. Furthermore, since there have been relatively few studies of failure in cooperatives, it would be worth exploring this issue in more depth by focusing on different sectors of activity.

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