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TABLE OF CONTENTS

EDITORIAL

A new stage for EAMR: institutional vision and methodological frontiers "The compositional-data methodology for financial ratios"

Guillermo Mateu-Bartolomé

ARTICLES

Ten years of compositional analysis of financial ratios. Review, guidelines and future directions..... 1–32

Germà Coenders and Núria Arimany-Serrat

Subsidies and financial performance in the rural tourism sector 33–54

Maria Àngels Farreras-Noguer, Marc Carreras-Pijuan, Salvador Linares-Mustarós, and Núria Arimany-Serrat

Financial resilience of agricultural and food production companies in Spain: A compositional cluster analysis of the impact of the Russia–Ukraine war (2021-2023) 55–80

Mike Hernandez-Romero and Germà Coenders

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EDITORIAL

A new stage for EAMR: institutional vision and methodological frontiers (The compositional-data methodology for financial ratios)

This Volume 11, Issue 1, marks the beginning of a significant new chapter for the European Accounting and Management Review (EAMR). Although this issue corresponds to the 2025 editorial calendar, its publication has been rescheduled to May 2026 due to the transition in the journal's leadership and the renewal of the Editorial Team in July 2025. This transition was necessary to ensure the continuity of the journal's quality standards and editorial processes. I am honored to introduce this first issue under my leadership as Editor-in-Chief. This stage is further strengthened by the new co-publication agreement between the Associació Catalana de Comptabilitat i Direcció (ACCID) and Asociación Iberoamericana de Control de Gestión (AICOGestión). This partnership reflects our commitment to internationalization, the promotion of high-quality research, and the creation of a bridge between academic rigor and professional practice in the global accounting and management community.

To celebrate this new era, we have dedicated this issue to a methodological frontier that is reshaping financial analysis: The Compositional Data (CoDa) methodology for financial ratios.

It is now ten years since Salvador Linares-Mustarós and Germà Coenders published the seminal work on compositional financial ratios "Liquidity and debt profiles. From classification according to financial ratios to compositional classification" in the proceedings of the II International Workshop on Proximity Data, Multivariate Analysis, and Classification held in Barcelona in 2016.

While using financial ratios in diagnostics of the financial health of single firms (or comparing, e.g., two firms) is straightforward, using them as variables in statistical analyses has been related to many serious problems, such as non-normality of the distributions, non-linearity of the relationships, extreme outliers, and even dependence of the results on the arbitrary decision regarding which accounting figure appears in the numerator and which in the denominator of the ratio. The Compositional Data (CoDa) methodology developed in other scientific fields for the statistical analysis of data conveying relative information expressed as ratios solves all these problems and can be readily adapted to financial statement analysis. Far from being a statistical refinement, the CoDa methodology leads to very substantial differences in the analysis results whenever it has been compared with standard financial ratios.

During the last ten years, the CoDa methodology has been successfully applied in conjunction with many statistical methods including principal component analysis, cluster analysis, static, dynamic and panel regression models, structural equation models, discrete choice models, and machine learning methods to draw financial performance profiles, predict bankruptcy, relate asset and capital structures, relate financial, environmental, social and governmental performance, and study the resilience to crises, among others.

The article "Ten years of compositional analysis of financial ratios. Review, guidelines and future directions" by Germà Coenders and Núria Arimany-Serrat reviews the relevant

literature and the extant applications of the CoDa methodology over the last ten years. It presents the advantages of the CoDa methodology and an easy how-to guide to encourage new adopters based on a toy example of Spanish wineries. This includes some transformations within the CoDa methodology that are particularly useful for financial statement analysis, and some simple visualization tools and statistical hypothesis tests. The key idea is that when the financial data are pre-processed according to the CoDa methodology using simple rules, researchers can use their favourite statistical techniques, with at most minor changes in the way of interpreting the results. The article finishes by discussing in which cases CoDa analysis is essential and in which it can be dispensed with, as well as current debates, future challenges, and avenues for further research.

The article "Subsidies and financial performance in the rural tourism sector" by Maria Àngels Farreras-Noguer, Marc Carreras-Pijuan, Salvador Linares-Mustarós, and Núria Arimany-Serrat uses compositional regression models to study the effect of subsidies on the financial performance in the Spanish rural tourism sector. Tourism farms that receive subsidies exceeding 25 % of their total assets show higher turnover, a more tangible asset structure, and longer debt maturity, thus confirming the importance of the many subsidies in the sector following European, national, and regional policies.

The article "Financial resilience of agricultural and food production companies in Spain: A compositional cluster analysis of the impact of the Ukraine-Russia war (2021-2023)" by Mike Hernandez-Romero and Germà Coenders analyses the financial resilience of agricultural and food production firms in Spain amid the Ukraine-Russia war using compositional cluster analysis. The analysis reveals distinct clusters of firms with varying financial resilience, characterized by metrics of solvency and profitability. The results underscore the sectoral adaptation to the conflict's economic challenges by 2023, when firms have tended to transit to the more resilient clusters.

We hope that this Volume 11 (issue 1) is helpful to make this methodology better known among professionals and applied researchers in accounting and management, and to provide them with sufficient material to apply it confidently.

Guillermo Mateu-Bartolomé
Editor-in-Chief
On behalf of the Editorial Team

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EUROPEAN ACCOUNTING AND MANAGEMENT REVIEW

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Ten years of compositional analysis of financial ratios. Review, guidelines, and future directions

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ABSTRACT

Compositional data are contemporarily defined as positive vectors, the ratios among whose elements are of interest to the researcher. Financial statement analysis by means of accounting ratios a.k.a. financial ratios fulfils this definition to the letter. Compositional data analysis solves the major problems in statistical analysis of standard financial ratios, such as skewness, non-normality, non-linearity, outliers, and dependence of the results on the choice of which accounting figure goes to the numerator and to the denominator of the ratio. In this article, we review the literature on said problems and the applications of the compositional data methodology since the first publication 10 years ago. We present a how-to guide for early adopters of the methodology. This includes some transformations within compositional data analysis that are particularly useful for financial statement analysis, how to visualise firms in an industry with a compositional principal-component-analysis biplot and how to do statistical inference on the financial performance by groups of firms. We discuss in which cases compositional data analysis is essential and in which it can be dispensed with, as well as current debates, future challenges and avenues for further research.

KEYWORDS

CoDa, log-ratios, margin, turnover, leverage, ROE, SABI

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1. Introduction and literature review

The relative nature of *financial ratios*, a.k.a. *accounting ratios* (i.e., ratios comparing selected figures in financial statements), enables them to evaluate the firm's position compared to its counterparts in the industry or to itself over time, taking into account differences or evolution in firm size (e.g., Ross et al., 2003). Financial ratios have been used in practical management performance and strategic assessment and in research relating them to other financial or non-financial variables (Altman, 1968; Amat Salas, 2020; Barnes, 1987; Faello, 2015; Horrigan, 1968; Ros et al., 2019; Soukal et al., 2024; Staňková and Hampel, 2023; Veganzones and Severin, 2021; Willer do Prado et al., 2016) including, for instance, fraud detection, stock market returns, and firm survival, default or bankruptcy. A typical example of financial ratio is that of assets over equity. This ratio tells how indebted a firm is, since assets can be decomposed into equity and liabilities, i.e., debt. It is also referred to as the leverage ratio.

While the use of standard financial ratios in diagnostics of the financial health of single firms (or comparing, e.g., two firms) is straightforward, analysing a sample of firms from an industry requires statistical methods. Using standard financial ratios as variables in statistical analyses has been related to a number of serious problems, such as *asymmetry* (Faello, 2015; Frecka and Hopwood, 1983; Linares-Mustarós, et al., 2018; Oktaviano et al., 2024), connected to it severe *non-normality* of the distributions (Buijink and Jegers, 1986; Deakin, 1976; Durana et al., 2025; Iotti et al., 2023; 2024a; 2024b; 2024c; Lueg et al., 2014; Martikainen et al., 1995; McLeay and Omar, 2000; So, 1987; Valaskova et al., 2023), *non-linearity* of the relationships (Balcaen and Ooghe, 2006; Carreras-Simó and Coenders, 2021; Cowen and Hoffer, 1982; Keasey and Watson, 1991; Taoushianis, 2025), extreme *outliers* (Deshpande, 2023; Ezzamel and Mar-Molinero, 1990; Frecka and Hopwood, 1983; Kane et al., 1998; Lev and Sunder, 1979; Liu et al., 2025; Magrini, 2025; McLeay, 1986; Nyitrai and Virág, 2019; Oktaviano et al., 2024; Watson, 1990), and even dependence of the results on the arbitrary decision regarding which accounting figure appears in the numerator and which in the denominator of the ratio (Coenders and Arimany-Serrat, 2025; Coenders et al., 2023a; Frecka and Hopwood, 1983; Linares-Mustarós, et al., 2022). The results of many statistical analyses are invalid when all or some of these problems occur and the results and conclusions of said analyses can be affected to a great extent. It has long been known that these problems not only have serious consequences for single ratios but also when combining ratios into composite indicators by means of factor analysis and related methods (Cowen and Hoffer, 1982; Martikainen et al., 1995). Readers unfamiliar with the statistical consequences of asymmetry, outliers, non-linearity, and so on, can resort to any introductory statistics or econometrics handbook.

These serious problems have also been reported in other scientific fields using ratios (Isles, 2020). It must be noted that when financial ratios were first developed in the late 19th century (Brown Sister, 1955; Horrigan, 1968), statistical analysis methods were in their infancy, which speaks by itself for the fact that financial ratios were not conceived

with a statistical usage in mind. The theory on *ratio measurement scales* (Stevens, 1946) had not even been developed. This situation has changed dramatically, with a large body of statistical and econometrical research in the field of accounting being available nowadays (Gruszczyński, 2022). As a matter of fact, the first use of the term *econometrics* was made by Paweł Ciompa in 1910 in the accounting field (Ciompa, 1910). The aim of this article is to review the solutions presented to these problems and present one of them, which is called *Compositional Data* (CoDa) approach.

Until recently, only rarely has the accounting research community recognised the importance of these problems, and when this has been the case, diverse ad-hoc solutions have been applied on the spot for a problem at a time. For instance, outliers have been dealt with by just removing them, which is called trimming or pruning (Ezzamel and Mar-Molinero, 1990; Frecka and Hopwood, 1983; Kubenka and Myskova, 2022; Martikainen et al., 1995; Magrini, 2025; So, 1987; Watson, 1990) or replacing them with the nearest non-outlying values, which is called wisorizing (Demiraj et al., 2024; Deshpande, 2023; Duong et al., 2025; Gupta, 2024; Lev and Sunder, 1979; Laus et al., 2025; Liu et al., 2025; Naz et al., 2023; Nyitrai and Virág, 2019; Vu et al., 2023). The number of identified outliers in at least one ratio has in some cases neared one third of all firms, and these procedures have thus seriously impaired the sample representativeness (Martin-Melero et al., 2025). Asymmetry has been dealt with by using hard-to-interpret transformations such as the square root, the cubic root or generalised polynomials (Akbar et al., 2025; Deakin, 1976; Ezzamel and Mar-Molinero, 1990; Frecka and Hopwood, 1983; Martikainen et al., 1995; Taoushianis, 2025), their generalization as Box-Cox transformations (Mcleay and Omar, 2000; Watson, 1990), or by ignoring the original ratio values and considering only their rank order (Cheng and Fang, 2025; Kane et al., 1998; Lueg et al., 2014). Non-normality has been dealt with non-parametric statistics (Durana et al., 2025; Hazami-Ammar, 2024; Iotti et al., 2023; 2024a; 2024b; 2024c; Latief and Suhendah, 2023; Valaskova et al., 2023). Rather than that, here we present a simple unified approach to deal with all problems simultaneously which makes it possible to use the full sample without removing outliers and is compatible with any statistical method and not just with non-parametric methods.

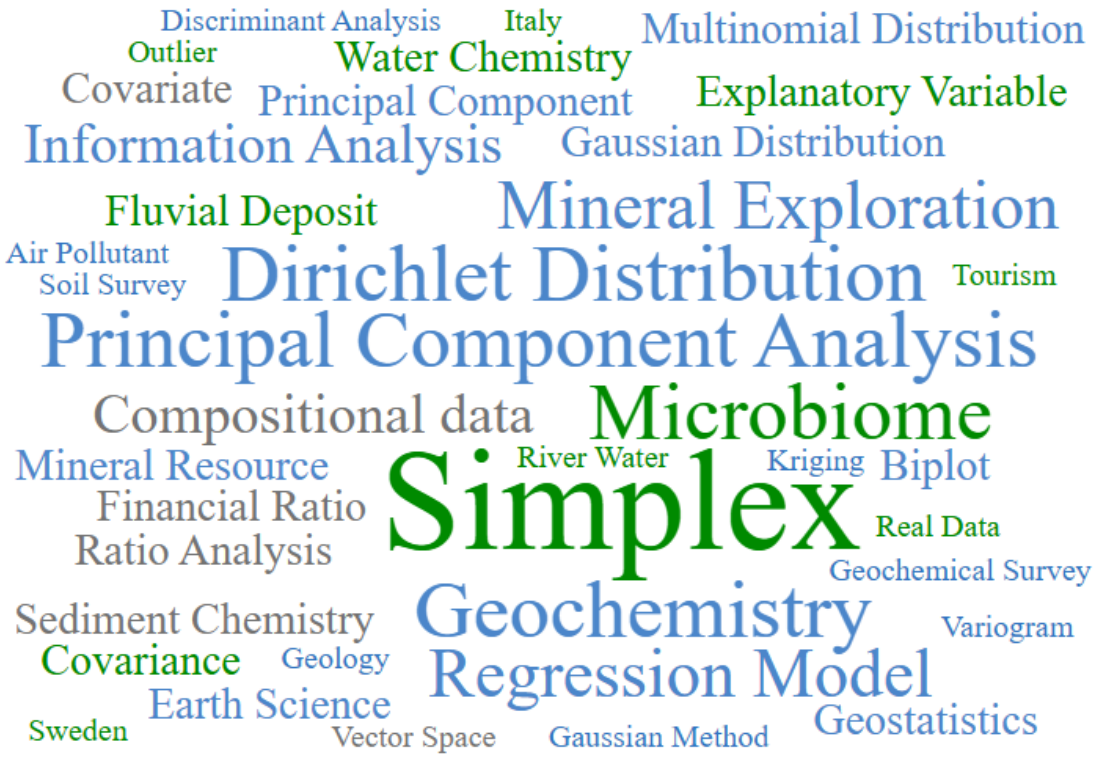
Financial ratios constitute a genuine case of researchers' and professionals' interest in relative rather than absolute magnitudes of accounting figures and thus a natural field of application of CoDa analysis, which has the same objective. Essentially, CoDa are arrays of strictly positive numbers for which ratios between them are considered to be relevant (Egozcue and Pawlowsky-Glahn, 2019) which perfectly fits the notion of financial statement analysis. The CoDa methodology offers a number of advantages in statistical analysis of financial statements, as compared to standard financial ratios. Among other features, CoDa treat accounting figures in a symmetric fashion in such a way that results do not depend on numerator and denominator permutation. CoDa also tend to reduce outliers, asymmetry, and non-normality, and to linearize relationships. Far from being a statistical refinement, the CoDa methodology leads to very substantial differences in the analysis results whenever it has been compared with standard financial ratios, like clusters composed only of outliers under the standard approach (Dao et al., 2024; Hernandez-Romero and Coenders, (2025); Jofre-Campuzano and Coenders, 2022; Linares-Mustarós et al., 2018), variables whose effect is statistically significant under the standard approach but not the compositional approach, or vice-versa (Arimany-Serrat et al., 2022; Carreras-Simó and Coenders, 2021; Coenders et al., 2023a; Creixans-Tenas et al., 2019; Escaramís and Arbussà, 2025; Linares-Mustarós et al., 2022), and substantial differences in forecasts

(Magrini, 2025).

Since the seminal works by Aitchison (1982, 1986), CoDa analysis has become a well-established methodology, notably present in accessible textbooks (van den Boogaart and Tolosana-Delgado, 2013; Filzmoser et al., 2018; Greenacre, 2018; Pawlowsky-Glahn et al., 2015) and software (Comas-Cufí and Thió-Henestrosa, 2011; van den Boogaart and Tolosana-Delgado, 2013; Filzmoser et al., 2018; Greenacre, 2018; Palarea-Albaladejo and Martín-Fernández, 2015; Thió-Henestrosa and Martín-Fernández, 2005), and continues to be further developed well after forty years (Coenders et al., 2023b; Greenacre et al., 2023).

The study of the relative importance of chemical elements in geological analysis spurred most of the early interest in CoDa (Aitchison, 1986; Buccianti et al., 2006). Nowadays, CoDa are being used in the social sciences and economics in general (Coenders and Ferrer-Rosell, 2020; Fry, 2011; Martínez-Garcia et al., 2023) and in finance in particular, to answer research questions concerning the relative importance of magnitudes (see Arimany-Serrat and Coenders, 2025; Arimany-Serrat et al., 2022; Coenders, 2025; Coenders and Arimany-Serrat, 2023; 2025; Linares-Mustarós et al., 2022 for reviews on the topic). Examples include crowdfunding, bond ratings, financial markets, municipal budgeting, insurance, exchange rates, banking, portfolios, systemic risk, household finance, intermediary market share, and equity ownership structure. The word cloud of the CoDa topic according to the SCOPUS data base shows “Financial ratio” to be a leading subtopic (Figure 1), surrounded by mathematical, statistical, geological, chemical, biological and medical concepts.

Figure 1. SCOPUS word cloud of the CoDa topic (accessed 19/09/2025)



The foundations of CoDa in financial-ratio analysis were laid for the first time in Linares-

Mustarós and Coenders (2016). Since then, the method has been applied in the industries of manufacture of pharmaceutical preparations (Linares-Mustarós et al., 2018), manufacture of wearing apparel (Linares-Mustarós et al., 2018; Molas-Colomer et al., 2024), hospitals (Creixans-Tenas et al., 2019), groceries (Carreras-Simó and Coenders, 2020), retail trade (Carreras-Simó and Coenders, 2021), wineries (Arimany-Serrat et al., 2022; 2023; Coenders, 2025; Coenders and Arimany-Serrat, 2023; 2025; Linares-Mustarós et al., 2022), breweries (Arimany-Serrat and Sgorla, 2024; Coenders and Arimany-Serrat, 2025; Coenders et al., 2023a), hospitality (Farreras-Noguer et al., 2025; Mulet-Forteza et al., 2024; Saus-Sala et al., 2021; 2023; 2024), beekeeping (Arimany-Serrat and Coenders, 2025), fisheries (Dao et al., 2024), food and beverage processing (Dao et al., 2024; Rondós-Casas et al., 2026), grain and fat cultivation and processing (Hernandez-Romero and Coenders, 2025), and sale of automotive fuel (Jofre-Campuzano and Coenders, 2022). It has also been applied to more general populations, such as family firms (Escaramís and Arbussà, 2025) or even a country's economy at large (Magrini, 2025). To the best of our knowledge, these are all CoDa applications to financial ratios published so far in any academic format (articles, books, book chapters, and preprints), the search not being restricted to any particular data base. To avoid duplication, conference proceedings have been excluded when there is a corresponding full article of the same research work.

One of the strong points of the CoDa approach is that it provides a unified approach which suits itself to any statistical analysis. After log-ratio transformation, any statistical method can be applied in a standard manner and then interpreted from a compositional perspective. The range of statistical methods used so far includes regression models (Arimany-Serrat et al., 2023; Coenders, 2025; Coenders and Arimany-Serrat, 2023; 2025; Farreras-Noguer et al., 2025; Mulet-Forteza et al., 2024), principal component analysis and biplots (Carreras-Simó and Coenders, 2020; Coenders, 2025; Coenders and Arimany-Serrat, 2023; 2025; Rondós-Casas et al., 2026; Saus-Sala et al., 2021; 2023), cluster analysis (Arimany-Serrat and Coenders, 2025; Arimany-Serrat and Sgorla, 2024; Coenders, 2025; Coenders and Arimany-Serrat, 2023; 2025; Hernandez-Romero and Coenders, 2025; Linares-Mustarós et al., 2018; Saus-Sala et al., 2021; 2023; 2024), weighted clustering (Dao et al., 2024; Jofre-Campuzano and Coenders, 2022), fuzzy clustering (Molas-Colomer et al., 2024), logit models (Magrini, 2025), random forests (Magrini, 2025), partial-least-squares structural equation modelling (Creixans-Tenas et al., 2019), vector autoregressive models (Carreras-Simó and Coenders, 2021), and panel regression models (Escaramís and Arbussà, 2025).

The compositional methodology has potential for any business research project using statistical models and including financial ratios among the set of study variables. Carreras-Simó and Coenders (2021) relate asset and capital structures, Escaramís and Arbussà (2025) compare capital structures of family and non-family firms, Magrini (2025) predicts bankruptcy, Creixans-Tenas et al. (2019) study the impact of social responsibility on profitability and solvency, Mulet-Forteza et al. (2024) the impact of expansion strategies, Farreras-Noguer et al. (2025) the impact of subsidies, Coenders (2025), and Linares-Mustarós et al. (2022) the impact of branding, Coenders et al. (2023a) the impact of non-financial reporting, Hernandez-Romero and Coenders (2025) the impact of the Ukraine war, and Arimany-Serrat et al. (2023), Arimany-Serrat and Sgorla, (2024), Dao et al. (2024), and Saus-Sala et al. (2024) the impact of Covid-19.

After this literature review, this article presents a simple how-to guide to motivate the use

of the CoDa approach to financial statement analysis. It starts explaining why and how financial statements and financial ratios should be considered as CoDa, including the necessary transformations. *DuPont analysis*, a very simple case of financial statement analysis is used as storyline. Then, the dataset of an example in the Spanish winery industry is presented. Next, financial statements are summarised and visualised. Next, the equality of financial structures is tested by groups of firms. The final section concludes.

2. Financial statements as compositional data

A D–part composition is defined as an array $\mathbf{x}$ of D strictly positive numbers x_j, called *parts*, the relative magnitude of which is of interest to the researcher (Aitchison, 1986):

$$\mathbf{x} = (x_1, x_2, ..., x_D) \text{ with } x_j > 0,\ j = 1, 2, ..., D\ , \tag{1}$$

Some rules have to be followed in order to introduce accounting figures in financial statements in a D–part composition, which boil down to avoiding negative accounting figures and their overlap (Creixans-Tenas et al., 2019):

- Even if sometimes financial ratios involve accounting figures which may be negative, its use is advised against in the financial literature, because they can cause a discontinuity, outliers, or even a reversal of interpretation when the accounting figure which may be negative is in the denominator (Lev and Sunder, 1979; Linares-Mustarós et al., 2022). Negative accounting figures are also advised against from the point of view of *measurement theory*. Computing a ratio is a meaningful operation only for variables in a *ratio scale*, which need to have a meaningful absolute zero (Stevens, 1946) and thus no negative values.
  In general, accounting figures are negative because they imply the subtraction of other positive accounting figures, which are the ones to be used. This means, for instance, that when building ratios, one should directly use revenues and costs rather than profit or current assets and current liabilities rather than working capital. This limitation implies no loss of information whatsoever. For instance, a ratio conveying the same information as the standard *margin* ratio (profit/revenues) can be constructed from only the non-negative revenue and cost figures. Let x_1=revenues, x_2=costs, x_3=x_1–x_2=profit. The always positive revenues over costs ratio (x_1/x_2) can easily be shown to be just a transformation of the problematic profit over revenues ratio (x_3/x_1):

$$\frac{x_1}{x_2} = \frac{x_1}{x_1 - x_3} = \frac{1}{\frac{x_1 - x_3}{x_1}} = \frac{1}{1 - \frac{x_3}{x_1}}\ . \tag{2}$$

- It must also be taken into account that parts may not overlap (Creixans-Tenas et al., 2019). For instance, one could not use x_4: assets and x_5: non-current assets because x_5 is a part of x_4. In compositional data terminology, x_4: assets are an *amalgamation* of x_5: non-current assets and x_6: current assets. Using both amalgamations and their constituent parts is extremely problematic (Pawlowsky-Glahn et al., 2015). Rather, the choice between using only the amalgamation or only the individual parts should be made at the problem definition stage and cannot be changed afterwards (van den Boogaart and Tolosana-Delgado, 2013).

> It is not essential to use all constituent parts, which is referred to as a *subcomposition* in compositional data terminology. Accordingly, the feasible choices to handle x_4 to x_6 are: a) to use only x_4; b) to use x_5 and x_6; c) to use only x_5; and d) to use only x_6.

The ultimate choice of parts will depend on the analysis objectives or research questions. The researchers will in principle like to select the accounting figures needed to compute their favourite standard financial ratios and refine the choice by avoiding overlap and subtraction. In the example we use in this article, the parts represented by the x_j variables are the following D=4 positive and non-overlapping financial statement account categories:

- x_1: revenues,
- x_2: costs,
- x_3: liabilities,
- x_4: assets.

These account categories are very relevant in practice because they make it possible to compute the common *turnover*, margin, and *leverage* ratios in classical DuPont analysis (Saus-Sala et al., 2021; 2023). Return on equity can be decomposed as the product of the three.
Turnover measures the efficiency of a firm's use of its assets in generating sales revenue:

$$\text{Turnover}=\text{revenues}/\text{assets}=x_1/x_4. \quad (3)$$

Margin is the percentage of sales revenue that is turned into profit:

$$\text{Margin}=\text{profit}/\text{revenues}=(x_1-x_2)/x_1. \quad (4)$$

Leverage measures assets generated per unit of shareholders equity. It is also a measure of indebtedness:

$$\text{Leverage}=\text{assets}/\text{equity}=x_4/(x_4-x_3). \quad (5)$$

DuPont analysis is chosen as storyline in this article both because of its simplicity (with only D=4 account categories involving just a handful of ratios) and its popularity. It goes without saying that account categories could be considered in greater detail, by increasing both the number of accounting figures D and the set of feasible financial ratios computed from them, which would make for a more detailed financial statement analysis.

3. CoDa transformations

3.1. Pairwise log-ratios

The usual approach to statistical analysis of CoDa is to use existent standard statistical methods on transformed data. *Logarithms of ratios* are the standard transformation in CoDa (Aitchison, 1986). The simplest case of a log-ratio is that between only two accounting figures which is called *pairwise log-ratios* (plr) in Coenders and Arimany-Serrat (2025); Creixans-Tenas et al. (2019); Farreras-Noguer et al. (2025); Greenacre

(2018; 2019); Mulet-Forteza et al. (2024); and Saus-Sala et al. (2021). It can also be understood as the log difference between the two accounting figures:

$$\log\left(\frac{x_1}{x_2}\right) = \log\left(x_1\right) - \log\left(x_2\right). \tag{6}$$

Unlike a standard ratio, which is bounded between zero and infinity, a plr is symmetric in the sense that its range is from minus infinity to plus infinity (Linares-Mustarós et al., 2018). This has two key advantages.

- On the one hand it coincides with the support of the normal probability distribution. It is clear that a bounded variable cannot possibly be normally distributed. Although there is never the guarantee that an unbounded real variable will be normally distributed, it is often the case for plr in empirical data sets (Aitchison, 1982).
- On the other hand, when predicting a standard ratio in a statistical model, some predicted values could actually be impossible negative values. The prediction for a plr will never be an impossible value.

Besides, a plr is symmetric in the sense that permuting the numerator and denominator parts leads to the same distance from zero and affects no other property of the plr than the sign (Linares-Mustarós et al., 2022):

$$\log\left(\frac{x_1}{x_2}\right) = \log\left(x_1\right) - \log\left(x_2\right) = -\left(\log\left(x_2\right) - \log\left(x_1\right)\right) = -\log\left(\frac{x_2}{x_1}\right). \tag{7}$$

For instance, the Pearson correlation coefficient of an external non-financial indicator with a permuted plr equals the correlation with the original plr with a reversed sign. This property does not hold for standard financial ratios. Correlating x_1/x_2 with a non-financial indicator can give conflicting results with respect to correlating it with x_2/x_1 (Coenders et al., 2023a; Linares-Mustarós et al., 2022). There is no other reason than agreement to use one ratio or its permutation. For a single firm, the fact that $x_1/x_2=0.5$ provides the same information as the fact that $x_2/x_1=2$. However, in statistical analyses, the results of the one and the other ratio may stand in contradiction. These ratio permutations are common in practice. The well-known solvency ratio or equity to assets ratio is the inversion of the leverage ratio in Equation (5):

$$\text{Solvency=equity/assets}=(x_4-x_3)/x_4. \tag{8}$$

Finally, if one of the accounting figures being compared in the ratio is close to zero, it may lead to an outlying standard ratio when placed in the denominator and to a typical ratio when placed in the numerator (Ezzamel and Mar-Molinero, 1990; Frecka and Hopwood, 1983; Kane et al., 1998; Lev and Sunder, 1979; Martikainen et al., 1995). For plr, placement makes no difference (Coenders et al., 2023a; Linares-Mustarós et al., 2018; 2022; Molas-Colomer et al., 2024).

Table 1 shows a toy example of seven fictional firms and two accounting figures x_1 and x_2. For ease of computation, we show logarithms to base 10 represented as $\log_{10}(x)$, which just tell how many times 10 has to be multiplied by itself in order to get the desired value.

$\log_{10}(1{,}000{,}000)=6$ because $10^6=1{,}000{,}000$. There is perfect symmetry around 1 and 0: $0.000001 = 1/1{,}000{,}000 = 1/10^6 = 10^{-6}$, so that $\log_{10}(0.000001) = -6$.

The interpretation of the plr with respect to standard ratios is straightforward. When x_1/x_2 is larger than 1, $\log_{10}(x_1/x_2)$ is positive. When x_1/x_2 is smaller than 1, $\log_{10}(x_1/x_2)$ is negative. The larger x_1/x_2, the larger $\log_{10}(x_1/x_2)$.

Note that, like ratios, logarithms focus on relative differences between firms. Ratios and logarithms are thus mutually compatible (Stevens, 1946) and should be routinely used together for data in a ratio scale, when the meaningful difference between two figures is relative, meaning that it lies in their ratio and not in their subtraction.

For example, if we take firms 3,4, and 5 in the toy example in Table 1 (x_2 values 100, 1,000 and 10,000), in relative terms, the difference between 1,000 and 100, which is 1,000/100=10, is the same as the relative difference between 10,000 and 1,000, which is 10,000/1,000=10. Accordingly, their log differences 3–2=1 and 4–3=1 are the same.

Note that the values of x_1 and x_2 in Table 1 are fully symmetrical while the standard ratios x_1/x_2 and x_2/x_1 are not symmetrical at all. In the ratio x_1/x_2, firms 1 and 2 appear as outliers and, in the ratio x_2/x_1, firms 6 and 7. In the ratio x_1/x_2, firms 4, 5, 6, and 7 are concentrated in the very short [0, 1] interval. In the ratio x_2/x_1 the same holds for firms 1, 2, 3, and 4.

Conversely, the logarithms of the ratios $\log_{10}(x_2/x_1)$ and $\log_{10}(x_1/x_2)$ are fully symmetrical, have no outliers, and permutation of numerator and denominator only leads to a sign reversal.

Table 1. Toy example with seven firms showing the symmetry of log-ratios and the asymmetry of standard ratios

Firm	x_1	x_2	x_2/x_1	x_1/x_2	$\log_{10}(x_1)$	$\log_{10}(x_2)$	$\log_{10}(x_2/x_1)$	$\log_{10}(x_1/x_2)$
1	1,000,000	1	0.000001	1,000,000	6	0	–6	6
2	100,000	10	0.0001	10,000	5	1	–4	4
3	10,000	100	0.01	100	4	2	–2	2
4	1,000	1,000	1	1	3	3	0	0
5	100	10,000	100	0.01	2	4	2	–2
6	10	100,000	10,000	0.0001	1	5	4	–4
7	1	1,000,000	1,000,000	0.000001	0	6	6	–6

Natural logarithms (to base e=2.718281828…) represented as $\log(x)$ are commoner in economics, finance, and CoDa but any base could be used without affecting the analysis.

Some plr between pairs of accounting figures are especially interesting in DuPont analysis. By definition, turnover compares revenues and assets:

$$y_1 = \log\left(\frac{x_1}{x_4}\right). \tag{9}$$

As shown in Equation (2), comparing revenues and costs provides a notion of margin:

$$y_2 = \log\left(\frac{x_1}{x_2}\right). \tag{10}$$

In the same vein, comparing liabilities and assets provides a notion of leverage. Even if it does not correspond with the standard leverage definition in Equation (5), higher liabilities with respect to assets do imply higher leverage:

$$y_3 = \log\left(\frac{x_3}{x_4}\right). \tag{11}$$

The inversion of leverage as a solvency indicator can indeed be performed, but it is just the original leverage indicator with a reversed sign $-y_3 = \log(x_4/x_3)$.

Potentially, $D(D\text{-}1)/2$ different plr can be computed, although some of them may fail to have any financial interpretation or theoretical interest, ratio choice becoming a potentially problematic issue. Great care must also be taken to prevent ratios from being mutually redundant, meaning that the information of some ratios is already contained in other (Barnes, 1987; Chen and Shimerda, 1981; Magrini, 2025; Pohlman and Hollinger, 1981). For instance, in the above example, through simple algebra it can be shown that a plr computed as the ability of revenues to pay for liabilities $y_4 = \log(x_1/x_3)$ is equal to $y_1 - y_3$:

$$\begin{aligned} y_1 - y_3 &= \log\left(\frac{x_1}{x_4}\right) - \log\left(\frac{x_3}{x_4}\right) = \log(x_1) - \log(x_4) - \left(\log(x_3) - \log(x_4)\right) = \\ &\log(x_1) - \log(x_3) = \log\left(\frac{x_1}{x_3}\right) = y_4. \end{aligned} \tag{12}$$

Greenacre (2019); and Creixans-Tenas et al. (2919) recommend drawing a graph in which the accounting figures are *vertices* (*nodes*), and the plr are *connections* (*edges*). In order to prevent redundancy, the graph must necessarily be connected and acyclic. This means that:

- It is possible to join any two accounting figures following the connections (i.e., the plr).
- There may not be closed circuits, that is, there is only one possible path to join any two accounting figures.

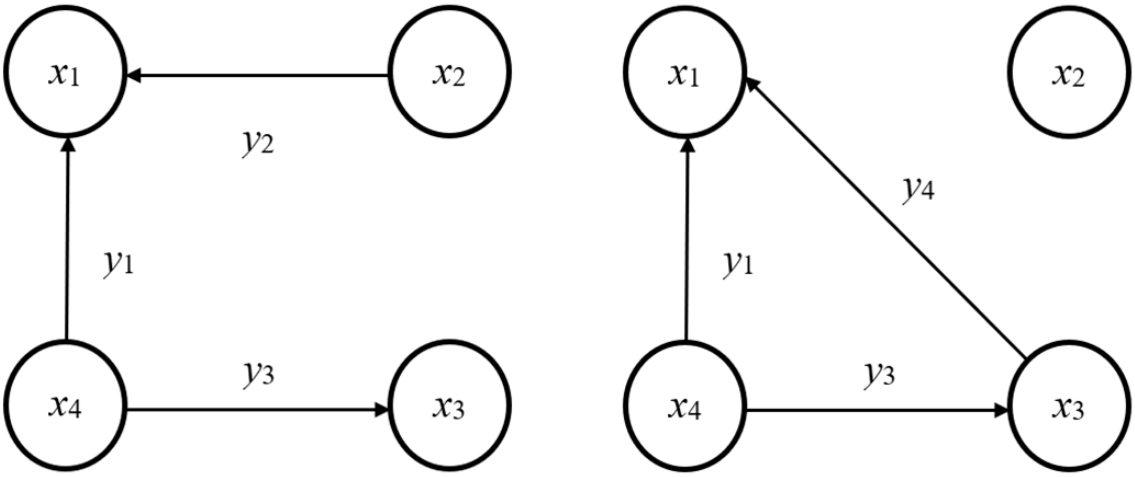
An acyclic connected graph has exactly $D-1$ plr (Greenacre, 2019). D-1 plr so chosen can be proven to contain all information about the D-part compositional dataset, in other words all information about the relative importance of the D accounting figures.

While any graph fulfilling these conditions will do the job, statistically speaking, it is good practice to use a graph based on expert knowledge on the interpretation of the ratios. In our DuPont analysis case, we want plr to be related to the concepts of turnover, margin and leverage, namely y_1, y_2 and y_3, which fortunately fulfil the conditions according to

the connected acyclic graph in the left panel of Figure 2. Edges can be drawn as arrows without affecting the graph properties, the arrows pointing at the numerator of the plr for clarification purposes only. In other words, accounting figures are considered joined even when going against the arrow directions.

As an example of inappropriate plr choice, when substituting $y_4 = \log(x_1/x_3)$ in Equation (12) for y_2, there would be a cycle connecting x_1, x_3 and x_4 (in other words, one could go from x_1 to x_3 either directly or through x_4) while x_2 would not be connected to any of the other parts (right panel in Figure 2).

Figure 2. Connected acyclic graph (left). Unconnected cyclic graph (right)



Users must be warned that there may be more than one way to choose a sensible set of D-1 interpretable and non-redundant plr, and the results of some statistical analyses which are based on distances (e.g., biplots and principal component analysis as used in Section 5) depend on this choice (Hron et al., 2021). These methods require alternative log-ratios, as shown in Section 3.2. Conversely, plr are appropriate for statistical inference (Section 6).

3.2. Centred log-ratios

Centred log-ratios -clr- (Aitchison, 1983) dispense with log-ratio choice and also contain all information about the relative importance of D accounting figures. clr compare each part, in the numerator, with the *geometric mean* of all parts for each individual firm, in the denominator:

$$
\begin{aligned}
clr_1 &= \log\left(\frac{x_1}{\sqrt[4]{x_1x_2x_3x_4}}\right) \\
clr_2 &= \log\left(\frac{x_2}{\sqrt[4]{x_1x_2x_3x_4}}\right) \\
clr_3 &= \log\left(\frac{x_3}{\sqrt[4]{x_1x_2x_3x_4}}\right) \\
clr_4 &= \log\left(\frac{x_4}{\sqrt[4]{x_1x_2x_3x_4}}\right).
\end{aligned}
\tag{13}
$$

All possible plr are contained in the clr. As an example, note how y_1 can be obtained from clr_1 and clr_4 by just subtracting them:

$$
\begin{aligned}
&clr_1 - clr_4 = \log\left(\frac{x_1}{\sqrt[4]{x_1x_2x_3x_4}}\right) - \log\left(\frac{x_4}{\sqrt[4]{x_1x_2x_3x_4}}\right) = \\
&\log(x_1) - \log\left(\sqrt[4]{x_1x_2x_3x_4}\right) - \left(\log(x_4) - \log\left(\sqrt[4]{x_1x_2x_3x_4}\right)\right) = \\
&\log(x_1) - \log(x_4) = \log\left(\frac{x_1}{x_4}\right) = y_1.
\end{aligned}
\tag{14}
$$

The clr have no accounting interpretation in themselves, but they are used as raw data in multivariate descriptive analysis methods such as principal component analysis and biplots, as shown in Section 5, while the interpretation is made in terms of plr.

3.3. Zero replacement

A commonly mentioned limitation of CoDa is that the accounting figures of interest may contain no zero values for log-ratios to be computed (Martín-Fernández et al., 2011). However, a fact that is often overlooked is that exactly the same holds for standard financial ratios: a zero accounting figure is not relative to anything and thus the ratio is not a feasible operation according to measurement theory (Stevens, 1946). The ratio is used to measure how many times a magnitude contains another, and this has no answer when one of the magnitudes is zero. If the zero value is the denominator, the standard ratio cannot even be computed.

Unlike the case in standard financial ratio analysis, CoDa include an advanced toolbox for *zero imputation* (a.k.a. *zero replacement*) prior to log-ratio computation under the most common assumptions (Martín Fernández et al., 2012). This provides CoDa with a head advantage compared to standard financial ratio analysis in the presence of zeros and ultimately makes financial statement analysis possible even when some accounting figures of interest equal zero. Shortly stated, zeros are replaced with a meaningful small value following certain statistical properties. See Mariadassou and Coenders (2025); and Coenders et al. (2023b) for recent reviews on the topic.

In the reviewed literature of compositional financial statement analysis, the most popular imputation method by far is the *log-ratio Expectation-Maximization* (*EM*) *method* (Palarea-Albaladejo and Martín-Fernández, 2008). This method is similar to the standard EM method for imputing missing data, as the imputed value is predicted from the available values with a statistical model. However, in the compositional case it adds the restriction that the imputed values must be "small". In particular, they are constrained to be below the minimum observed value of each part or below any other value specified by the user, called *detection limit*.

User-defined detection limits are particularly useful in the following case. If the minimum non-zero value corresponds to a firm with a very low figure, replacement below this limit could cause replaced values to be outliers. In this case, we recommend setting the detection limit to be a bit higher.

The zero imputation methodologies require the number of zero values to be small, ideally below 20 % for any of the accounting figures (Palarea-Albaladejo and Martín-Fernández, 2008). Before imputation, percentages of zeros should thus be examined. This may impede dividing assets and liabilities into very detailed accounts, such as buildings, trade names, inventory, accounts receivable, marketable securities, accounts payable, short-term loans, bonds, long-term loans, capital leases, and so on, some of which are zero for a large portion of firms, especially if the sample contains small and medium enterprises.

In other words, the choice of the number and detail of the D accounting figures has to be subject to the presence of zeros. If some accounting figures contain more than 20 % zeros, the user may want to sum them with other conceptually similar accounting figures with fewer zeros and thus reduce D. These aggregations are called amalgamations in the CoDa literature.

Related to the zero problem, inactive firms, as revealed by having zero revenues and/or zero assets should be removed from the dataset. If firms are inactive, they just do not belong to the study population, and it makes no sense to replace their missing accounting information with any sort of meaningful small value (just imagine what margin or turnover would look like with revenues or assets replaced with very small values). This situation is called *essential zeros*, *structural zeros*, *absolute zeros* or *true zeros* in the CoDa literature.

4. Example data

The financial statements in this example were obtained from the SABI (Iberian Balance sheet Analysis System, accessible at https://sabi.bvdinfo.com/) database, developed by *INFORMA D&B* in collaboration with *Bureau Van Dijk*. Search criteria were wine producers in Spain (NACE Rev.2 classification code 11.02 "manufacture of wine from grape") with available data for 2016. Inactive firms with zero revenues and/or zero assets were removed from the dataset. The final sample size after filtering inactive firms was n=109 and there were no remaining zero values. When using few and broad account categories as in DuPont analysis, zeros are rarely a problem (Saus-Sala et al., 2021; 2023).

In addition to x_1 to x_4, we consider the qualitative variable indicating if the firm sells at least some products using its own brand. This indicator is of especial interest, since it

reflects two winery business models which have deep implications. Firms without brands tend to sell non-bottled young wines at lower prices, while branded wines tend to be aged and expensive. Thus, firms without brands tend to have lower margins but higher turnovers and firms with brands the opposed characteristics. They constitute two *strategic groups* pursuing high return on equity through two different means. This dataset was also used in Linares-Mustarós et al. (2022); Coenders and Arimany-Serrat (2023); and Coenders (2025).

All analyses were carried out with CoDaPack2.03.10 (Comas-Cufí and Thió-Henestrosa, 2011; Thió-Henestrosa and Martín-Fernández, 2005), a menu-driven freeware available at https://ima.udg.edu/codapack/ .

The *boxplot* is an exploratory graphical display showing the division of firms into four equal-sized groups. Below the box there are 25 % of firms with the lowest values. Above the box there are 25 % of firms with the highest values. The line dividing the box is the median. Half of the firms have values below and above the median and also half of the firms have values within the box edges. Outliers are identified as separate points and the overall appearance of the boxplot tells about symmetry.

As reported in the reviewed literature, plr and clr (Figures 4 and 5) tend to be better behaved than standard ratios (Figure 3) in terms of asymmetry and outliers. In our example, the standard leverage ratio has one especially extreme outlier and strong asymmetry. The standard turnover ratio has strong asymmetry. Neither plr nor clr exhibit strong asymmetry or any extreme outlier. Moderate outliers are usually not harmful to the results of statistical analysis. Extreme outliers are.

Figure 3. Boxplots of standard ratios in Equations (3) to (5) showing extreme asymmetry and extreme outliers

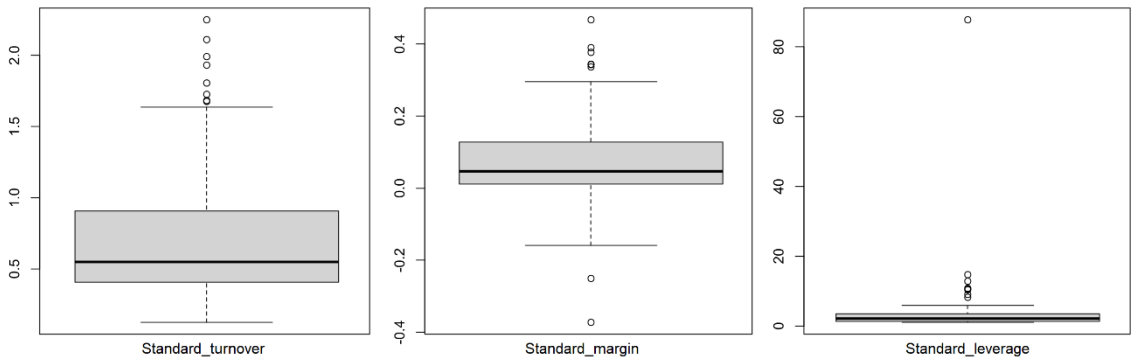


Figure 4. Boxplots of plr in Equations (9) to (11) showing at most mild asymmetry and few and non-extreme outliers

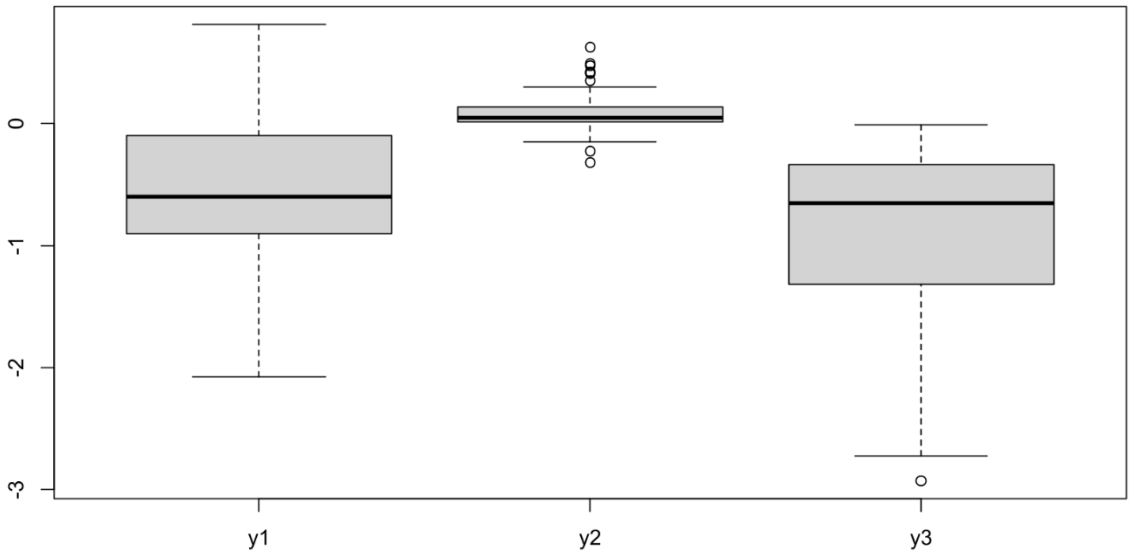
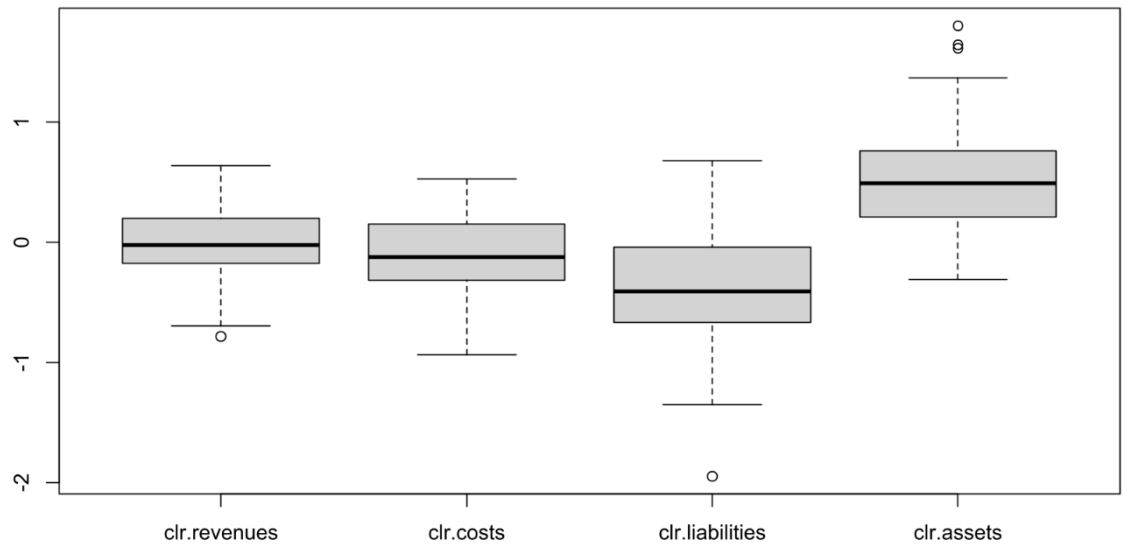


Figure 5. Boxplots of clr in Equation (13) labelled according to the accounting category in the numerator showing at most mild asymmetry and few and non-extreme outliers



5. Visualisation of ratios and individual firms with the CoDa biplot

Beyond simple graphics of one or two variables, multivariate visualization tools help researchers interpret large data tables with many firms and parts in just one graph. To this end, Aitchison (1983) extended the well-known *principal component analysis* procedure to the compositional case by using the *D* clr in Equation (13). A compositional principal component analysis computes a small number of uncorrelated dimensions, which explain the highest possible portion of the variances of all clr. In this way the original data set with potentially many clr can be summarized with just a few dimensions which are suitable for a graphical display.

The two first dimensions are represented in the so-called covariance *CoDa biplot* (Aitchison and Greenacre, 2002), which can be understood as the most accurate graphical representation of a compositional data set in two dimensions. The goodness of fit is indicated by the percentage of explained variance of the clr by the first two dimensions. In our example, the percentage of explained variance is very high at 99.0 % thus arguing for an extremely good biplot accuracy. Percentages above 70 % are considered acceptable, above 80 % good and above 90 % very good.

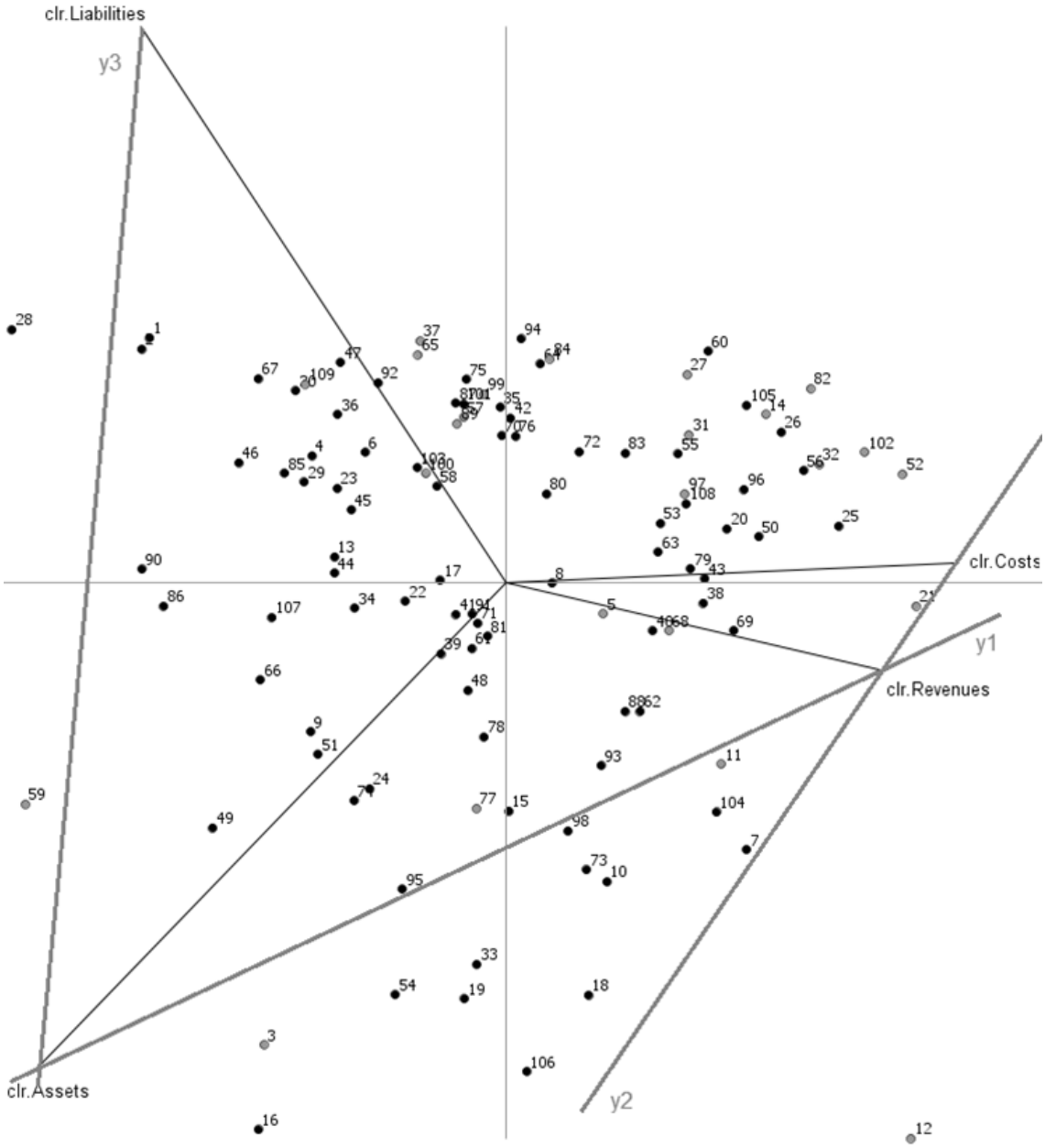
The CoDa biplot for financial statement data plots each clr representing the accounting figure in the numerator as a line called *ray*. Individual firms appear as points. Carreras-Simó and Coenders (2020); and Saus-Sala et al. (2021; 2023) highlight the most important interpretational tool of the CoDa biplot in financial statement analysis. Additional lines can be drawn linking the extremes of a pair of rays and representing the plr between the corresponding two accounting figures of the numerators of the clr. These additional lines are called *links*. The *orthogonal projection* of all firms along the direction defined by the link shows an approximate ordering of firms according to the plr between the corresponding two accounting figures. The orthogonal projection is made by dropping firms on the link in such a way that the direction in which the firms fall forms a 90-degree angle with the link.

In this way, the CoDa biplot is also a visual representation of any of the $D(D\text{-}1)/2$ possible financial ratios computed from any two accounting figures. The user can draw as many links as he or she wishes. Since the analysis is anyway run on clr, redundancy is not a problem, although only long links showing high variance plr tend to lead to informative directions. Thus, plr should not be drawn when the links are very short, in other words, when the vertices of the rays are close together.

The ability to visually interpret ratios between any two accounting figures is of great interest in financial statement analysis as it allows researchers to quickly identify the financial profile of individual firms (Carreras-Simó and Coenders, 2020; Coenders, 2025; Coenders and Arimany-Serrat, 2025; Rondós-Casas et al., 2026; Saus-Sala et al., 2021; 2023). The y_1 line representing turnover links the vertices of revenues and assets in Figure 6. Firms situated at the top and to the right (in the high-revenue side of the link) are the ones with the highest turnover. Firms situated at the bottom and to the left (in the high-asset side of the link) are the ones with the lowest turnover. The y_2 line representing margin links the vertices of revenues and costs. Firms situated at the bottom and to the left are the ones with the highest margin and firms situated at the top and to the right are the ones with the lowest margin. The y_3 line representing leverage links liabilities and assets. Firms at the top of the biplot are the most leveraged.

When firms are dropped forming a 90-degree angle on each of the y_1, y_2 and y_3 lines, firm 16 has the highest orthogonal projection on y_2 and the lowest on y_3. Thus, it is a firm with a very high margin and a very low leverage. Firm 59 has a very low turnover and firm 52 has a very high turnover. As a whole, firms without a brand (marked as grey) have a comparatively lower margin, higher leverage and higher turnover than firms with a brand (marked as black). The closest firms to the origin of coordinates (industry average) are 8, 17, 41, 71, 81 and 91.

Figure 6. CoDa biplot with added turnover (y1) margin (y2) and leverage (y3) directions. Firms with an own brand in black, without in grey. Firms can be projected on the y1, y2 and y3 directions



6. Statistical inference by groups of firms

Up to now we have dealt with descriptive statistical methods. This section is devoted to statistical inference and testing with the aim of drawing conclusions about the population from which the sample of firms was drawn. To this end, compositional financial ratios act as variables in any statistical model or test together with any firm characteristic. clr are not directly interpretable, while in statistical testing the interpretation of the included variables is a crucial issue, which makes plr a preferable option.

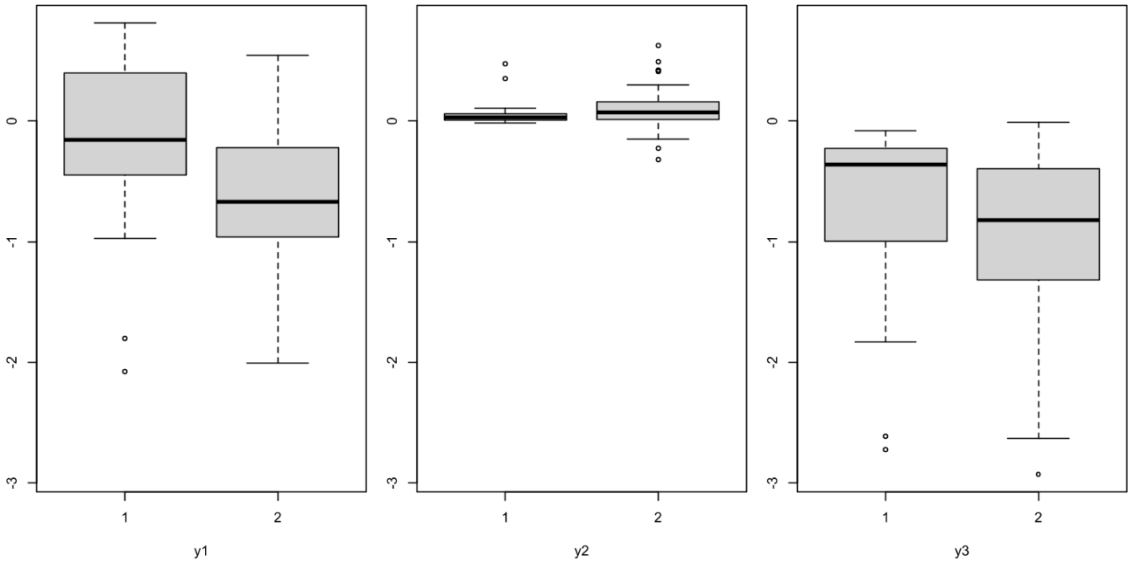
We consider the simplest possible case in which we want to test the equality of the plr between two groups of firms having or not an own brand (Linares-Mustarós et al., 2022;

Coenders et al., 2023a). Before testing, some graphical display relating the plr with the groups is very useful. According to the boxplots (Figure 7) firms with a brand have higher margin (y_2) but lower turnover (y_1) and lower leverage (y_3) in the sample. Testing will then refer to the population differences, if any.

The following statistical hypothesis is tested for each plr indicating that firms without (1) and with (2) a brand brand have the same population average plr (μ):

H_0: $\mu_1=\mu_2=0$

Figure 7. Boxplots of turnover (y1) margin (y2) and leverage (y3), for wineries without (1) and with (2) their own brand showing sample differences between groups



The *p-value* associated to each statistical hypothesis indicates the risk involved in rejecting the hypothesis. If it is low (e.g., lower than 0.05), the hypothesis can be rejected with the conclusion that the averages of the plr at hand differ significantly in the population. The test used is the well-known *t-test for two independent samples*:

$$t = \frac{\overline{x}_2 - \overline{x}_1}{\sqrt{\frac{(n_1-1)s_1^2 + (n_2-1)s_2^2}{n_1+n_2-2}}\sqrt{\frac{1}{n_1}+\frac{1}{n_2}}} \qquad (15)$$

where $\overline{x}$ s^2 and n stand for the sample mean, variance, and number of sample cases for firms without (1) and with (2) a brand.

Table 2. Independent sample t-test results

	$\overline{x}_2 - \overline{x}_1$	t	p-value
y_1 (turnover plr)	–0.409	–2.922	0.004
y_2 (margin plr)	0.037	1.178	0.241
y_3 (leverage plr)	–0.214	–1.335	0.185
$-y_3$ (permuted leverage plr)	0.214	1.335	0.185
Standard leverage ratio in Equation (5)	-0.791	-0.401	0.689
Permuted standard leverage ratio: solvency in Equation (8)	0.126	2.163	0.033

In the three first rows of Table 2, the p-values indicate that only turnover is significantly different for firms with and without brand (0.004 < 0.05). The negative sign of $\overline{x}_2 - \overline{x}_1$ indicates that firm with an own brand (2) have a lower turnover than firms without a brand. As expected, when permuting the numerator and denominator of y_3, the results are the same with a reversed sign. On the contrary, when doing the analysis on standard financial ratios, permutation does make a difference. When using the standard leverage ratio in Equation (5) no differences can be established between groups (p-value = 0.689 > 0.05), and when using the standard solvency ratio in Equation (8) firms with a brand have higher solvency, i.e., lower leverage (p-value = 0.033 < 0.05, positive sign of $\overline{x}_2 - \overline{x}_1$). In any case, these results on the standard ratios are suspect due to the extreme outliers in Figure 3. Linares-Mustarós et al. (2022); and Coenders et al. (2023a) obtained similar results.

7. Concluding remarks

7.1. Extensions and future perspectives in accounting research

Compositional Data (CoDa) can be used to advantage to distil the relative magnitude of accounting figures, which lies at the ground of researchers' and professionals' interests when computing financial ratios. CoDa solve the main drawbacks of standard financial ratios in statistical analysis, such as the extreme skewness and outliers shown in Figure 3, and the dependence of the results on the arbitrary permutation of numerator and denominator shown in Table 2. Over ten years, the accounting community has learnt that the violations of the assumptions of standard ratios can be severe, and that the improved CoDa methodology leads to results that are different enough to modify (for the better) the main conclusions of applied research. In this respect, the CoDa approach represents a vast improvement in applied accounting research using statistical methods on financial ratios. We can only encourage its widespread adoption, which should neither affect the researchers' objectives nor their statistical tastes.

Classical multivariate analysis tools can be used on CoDa after transforming the data by means of clr. In particular, the principal-component-analysis biplot visualizes all firms with respect to the ratio of any pair of accounting figures. The biplot can immediately be extended to panel data to plot trajectories of individual firms over time (Saus-Sala et al., 2023). Simple statistical inference is also possible by means of $D-1$ plr. plr can also play the role of dependent or explanatory variables in a linear regression model (Coenders and Arimany-Serrat, 2023; 2025; Farreras-Noguer et al., 2025; Mulet-Forteza et al., 2024)

and in other statistical models (Creixans-Tenas et al., 2019).

The reviewed applications in Section 1 show a variety of fields of study and research questions. The CoDa Methodology can potentially be applied to any research project which uses a statistical sample of firms and some of the variables of interest are financial ratios. The population of interest may be any industry or meaningful group of industries, or any other firm category of interest (by region, size, societal type, etc.).

Any positive non-overlapping accounting figures may be used to define any set of ratios, beyond the very simple DuPont-analysis case (Saus-Sala et al., 2021; 2023). For instance, current and non-current assets could have been used instead of total assets, and current and non-current liabilities could have been used instead of total liabilities bringing the number of accounting figures D to 6. This would have made it possible to define ratios of asset structure (non-current over current assets), debt maturity (non-current over current liabilities), and short-term solvency (current assets over current liabilities). See Arimany-Serrat and Coenders (2025); Arimany-Serrat et al. (2023); Coenders (2025); Creixans-Tenas et al. (2019); Dao et al. (2024); Hernandez-Romero and Coenders (2025); Jofre-Campuzano and Coenders (2022); and Saus-Sala et al. (2024). So far, the highest number of accounting figures found in the literature is D=14 (Carreras-Simó and Coenders, 2020).

To use accounting figures from other financial statements than the balance sheet and the income statement is also possible. Arimany-Serrat et al. (2022) extend the CoDa methods to the analysis of the cash-flow statement. It is also possible to include non-financial figures if they result into meaningful ratios. For instance, the number of employees appears in the average-wage ratio, the sales-per-employee ratio, the assets-per-employee ratio, and so on (Carreras-Simó and Coenders, 2020), and the number of rooms is a key variable to define management ratios in hotels (Mulet-Forteza et al., 2024). Another source of ratios is in the environmental, social and governance indicators. For instance, the ratio of energy consumption on revenues is defined as energy intensity and can be treated compositionally (Rondós-Casas et al., 2026; Todorov and Simonacci, 2020). Similar intensity ratios exist for water consumption, green-house gas emissions, waste generation, and so on.

CoDa is not needed when there is no substantial statistical analysis of a data sample. This includes case-study research, in which typically the evolution of key standard ratios is plotted over time for just one or two firms, and all qualitative research paradigms. It is not either needed to monitor the performance of one's own firm. However, CoDa is necessary to compute reliable means of the ratios at the industry level. So, comparing one's own firm to the industry average requires industry averages to be properly computed (Hernandez-Romero and Coenders, 2025; Saus-Sala et al., 2021). CoDa is not needed either when using statistical methods that are robust to extreme asymmetry and outliers, which incudes but is not limited to certain non-parametric methods (Iotti et al., 2023; 2024a; 2024b; 2024c).

There are of course interpretational trade-offs. Standard ratios have a simpler interpretation. This has indeed been a matter of concern. To this end, most cluster analysis applications back-transform compositional cluster means into standard ratios (Arimany-Serrat and Coenders, 2025; Arimany-Serrat and Sgorla, 2024; Coenders, 2025; Coenders and Arimany-Serrat, 2023; 2025; Dao et al., 2024; Hernandez-Romero and Coenders,

2025; Jofre-Campuzano and Coenders, 2022; Saus-Sala et al., 2021; 2023; 2024). The same is done when computing ratio averages at industry level (Arimany-Serrat and Coenders, 2025; Arimany-Serrat and Sgorla, 2024). In statistical modelling, the researchers' interests may lie in statistical testing, for which purpose the matter is irrelevant, or in the estimation of effect sizes, for which purpose it is very relevant. Farreras-Noguer et al. (2026) show how to interpret CoDa effect sizes in terms of standard ratios. A promising development is the computation of logarithms to base 2. Increasing the log-ratio by one unit is tantamount to doubling the standard ratio (Müller et al., 2018). Elasticities can also be used to advantage in the interpretation of log-ratio effects (Coenders et al., 2025).

7.2. Current methodological debates, potential application difficulties and challenges for further research

A current methodological debate in financial-ratio application is the choice of log-ratio transformation. Apart from plr and clr, another log-ratio transformation is also common in the applied works cited -ilr- (Egozcue et al., 2003; Egozcue and Pawlowsky-Glahn, 2005). There is not much to choose from in distance-based methods such as cluster analysis, but ilr are a powerful alternative to plr in statistical modelling. In most cases, rather than being a technical matter, the choice depends on the researcher's favourite way to interpret the results. Ilr have been used in Carreras-Simó and Coenders (2021); Escaramís and Arbussà (2025); and Magrini (2025). Coenders and Arimany-Serrat (2023) compare plr and ilr in practice. In this article we have chosen to present plr for their greater simplicity.

Another current debate is the role of weights. In financial applications of CoDa methods, they have so far only been assessed on cluster analysis (Dao et al., 2024; Jofre-Campuzano and Coenders, 2022) with substantial improvements on the interpretability of the results. They have potential for other distance-based methods such as biplots. This is a promising avenue for further research.

The main obstacle to the practical applicability of ratios (be they standard or compositional) is the presence of zeros. As stated in section 3.3, a too detailed subdivision into a large number D of accounting figures may not be advisable on the grounds of large percentages of zeros, especially if the sample contains small firms. From the experience in the reviewed literature, D=4 as used in the examples here is fine even when the sample contains micro enterprises. D=6, as defined above, is fine for small firms, and D>6 should be used for medium to large firms only.

Some statistical methods have been used only rarely in conjunction with CoDa, or not at all. This includes penalized regression (Saperas-Riera et al., 2024), Bayesian computation (Coenders et al, 2025), and many recent machine learning methods, which are becoming popular in financial forecasting problems with standard ratios (Martin-Melero et al, 2025). For some of these methods neither plr, clr or ilr may be the best transformation, which is also a promising avenue for further research.

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AUTHOR CONTRIBUTIONS

Conceptualization: NAS and GC; methodology: GC; formal analysis: GC; data curation: NAS; writing - original draft: GC; writing - review & editing: NAS; Supervision: NAS; funding acquisition: GC.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY

The data are available in Coenders and Arimany-Serrat (2023).

USE OF ARTIFICIAL INTELLIGENCE (AI)

AI tools were not used in any part of the article.

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Subsidies and financial performance in the rural tourism sector

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ABSTRACT

In 2023, the World Tourism Organisation stated that rural tourism in member states faces the challenge of improving rural infrastructure, overcoming depopulation and seasonality, and enhancing competitiveness, while providing the necessary knowledge for rural development. Rural tourism receives international, national, and local subsidies, as it is an essential sector for sustainable development and the implementation of the SDGs of the 2030 Agenda. Moreover, it contributes to reducing rural depopulation and provides complementary income to the primary sector. This research assesses the sector's financial performance and the relationship between subsidies and said performance. The data used in the study were obtained from the SABI - Bureau van Dijk database and correspond to the period 2018–2022. A set of robust financial ratios was derived using compositional data analysis as representative indicators of the companies' financial performance. The importance of subsidies was examined through regression models. Although it is not uniform across all ratios, companies that received subsidies exceeding 25 % of their total

assets show higher turnover, a more tangible asset structure, and longer debt maturity. These factors support the sector's financial health and, in turn, firm survival.

KEYWORDS
CoDa, log-ratios, margin, turnover, leverage, ROE, SABI

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1. Introduction

Rural tourism was born in Spain in the middle of the last century, as an activity that supports the agricultural sector. At that time the government already aided this activity through the Ministry of Agriculture and the Ministry of Information and Tourism to avoid the depopulation of rural areas (Cànoves *et al*., 2004). Subsequently, with tourism planning, the autonomous communities have competences in tourism management, and specifically in the management of rural tourism, and this sector is growing at different rates throughout Spain.

The rural tourism sector receives international, national and local subsidies to ensure firm survival (Galluzzo, 2021), as it is an essential sector for sustainable development and the implementation of the Sustainable Development Goals (SDGs) of the 2030 Agenda (Barba Bayas & Morales Noriega, 2019). Furthermore, it helps to reduce rural depopulation and also helps the primary sector get better profitability (Cànoves *et al.,* 2004).

Subsidies to the sector have been present from 1962 to the present day, specifically from the "Vacaciones en casas de Labranza" (Spain) grants to the current Next Generation Funds of the European Union (EU), through various subsidies, such as the CAP (Common Agricultural Policy), LEADER (Liaison Entre Actions de Développement de l'Économie Rurale), INTERREG Europe (Programme for Interregional Cooperation) and PRODER (Operational Programme for the Development and Economic Diversification of Rural Areas in the Regions).

Since the beginning of the integration of the EU, the CAP, created in 1962, until the current CAP 2023-2027, continues to promote the agricultural and rural tourism sector, with subsidies derived from the EU policy. On the other hand, the LEADER programme created by the EU in 1989, provides subsidies from the European Agricultural Fund for Rural Development (EAFRD), to rehabilitate buildings and digitalise these businesses (Abellán, 2003), which are extended with subsidies from the European Regional Development Fund (ERDF) and the European Social Fund (ESF).

Regarding the INTERREG Europe programme of 1990, there are also EU subsidies to

reduce the differences between the regions of Europe, which go to local, regional and national governments throughout Europe. Since 2014, new cross-border cooperation programmes have appeared that help to promote sustainable tourism with sustainable economic development criteria, such as the INTERREG Euro-MED programmes, which encourage cooperation across the borders of the Mediterranean. Specifically, the INTERREG POCTEFA is a programme that promotes the sustainable development of the border territory between Spain, France and Andorra. The aim of the INTERREG SUDOE programme is to preserve the natural capital of south-west Europe and its adaptation to climate change, as well as to strengthen social cohesion and territorial and demographic balance.

From 1996 to 2006, the PRODER programme aims to develop the rural environment, by strengthening and diversifying its economy, maintaining the population, increasing the income and social welfare of the inhabitants, as well as preserving space and natural resources.

In short, all the grants highlight the strategic importance of the rural tourism sector and indicate that the subsidies granted contribute to the survival of firms in the sector.

The aim of this research is to assess the sector's financial performance and its relationship with subsidies. The research evaluates subsidies derived from public policies, used to reduce the “Spain of poverty” by means of rural tourism, in order to favour the primary sector and the GDP of the rural areas. Therefore, the study is relevant to assess the usefulness of public administration subsidies that support the rural tourism sector.

Conceptually, subsidies may affect firms through (i) investment additionality and balance-sheet reallocation toward non-current assets, (ii) maturity matching in financing long-lived investments, and (iii) the alleviation of financing constraints, with potentially ambiguous short-run effects on operating performance.

The article analyses the financial performance of the sector, according to the subsidies received, the size and age of the companies in the sample under study and various financial indicators. Performance is measured as the companies’ short-term solvency, debt maturity, margin, turnover, and asset tangibility using the Compositional Data (CoDa) methodology (Coenders & Arimany-Serrat, 2025a), to achieve statistically reliable results and to make better financial decisions possible.

Building on this conceptual framing, we state research questions and hypotheses for five CoDa log-ratio dimensions linking subsidy intensity to operating activity, profitability, short-term solvency, asset tangibility, and debt maturity. The empirical analysis estimates associations consistent (or not) with these expectations.

After the introduction, the literature review is presented, followed by the methodological part, in order to highlight the results obtained, and, finally, to discuss the research strengths and weaknesses and draw conclusions.

2. Theoretical framework

The theoretical framework of this study is based on the characterisation of the rural

tourism sector, followed by a detailed review of the academic literature on this sector of activity, with emphasis on official subsidies, the firms' financial health, and actions to exploit their potential and ensure their survival. It should be borne in mind that in the Spanish case, the rural tourism sector is growing, with differences according to the autonomous communities.

The theoretical framework and literature review argue for the need to support rural tourism, with different subsidies to address rehabilitation, digitisation and the fulfilment of environmental, social and governance (ESG) criteria according to established standards, for the continuity of a sector that promotes agriculture and the repopulation of rural areas.

2.1. Relevance of the rural tourism sector

The World Tourism Organisation (UNWTO) in 2023 asserts that the situation of rural tourism in member states has the challenge of improving the infrastructures of rural areas, to overcome rural depopulation, reduce seasonality, and improve the competitiveness of the rural sector, providing the necessary knowledge for rural development (Hitchins *et al.*, 2005).

Other important challenges for the rural tourism sector are focused on accessing funding to rehabilitate property and innovate in this sector, striving to conserve the natural resources of rural areas and advancing in digitisation (Chengcai *et al*., 2024; Wibisono *et al*., 2024). Therefore, it is a typology of tourism with potential to promote the SDGs. With regard to this boost, the UNWTO highlights the potential of rural tourism to contribute to SDG 8 (decent work and economic growth) and SDG 1 (no poverty). The indicators of rural tourism market penetration and frequency are growing by 2024 and the diversity of experiences in rural tourism makes it easier to receive visitors at different times of the year, attracting visitors to agricultural, cultural, gastronomic, and wine tourism activities, among others (Dudziak *et al.*, 2017; Vysochan *et al*., 2022; Wartini *et al*., 2022; Stanciu *et al*., 2023).

Rural tourism is a growing sector that affects the local population, local suppliers, local authorities and in general the whole geographical area where the rural tourism activity takes place, as it involves local development, preserves traditions, respects the environment, preserves agriculture and offers tourists an experience that provides well-being (Tu & Long, 2017; Van der Ploeg *et al*., 2017; Giaccio *et al*., 2018; Liu *et al*., 2020).

The development of rural tourism has become one of the main forces to promote rural reconstruction (Tu & Long, 2017; Shen *et al*., 2019). There are different types of rural tourism, such as ecotourism, nature tourism, adventure tourism, agro-tourism, gastronomic tourism and educational tourism, among others, and several studies point out the projection of these types of tourism (Dudziak *et al*., 2017; Siddiqui *et al*., 2021; Wartini *et al*., 2022; Vysochan *et al*., 2022; Stanciu *et al*., 2023).

It is therefore a growing sector, which benefits from official subsidies at international, European, national and local levels (Fotiadis *et al*., 2019; Fleischer & Felsenstein, 2000; Khatua & Panda, 2024). These official subsidies are of different types: those of the CAP,

for farmers; the subsidies of the LEADER programme, for small rural villages that rehabilitate rural tourism lodgings, while respecting the environment (Galluzzo, 2020), and the Next Generation EU subsidies for rural tourism to promote sustainability and modernise the sector, with more energy efficiency and circular economy in lodgings (e.g., installing solar photovoltaic panels in rural areas, waste management and reuse systems). Rural tourism has received various European, national and local public subsidies to revitalise rural areas, improve the environment and sustainable development, and prevent the depopulation of these areas by diversifying sources of income (Roberts *et al*., 2017; Calatayud Prats, 2021). Furthermore, rural tourism promotes the role of women, due to their empowerment and dynamism in the sector (Nicolas Martinez *et al*., 2021). In other words, rural tourism is characterised by its diversity, sustainability and ability to offer unique experiences in authentic and peaceful environments. It is a commitment to quality rather than quantity, and subsidies contribute positively to the development of less populated areas (Khatua & Panda, 2024).

It should be borne in mind that post-COVID-19 grants under the Next Generation EU programme have provided subsidies for digitisation and digital marketing, bringing customers and suppliers closer together, with greater knowledge of rural areas (Senyao & Ha, 2022). With subsidies, tourism destinations and their impact on rural areas have become more visible, as in the case of LEADER subsidies (Yubero & Garcia, 2019), although not all municipalities are equally visible (Soler Vayà & San-Martín González, 2023).

Depopulation and socio-demographic transformations in different rural territories (Spain, Italy and France) show that all municipalities have had at least one LEADER and/or PRODER project, but also that there are large inequalities in the number of projects carried out, and in their employment (Maroto Martos & Pinos Navarrete, 2019).

The survival of firms in the sector depends on the correct application and use of subsidies, as well as the digitisation and sustainability. It also involves analysing the sector at a financial level, using the CoDa methodology, in order to diagnose the financial health of the firms in the sector reliably, both from an accounting and a statistical perspective.

2.2. Subsidies received and success in rural tourism

Rural tourism has been the subject of growing interest in the strategy of economic diversification and territorial revitalization with diverse demographic and socioeconomic characteristics. Various studies agree in their assessment of public intervention, in the form of subsidies, investments, and specific programmes, which can act as catalysts for tourism development and the improvement of the living conditions of rural communities.

Internationally, research shows that subsidies provided to support rural tourism have a positive effect on rural incomes, contributing to consolidating the tourism sector as an alternative or complement to farming activity (Yang *et al.*, 2021). Furthermore, Khatua and Panda (2024) argue that subsidies can be key instruments for promoting sustainable tourism, if they comply with efficiency and sustainability criteria and maintain a balanced relationship between tourism development and environmental sustainability.

At the European level, the CAP and LEADER programmes have been expanded to contribute to rural tourism. According to the Network EUCAP (2023), advances in economic diversification have strengthened the resilience of tourism in rural areas, promoting initiatives linked to heritage, gastronomy, and cultural services. Increasingly, recent studies in the context of the EU (Castilho & Fuinhas, 2025) show that investment in tourism infrastructure and services can reduce poverty and territorial inequality, with variations between states and regions. Specifically, Ion and Petre (2024) show that the founding countries of the EU have the most developed rural tourism sector, with the most overnight stays in France, the most establishments in Italy, and the most employees in Germany. Bearing in mind that at the end of the 20th century, rural tourism was a key driver of these public LEADER initiatives, and all these initiatives have been considered successful, the funding has yielded mixed results. Specifically, in the Spanish case, there are studies that show that this funding focuses on factors such as investment concentration, accessibility to urban spaces, and natural resources in mountain areas that favour the sustainability of the tourism sector (Engelmo Moriche *et al.*, 2021), but there are also studies that highlight imbalances in the territories where this funding is implemented (Nieto Masot & Rios Rodríguez, 2020).

In the case of Catalonia, the academic literature evaluating the impact of the LEADER subsidies notes a significant increase in job creation in areas investing in rural tourism (Gras *et al.*, 2025). Furthermore, the Generalitat de Catalunya (Catalan Government) has promoted subsidy programmes for housing rehabilitation in rural and mountain areas, which have contributed to the professionalization and modernization of the sector (Generalitat de Catalunya, 2024). In the academic field, there is research that supports subsidies for rural regeneration, provided that cultural and natural capital is preserved (Colomina Wiegerinck, 2024). Thus, the development of rural tourism with government support generates new revenue for the sector and enables business development, especially in rural areas that are economically, geographically, and agriculturally developed (Li *et al.*, 2025).

Finally, it should be noted that local and provincial subsidies also play a relevant role in supporting rural tourism projects, especially in relation to the promotion of heritage and tourism infrastructure (Diputació de Girona, 2022). These interventions, together with European sources, create an ecosystem of public support that allows rural tourism to be strengthened in these areas, through the creation of jobs, which improve the tourist offer and the economic diversification of rural territories.

There are few studies of the profitability and solvency of firms in the rural tourism sector using accounting data (Saus-Sala *et al.*, 2021; 2023; 2024), the majority relying instead on questionnaire data. To the best of our knowledge, no study based on accounting data examines the impact of subsidies at company level in this sector.

2.3 Conceptual framework and theoretical expectations

Public subsidies in rural/farm tourism are typically intended to co-finance investments (e.g., renovation of the farm building, equipment, digitization) and to support business continuity and upgrading. This motivates a conceptual framework linking subsidy intensity to five dimensions of financial performance and structure: (i) operating activity (turnover), (ii) operating profitability (margin), (iii) short-term solvency, (iv) asset structure (tangibility), and (v) liability structure (debt maturity).

First, investment-oriented subsidies are expected to increase the relative weight of non-current (often tangible) assets, as subsidized projects translate into capital formation and balance-sheet reallocation toward long-lived assets. This channel is consistent with the *additionality* perspective in public support policies, which conceptualizes subsidies as instruments intended to stimulate incremental investment rather than merely replacing private funding (Winckler Andersen *et al.*, 2021).

Second, investment co-financing and maturity-matching considerations suggest that firms may finance long-lived investments with longer-maturity liabilities, increasing the relative weight of non-current liabilities. This logic aligns with standard *capital-structure frameworks* (pecking order and trade-off) and with the *debt-maturity* literature highlighting the link between asset structure and maturity choice (Myers, 1984; Myers & Majluf, 1984; Kraus & Litzenberger, 1973; Stohs & Mauer, 1996).

Third, effects on operating activity and profitability are *a priori* ambiguous. Quality upgrading and market access may raise revenues, while compliance and adjustment costs, additional fixed costs, and transition frictions may offset profitability gains, especially in the short run. A complementary lens is the *financing-constraints* literature: if subsidies relax liquidity/financing frictions, firms may invest and scale up, but performance effects may be heterogeneous across firms and time horizons (Fazzari *et al.*, 1988; Kaplan & Zingales, 1997).

Fourth, short-term solvency may also react ambiguously depending on whether subsidies translate into cash buffers and faster current-asset accumulation, or are accompanied by short-term payables and working-capital needs. Finally, from a *soft budget constraint* perspective, support can improve viability and stability without necessarily improving operating efficiency in the short run (Kornai, 1986).

Given limited firm-level accounting evidence in this niche setting, we use this conceptual framework to state *theory-informed expectations*, while maintaining an *associational interpretation* of the estimates.

Section 3.1 translates this framework into research questions and hypotheses, section 3.2. describes the data, and Sections 3.3. and 3.4 details the CoDa operationalization of the five dimensions.

3. Methods

3.1. Research questions and hypotheses

Guided by the framework, we address the following research questions:

RQ1 (Current-asset turnover / operating activity): Is subsidy intensity associated with operating activity, measured by the turnover dimension (as operationalized in Section 3.4)?

RQ2 (Margin / operating profitability): Is subsidy intensity associated with operating profitability, measured by the margin dimension (as operationalized in Section 3.4)?

RQ3 (Short-term solvency): Is subsidy intensity associated with short-term solvency (as operationalized in Section 3.4)?

RQ4 (Asset tangibility): Is subsidy intensity associated with asset structure (tangibility) (as operationalized in Section 3.4)?

RQ5 (Debt maturity): Is subsidy intensity associated with liability maturity structure (as operationalized in Section 3.4)?

Based on these research questions, we formulate the following hypotheses:

H1 (Turnover, non-directional): Subsidy intensity is associated with turnover, but the sign is a priori ambiguous.

H2 (Margin, non-directional): Subsidy intensity is associated with margin, with ambiguous sign.

H3 (Short-term solvency, non-directional): Subsidy intensity is associated with short-term solvency, with ambiguous sign.

H4 (Asset tangibility, directional): Subsidy intensity is positively associated with asset tangibility (higher relative weight of non-current assets versus current assets).

H5 (Debt maturity, directional): Subsidy intensity is positively associated with debt maturity (higher relative weight of non-current liabilities versus current liabilities).

3.2. Data

The data used in the study were obtained from the SABI - Bureau van Dijk database (accessible at https://sabi.bvdinfo.com/) and correspond to the financial years 2018-2022.

To select the Spanish companies that operate in the rural tourism sector we filtered the NACE codes: I55 - Accommodation or L68.2 - Renting and operating of own or leased real estate, having at the same time in the description of the company's activities the phrase "turismo rural", the Spanish translation of rural tourism, farm tourism and agrotourism. The search term was: (Phrase ("turismo rural")) AND (NACE(55,682)). The NACE I55 code includes: I55.1 - Hotels and similar accommodation; I55.2 - Holiday and other short-stay accommodation; I55.3 - Camping grounds, recreational vehicle parks and trailer parks; I55.9 - Other accommodation. The results were refined by removing inactive companies in 2022 (zero revenues, zero costs, or zero total assets. See Coenders & Arimany-Serrat, 2025b). After the filtering process, n = 348 companies were included in the study.

To compute the ratios of turnover, margin, short-term solvency, asset tangibility and debt maturity for the companies included in the study, we collected the following accounting figures: non-current assets, current assets, non-current liabilities, current liabilities, revenues, and costs. These data refer to 2022.

Given that this article focuses on the relevance of public policies, which turn into subsidies for the sector, we calculated the main explanatory variable as Level of subsidy = Subsidies received in the last five years over total assets. Apart from the subsidies received, as control variables, we have also collected the company age and the number of employees. 70 % of the companies had no subsidies. The firms with subsidies were categorized into two equal-sized groups (15 % of firms each) so as to maximize statistical power, which led to a subsidy threshold equal to 25 % of total assets to separate both categories. Subsidies refer to 2018-2022. The rest of the variables to 2022.

The explanatory and control variables were thus defined in the model as follows:

- level of subsidy: [>0 % to 25 % of assets], binary variable; level of subsidy [> 25 % of assets], binary variable. Reference category: no subsidy;
- company age: log-transformed strictly positive numeric variable in years (log(age));
- company size: log-transformed in number of employees: strictly positive numeric variable (log(size)).

As for the set of control variables included in the model, the decision not to include additional controls stems from the lack of available data. Accordingly, only age and size were included as control variables, due to the unavailability of other relevant information, such as destination quality or digitalization level.

3.3. A compositional data (CoDa) perspective on financial analysis

The CoDa methodology, which originated in the fields of geology and chemistry in the late 20th century to study the relative importance of components in a chemical analysis, has expanded into numerous scientific fields, including economics and management (Coenders & Arimany-Serrat, 2025b). However, its application to accounting ratios is relatively recent. Nevertheless, this is a natural field of application for CoDa, as the methodology is primarily associated with the study of relative magnitudes expressed as ratios. A composition is defined as an array of D strictly positive numbers, called *parts*, the ratios among which are of interest to the researcher (Egozcue & Pawlowsky-Glahn, 2019). It is worth noting that when financial ratios were first developed in the late 19th century (Horrigan, 1968), statistical analysis methods were still in their infancy, and these ratios were not designed for use in statistical analysis.

Accounting ratios are useful for assessing the financial and economic status of companies on an individual level. However, their use in statistical studies generates significant issues (Linares-Mustarós *et al.*, 2018). The construction of these ratios causes a loss of symmetry, which significantly distorts the results of financial diagnostics, especially in regression models (Coenders & Arimany-Serrat, 2025a).

Although asymmetry in accounting ratios has been identified as a problem for some time (Deakin, 1976; Lev & Sunder, 1979; Cowen & Hoffer, 1982; Frecka & Hopwood, 1983), it still has not received the necessary attention in accounting. This is concerning, given the serious consequences of their use.

The CoDa methodology addresses the aforementioned asymmetry issue (Linares-Mustarós *et al.*, 2022; Molas-Colomer *et al.*, 2024). This problem may cause other

significant issues, such as the appearance of extreme outliers (Lev & Sunder, 1979; Magrini, 2025), non-linearity of the relationships (Cowen & Hoffer, 1982; Carreras-Simó & Coenders, 2021), non-normality of the distributions (Deakin,1976; Durana *et al.*, 2025), and incoherence of results when numerator and denominator are swapped in ratios (Frecka & Hopwood, 1983; Molas *et al.*, 2024).

To correct these deficiencies, the alternative to the standard use of accounting ratios is the CoDa methodology. This methodology features a mathematical formalism that has been widely applied across numerous scientific fields (Aitchison, 1986; Pawlowsky-Glahn *et al.*, 2015). Bibliometric studies by Martinez-Garcia *et al.* (2023), as well as the reviews by Coenders *et al.* (2023a) and Greenacre *et al.* (2023), highlight its current relevance.

For example, CoDa analysis produces accounting ratios in the interval (–∞, +∞), values consistent with those expected of normally distributed variables (Linares-Mustarós *et al.*, 2018). Since the assumption of normality is necessary in linear regression studies, the log-ratios computed with the CoDa methodology allow for the creation of variables that meet this requirement. In contrast, traditional ratios, which are defined in the interval (0, +∞), make this assumption inappropriate and can lead to computing impossible (i.e., negative) predicted values (Coenders & Arimany-Serrat, 2025a).

Additionally, the log-ratios created with the CoDa approach do not exhibit the serious issues of outliers in the upper tail (Linares-Mustarós *et al.*, 2022). In linear regression models, the results obtained with classical accounting ratios also tend to vary if the numerator and denominator of the ratio are permuted. With CoDa log-ratios, this methodological issue is resolved (Linares-Mustarós *et al.*, 2022; Coenders *et al.*, 2023b). Moreover, the CoDa approach helps reduce non-linearity of the relationships (Carreras-Simó & Coenders, 2021), thus improving compliance with the linearity assumption, which is essential in any linear regression study and is not met by classical ratios.

Finally, it is possible to construct an acyclic and connected graph from the accounting figures to create the so-called pairwise log-ratios (plr), such that no multiple paths exist to reach the same accounting figures. In this way redundancy among ratios is avoided while preserving all the information in the accounting figures. This prevents the inclusion of ratios that could be derived from linear combinations of other ratios in the model (Creixans-Tenas *et al.*, 2019; Greenacre, 2019).

Since previous studies have shown significant differences when comparing results obtained with traditional accounting ratios and those calculated using the CoDa methodology (Linares-Mustarós *et al.*, 2018; Creixans-Tenas *et al.*, 2019; Carreras-Simó & Coenders, 2021; Arimany-Serrat *et al.*, 2022; Jofre-Campuzano & Coenders, 2022; Linares-Mustarós *et al.*, 2022; Coenders *et al.*, 2023b; Dao *et al.*, 2024; Molas-Colomer *et al.*, 2024; Escaramís & Arbussà, 2025; Coenders & Arimany-Serrat, 2025a; 2025b; Hernandez-Romero & Coenders, 2025), while no study has reported equivalence between the two approaches, and CoDa log-ratio transformations provide statistically more coherent and reliable results by overcoming the asymmetry and inconsistency problems inherent in traditional ratios, it can be concluded that analyses based on the CoDa methodology provide a higher degree of statistical validity and reliability than those using classical ratios.

3.4. Statistical analysis and software

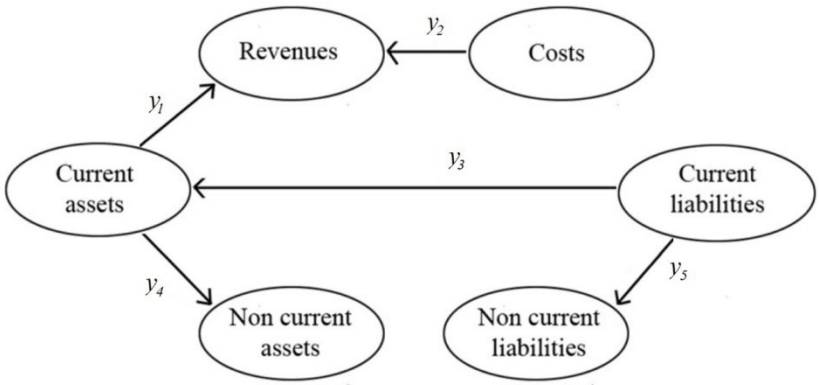
While CoDa offers various options for transforming ratios, such as additive log-ratios (alr), centred log-ratios (clr), pairwise log-ratios (plr), and isometric log-ratios (ilr), alr and clr are not interpretable in the accounting context. Coenders and Arimany-Serrat (2023) compare ilr and plr and conclude that there is little to choose between them apart from interpretational taste. In this study we have chosen to use plr (Creixans-Tenas *et al*., 2019; Greenacre, 2019; Mulet-Forteza *et al.*, 2024; Coenders & Arimany-Serrat, 2025a; 2025b). This choice is due to their resemblance to the result of applying a logarithm to certain classical ratios with only one accounting figure in the numerator and another in the denominator. This allows researchers to continue identifying with the ratios they are most familiar with, thereby avoiding resistance to a new accounting ratio paradigm. Table 1 shows the plr that will act as dependent variables in the model, and their conceptual correspondence with classical financial ratios and the dimensions of interest in the conceptual framework in Section 2.3.

Table 1. plr used as dependent variables in the model and their analogous classical ratios

Label	plr expression	Analogous classical ratio / dimension
y_1	log(revenues/current assets)	Current-asset turnover
y_2	log(revenues/costs)	Margin
y_3	log(current assets/current liabilities)	Short-term solvency
y_4	log(non-current assets/current assets)	Asset tangibility
y_5	log(non-current liabilities/current liabilities)	Debt maturity

From the previous definitions, the connected and acyclic graph shown in Figure 1 is obtained.

Figure 1. Connected acyclic graph defining the plr



Following Greenacre's (2019) construction principles, the arrows in the graph in Figure 1 indicate which variables are in the numerator (arrowhead) and which are in the denominator (arrow tail) of the CoDa ratios. This construction allows the formation of five plr as dependent variables. Since any element in the graph can be connected to another by a single path, it ensures the formation of a basis in a vector space, which in turn guarantees linear independence among the dependent variables and avoids data redundancy while capturing all relative information in the accounting figures.

In order to assess the relationship between subsidies and financial performance, we defined the following set of Ordinary Least Squares (OLS) regression models:

$y_i = \alpha + \beta_1$ subsidy [>0 % to 25 %] $+ \beta_2$ subsidy [>25 %] $+ \beta_3$ log(age) $+ \beta_4$ log(size) $+ \varepsilon_i$

For i = 1 to 5, a regression model is formulated for the corresponding plr, where ε_i is an independent, normal, and identically distributed error term. Subsidies refer to 2018-2022. The rest of the variables to 2022.

Both subsidy levels were operationalised as binary dummy variables, equal to 1 when the company belonged to the respective group and 0 otherwise. Age and size were included as control variables.

The log-ratio transformations were computed using CoDaPack 2.03.06 available at https://imae.udg.edu/codapack/ (Comas-Cufí & Thió-Henestrosa, 2011). The subsequent regression analyses were conducted in R 4.1.2 (R Core Team, 2021).

4. Results

Five OLS regression models were obtained, one for each plr included in the study. The coefficients in the models show the relationship of the explanatory variables with each plr connected to the financial performance of the companies. Table 2 shows the coefficients associated with each explanatory variable and model.

Table 2. Model coefficient estimates, standard errors and statistical significance for each plr

	y_1 Current-asset turn.			y_2 Margin			y_3 Short-term solv.		
	$\hat{\beta}$	SE	Sig.	$\hat{\beta}$	SE	Sig.	$\hat{\beta}$	SE	Sig.
Subsidy [>0 % to 25 %]	0.16	0.19		0.07	0.08		-0.33	0.35	
Subsidy [>25 %]	0.45	0.18	*	0.02	0.07		-0.45	0.33	
Log(age)	-0.06	0.10		0.03	0.04		-0.07	0.17	
Log(size)	0.41	0.08	***	0.01	0.03		0.01	0.15	
	y_4 Asset tangibility			y_5 Debt maturity					
	$\hat{\beta}$	SE	Sig.	$\hat{\beta}$	SE	Sig.			
Subsidy [>0 % to 25 %]	0.59	0.29	*	0.64	0.68				
Subsidy [>25 %]	0.98	0.27	***	1.54	0.65	*			
Log(age)	0.44	0.14	**	0.14	0.34				
Log(size)	-0.70	0.12	***	-0.22	0.29				

Sig: Significance codes: 0 *** <0.001 ** <0.01 * <0.05; SE: Standard error.

According to the OLS specification of the models and the CoDa transformation of the variables, the interpretation of the coefficients varies. In the case of the variables Subsidy [>0 % to 25 %] and Subsidy [>25 %] the regression model relates a dependent variable on a logarithmic scale (log-ratio) to a categorical variable. Previous research with

compositional regression of financial ratios has only dealt with statistical significance of the relationships, but effect sizes are also relevant. In this situation, to obtain and interpret the relationships in the natural scale of the classical (not log transformed) ratio, the coefficient must be exponentiated: exp ($\hat{\beta}$). On the other hand, in the case of variables age and size, the regression model relates a dependent variable on a logarithmic scale (log-ratio) with a quantitative variable also on a logarithmic scale. In this second situation, the value of the coefficient $\hat{\beta}$ can be interpreted, in its original scale, as an elasticity, indicating the percentage increase in the dependent variable associated to a one-point percentage increase in the independent variable.

Following the interpretation above, four key points can be inferred from the results in Table 2, implying a very strong relationship between subsidies and three of the plr:

- Receiving a subsidy higher than 25 % of the assets is associated to multiplying the value of the classical (not log transformed) current-asset turnover ratio (revenues / current assets) by 1.57 [exp(0.45)] (support for H1).
- Receiving subsidies has no relationship with the margin (revenues / costs) nor on the short-term solvency (current assets / current liabilities) ratios (no support for H2 and H3).
- All subsidy levels have a positive relationship with asset tangibility (non-current assets / current assets). Receiving a subsidy lower than 25 % of the assets multiplies the value of the ratio by 1.80 [exp(0.59)]. Receiving a higher subsidy multiplies the value of the ratio by 2.66 [exp(0.98)]. An increase in the relative weight of non-current assets is consistent with the fact that many subsidy programmes are intended for the improvement, rehabilitation and digitalisation of the rural properties (support for H4).
- Receiving a subsidy higher than 25 % of the assets implies multiplying the value of the debt maturity ratio (non-current liabilities / current liabilities) by 4.66 [exp(1.54)]. Companies co-financing the new investments with long-term loans and subsidies seem a reasonable explanation (support for H5).

With respect to the control variables:

- The control variables age and size act in opposite directions with respect to asset tangibility. A one percent increase in firm age is associated to raising the classical tangibility ratio by 0.44 % (i.e., multiplying it by 1.0044). A one percent increase in firm size is associated to reducing the ratio by 0.70 % (i.e., multiplying it by 0.9930).
- Company size has a positive relationship with current-asset turnover: a one percent increase in size is linked to multiplying the ratio by 1.0041.

5. Discussion

To ensure the validity of the models, the presence of outliers in both dependent and independent variables was evaluated. A boxplot analysis was used for this purpose. Additionally, diagnostic plots were reviewed: residuals vs. fitted values, normal Q-Q plots of the residuals, scale-location plots, and Cook's distances. The absence of patterns in the residuals vs. fitted plots confirmed that the residuals were randomly distributed. This supports the linearity assumption of the models. The normal Q-Q plots showed that

the residuals followed an approximately normal distribution. The scale-location plots did not indicate heteroscedasticity. Finally, the Cook's distances indicated that no observations had a disproportionate impact on any of the models. Overall, the results suggest that the models fit the data well and meet the fundamental assumptions necessary to ensure their validity. On the contrary, when replicating the analysis with classical financial ratios, all five regression models contained extreme outliers, either with Cook's distances above 0.5, standardized residuals above 8 in absolute value, or both. This had a dramatic impact on the models' results. Only the relationship between receiving a subsidy higher than 25 % and current-asset turnover (y_1) remained statistically significant at 5 %. Consequently, in this article the CoDa methodology once again performs better in this setting, in line with the literature on CoDa modelling of accounting ratios in regression studies and related research (Creixans-Tenas *et al*., 2019; Coenders & Arimany-Serrat, 2025a; Carreras-Simó & Coenders, 2021).

To the best of our knowledge, this is the first article relating subsidies to hard financial-statement data at company level in the rural tourism sector. It is also the first application of compositional regression on financial data showing how to numerically interpret regression coefficients in the original scale of classical ratios, as previous studies had only dealt with significance of the relationships.

The non-significant findings for profitability and short-term solvency may be explained by the fact that subsidies primarily affect the economic and financial structure of firms rather than their operational efficiency. This is reflected in improvements such as a greater proportion of non-current assets or longer-term debt, but not necessarily in profit margins. Moreover, there may be a temporal lag in their effects, as investments financed by subsidies require time to generate returns. In addition, the rural tourism sector is characterized by seasonality and limited demand, which slows the translation of structural improvements into economic results. Short-term solvency also depends on the management of current assets and liabilities, which responds more slowly. Therefore, this does not imply a lack of effectiveness of subsidies, but rather a different transmission channel, oriented more towards structural strengthening than immediate financial outcomes.

From this perspective, the concept of a soft budget constraint reflects that firms can finance investments without relying directly on immediate operational results. Subsidies exceeding 25% of total assets are associated with a higher proportion of non-current assets and longer-term debt, enabling a more solid and stable financial structure. This flexibility reduces the pressure on short-term profitability and prioritizes survival and territorial development over profit maximization, confirming that public policies function as a financial stabilization mechanism, mitigating the risks associated with seasonality in the rural tourism sector.

The first main limitation of this study is that the SABI database only applies to companies with a corporate structure, thus ruling out many of the smaller ones so common to the sector, run by individual entrepreneurs who are not required to present their financial statements to the Business Registry. Unfortunately, this limitation, which involves sample-selection bias and seriously affects the external validity of the results, is not easy to solve. There is a body of literature which uses surveys and qualitative interviews and includes firms of all sizes (Saus-Sala *et al.*, 2021), but the reliability of financial information is at best questionable.

The second main limitation is the inability to establish causal relationships. There is indeed potential endogeneity, as larger or more solvent firms may be able to invest more time and resources in applying for subsidies. There may also be regional heterogeneity. A panel-data design would be better at capturing dynamic causal effects. Panel-data models have been successfully applied on financial ratios using the CoDa methodology (Escaramís & Arbussà, 2025; Carreras-Simó & Coenders, 2021), as have structural equation models (Creixans-Tenas *et al.*, 2019).

The third main limitation is missing control variables, like region (called autonomous community in Spain), legal form (public and private limited companies, cooperatives), gender distribution of the workforce, or rural tourism sub-type (rural hotel, tourism farm, rural real estate agency).

Further research will include using a panel-data design with mixed models (Escaramís & Arbussà, 2025) including a wider range of control variables, a larger number of accounting figures and ratios indicating the cost structure, and separating subsidies by type.

6. Conclusions

As it was stated in the introduction, the aim of this research is to assess the sector's financial performance in relationship to subsidies derived from public policies. According to the results and using a robust construction of financial ratios, a level of subsidy higher than 25 % of the assets is associated with the financial stability of the companies, having a significant association with the turnover of assets, asset tangibility and debt maturity. On the contrary, subsidies did not show a significant relationship with the sector's profitability nor with its short-term solvency. Overall, the findings are consistent with the conceptual framework's balance-sheet channels (H4 and H5), and the activity hypothesis (H1), but do not yield statistically significant evidence for the margin and short-term-solvency hypotheses (H2–H3). This can be explained by the fact that rural tourism subsidies are aimed at non-financial objectives, such as territorial development, sustainability, and population retention, rather than profit maximization. Their effects are mainly reflected in the balance sheet, confirming H4 and H5 through an increase in the proportion of non-current assets and long-term debt, while also being associated with higher asset turnover (H1), thereby strengthening financial stability and firm survival. In contrast, no significant effect is observed on profit margins (H2) or short-term solvency (H3), indicating that subsidies do not immediately improve operational management, although they may cover structural weaknesses and prevent major deterioration rather than generate immediate profitability gains. Additionally, firms with lower financial performance may receive more subsidies, which could dilute the expected positive relationship.

The control variables included in the study (age and size of the company) had a marginal and inconclusive relationship with the financial performance. Although the importance of subsidies is not uniform in all the ratios studied, companies that have received a subsidy of more than 25 % show a more solid investment structure and a better debt maturity, a situation that can contribute to the long-term solvency of the sector, and subsequently to firm survival in the long term.

Policy recommendations regarding the public institutions would be to maintain the

subsidy programmes while not overburdening recipients with bureaucracy or additional requirements that may increase overhead costs and reduce profitability. Regarding firms in the sector themselves, margin has already been shown to be a critical variable in previous research on rural tourism unrelated to subsidies (Saus-Sala *et al.*, 2023; 2024), which implies paying attention to pricing and cost control, and not counting on subsidies as a substitute for good revenue and cost management.

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AUTHOR CONTRIBUTIONS

Conceptualization: MF-N and NA-S; methodology: SL-M; formal analysis: MC-P; data curation: MF-N and NA-S; writing - original draft: All; writing - review & editing: All.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY

The curated data are available from the corresponding author upon reasonable request.

USE OF ARTIFICIAL INTELLIGENCE (AI)

The authors used ChatGPT to improve the grammar and clarity of the manuscript. All scientific content of the article was developed entirely by the authors without the use of AI.

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Financial resilience of agricultural and food production companies in Spain: A compositional cluster analysis of the impact of the Ukraine-Russia war (2021-2023)

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ABSTRACT

This study analyses the financial resilience of agricultural and food production companies in Spain amid the Ukraine-Russia war using cluster analysis based on financial ratios. This research utilizes centred log-ratios to transform financial ratios for compositional data analysis. The dataset comprises financial information from 1197 firms in Spain's agricultural and food sectors over the period 2021-2023. The analysis reveals distinct clusters of firms with varying financial performance, characterized by metrics of solvency and profitability. The results highlight an increase in resilient firms by 2023, underscoring sectoral adaptation to the conflict's economic challenges. These findings together provide insights for stakeholders and policymakers to improve sectorial stability and strategic planning.

KEYWORDS

Accounting ratios; indebtedness; margin; turnover; ROE; classification

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1. Introduction

Tensions between Ukraine and Russia stem from a complex interplay of historical, political, and cultural factors, notably following Ukraine's independence from the Soviet Union in 1991 and Russia's annexation of Crimea in 2014 (Bielieskov and Szeligowski, 2024). The situation escalated dramatically on February 24, 2022, when Russia initiated a full-scale invasion of Ukraine. The war has had far-reaching consequences for global food supply and has prompted discussions on food security, as both Ukraine and Russia account for 30 % of the global grain export (FAO, 2023).

In addition to these direct impacts, the war has triggered cascading consequences that have amplified the ongoing global food crisis. These include labour shortages due to conscription and population displacement, disruptions in planting and harvesting cycles, and skyrocketing fertilizer prices that threaten to reduce agricultural yields (Ben Hassen and El Bilali, 2022). The rising food prices and the shift in global trade patterns have left many vulnerable economies struggling to maintain access to vital food supplies.

In this context, Spain's agricultural and food production sectors play a vital role in the country's economy, contributing significantly to the country's GDP (8.6 % in 2025) and employment (6.0 % in 2025). The sector is characterized by a diverse range of products, including fruits, vegetables, cereals, and livestock (Escudero et al., 2022). Notably, Spain is the largest worldwide producer of olive oil and the third largest of wine and ranks among the top exporters of fresh fruits and vegetables within the European Union (European Commission, DG Agriculture and Rural Development, 2024). Spain not only supplies the European Union but also relies on imports for critical agricultural inputs. The geopolitical instability has amplified the challenges in maintaining consistent food supply chains, with price volatility affecting everything from raw materials to consumer products.

In this study, specific sectors within Spain's agricultural and food production are analysed, focusing on activities classified under the Statistical Classification of Economic Activities in the European Community (NACE) 2009 codes: cereal cultivation (excluding rice), legumes and oilseeds (code 0111); the production of vegetable and animal oils and fats (code 104); milling products, starches, and starch products (code 106); and bakery and farinaceous products manufacturing (code 107).

For the cereal cultivation sector (NACE 0111), Teixeira Da Silva et al. (2023) highlight the significant disruptions caused by the closure of the Black Sea and Azov Sea ports, which severely impacted global grain exports. This disruption, coupled with rising fuel and fertilizer prices, placed a heavy strain on supply chains worldwide, including Spain's. Adding to this, Malik et al.'s (2024) findings offer a complementary perspective, particularly on the role of small businesses. In Ukraine, small enterprises in cereal, legume, and sunflower production demonstrated resilience during wartime due to their agility and compact management systems. For Spain, this could be an insightful parallel. Milling and starch products (code 106); and bakery and farinaceous products manufacturing (code 107) use cereals as raw materials.

Glauber et al. (2023) explain that vegetable oil prices—especially sunflower oil (included in code 104)—soared by over 40 % following the invasion, and the sector is now grappling with additional pressures from biofuel production and export restrictions. These factors have exacerbated supply-demand imbalances, driving prices even higher.

Spain is also significantly affected by the disruptions in Ukrainian maize production and exports. The country was expected to receive 1.9 million metric tons of maize in 2022, primarily intended as animal feed. This maize is critical for the livestock sector, which relies on high-quality feed to sustain meat and dairy production levels (Jagtap et al., 2022). With these exports disrupted by the conflict, Spain faces a rise in animal feed costs and a potential supply shortage in the domestic market. While other major producers, such as the United States, may partially compensate for this shortfall, the financial impact is inevitable due to increased transportation costs and heightened pressure on already-strained global cereal markets.

Given these challenges, understanding the financial resilience of Spain's agricultural and food production sectors is crucial. To address this, a *cluster analysis* is employed, a widely used technique for categorizing heterogeneous data into homogeneous groups, which helps identify patterns and trends within the dataset. Clustering enables the analysis of firms with similar financial characteristics, facilitating a clearer understanding of varying performance levels within a sector. The objective is to achieve high internal cohesion within each group while ensuring distinct separation between groups (Capece et al., 2010). In financial statement analysis, clustering is particularly valuable for distinguishing firms based on their financial health and resilience, empowering stakeholders to make more informed decisions about investments, risk management, and strategic planning (Caruso et al., 2018). To perform this clustering, *financial ratios* are a key instrument for assessing firm performance. These ratios provide a snapshot of various aspects of financial health, such as profitability, solvency, liquidity, and operational efficiency (Amat and Manini, 2017; Arimany-Serrat et al., 2017; Cavero Rubio et al., 2021; Krylov, 2018; Saleh et al., 2023; Tascón et al., 2018).

However, when using standard financial ratios in clustering, several challenges arise. Financial ratios often suffer from non-linearity (Carreras-Simó and Coenders, 2021; Cowen and Hoffer, 1982), asymmetry (Frecka and Hopwood, 1983; Iotti et al., 2024a; 2024b; Linares-Mustarós et al., 2018), outliers (Deshpande, 2023; Lev and Sunder, 1979) and the mutual redundancy of ratios that measure overlapping concepts (Chen and Shimerda, 1981; Linares-Mustarós et al., 2018).These issues can distort clustering results, leading to poor representation of the firms' financial profiles and the risk of forming very small clusters and even clusters composed by just one or two outliers (Dao et al., 2024; Feranecová and Krigovská, 2016; Jofre-Campuzano and Coenders, 2022; Linares-Mustarós et al., 2018; Molas-Colomer et al., 2024; Sharma et al., 2016). To overcome these limitations, this study employs the *Compositional Data* (CoDa) methodology (Aitchison, 1982; 1983; 1986; Pawlowsky-Glahn et al., 2015). This approach addresses many of the challenges posed by standard financial ratios. By means of suitable transformations, CoDa minimizes the impact of outliers, non-linearity, asymmetry and redundancy (Coenders, 2025; Coenders and Arimany-Serrat, 2025b; Dao et al., 2024; Jofre-Campuzano and Coenders, 2022; Linares-Mustarós et al., 2018; Magrini, 2025).

The application of CoDa in clustering has been widely studied since Linares-Mustarós et al. (2018) and has proven effective in various sectors. For example, Saus-Sala and colleagues used CoDa to identify clusters of firms in the farm-tourism sector based on leverage, margin, and turnover ratios (Saus-Sala et al., 2021; 2023; 2024). Similarly, Jofre-Campuzano and Coenders (2022) applied CoDa to automotive fuel companies in Spain, uncovering distinct financial profiles, including a cluster characterized by financial distress. Along the same lines, Coenders (2025) and Coenders and Arimany-Serrat (2025a) classify wine producing firms.

Arimany-Serrat and Sgorla (2024), Arimany-Serrat and Coenders (2025a), Dao et al. (2024) and Saus-Sala et al. (2024) draw clusters which are related to financial resilience during the COVID19 pandemic in the brewing, beekeeping, fishery, and farm tourism sectors, respectively. These are the articles most related to the one presented here, but none of them studies the effects of the Ukraine-Russia war.

In this study, CoDa clustering allows for the classification of firms in the agricultural and food sectors of Spain based on their financial health during the geopolitical crisis related to the Ukraine-Russia war in the hope of finding at least one cluster of financially resilient firms. These findings may serve as a useful guide for stakeholders and policymakers when considering policies aimed at enhancing the resilience of the sector in future crises.

This article is structured as follows: following the introduction, Section 2 presents a review of relevant literature and theoretical insights. Section 3 outlines the methodology, detailing the CoDa approach to clustering financial ratios and the rationale behind its use in this study. After a data description, Section 4 presents the results of the cluster analysis, highlighting the financial resilience patterns. Section 5 offers a discussion of the findings, their implications, and limitations.

2. Literature review

As shown by Arimany-Serrat et al. (2023) in their analysis of Spanish wineries, companies respond differently to economic shocks based on various financial and structural factors. The study revealed that during the COVID-19 lockdown, many wineries experienced a decline in margins and turnover, largely due to reduced sales. However, larger wineries with pre-existing subsidies were better able to weather the downturn, supported by stronger pre-pandemic financials. This disparity in resilience underlines the varied impact that economic shocks can have within a sector, leading to clusters of firms with differing performance outcomes. Similarly, Dao et al. (2024)'s study on Vietnamese fisheries and food production sectors identified distinct clusters, showing that those with lower leverage and higher profitability performed best. Meanwhile, Arimany-Serrat and Sgorla (2024) analysed the brewing sector in Spain and Italy during 2019–2021, revealing resilience through gradual recovery despite initial declines in profitability. Their findings emphasized sectoral heterogeneity, with distinct clusters of underperforming SMEs and high-performing corporations, and linked financial performance to transparency practices. Similar results are found by Arimany-Serrat and Coenders (2025a) in the beekeeping sector.

Based on this, within Spain's agricultural and food production sectors, the firms impacted by the Ukraine-Russia war will likely form distinct clusters. Firms with different levels of financial resilience may diverge in their ability to sustain performance and/or financial stability.

Sharif et al. (2020) highlight how major crises, such as COVID-19, drive significant volatility and uncertainty across markets. The findings show that pandemic-related shocks, heightened geopolitical risks, and economic policy uncertainty impact the U.S. stock market and alter firms' financial strategies. Baixauli-Soler et al. (2024) study the impact of such crises on the firms' optimal debt structure. Additionally, research by Chiang (2022) indicates that geopolitical risks, including the Ukraine-Russia war, significantly disrupt financial markets and corporate performance globally. Building on this, we expect that firms in the agricultural and food production sectors in Spain shift to

lower-performing clusters during the 2021-2023 period due to the economic instability caused by the Ukraine-Russia war.

Much research shows that firms can recover and return to higher performance levels over time as they adapt to crisis conditions (Cirera et al., 2021; Kong et al., 2022). Cirera's findings (2021) highlight that, while firms initially face steep declines, many gradually improve by adopting digital technologies, strengthening managerial practices, and diversifying into new markets. Similarly, Boungou and Yatié (2022) underscore the immediate negative impact of the Ukraine-Russia war on global stock markets, especially in countries geographically closer to the conflict or strongly condemning the invasion, but with some evidence of partial recovery over time.

These findings suggest that adaptation processes, supported by strategic realignments and resilience measures, enable firms to mitigate adverse impacts and eventually reposition themselves within higher-performing clusters. Based on these findings, we expect some firms to shift back to better-performing clusters as they adapt to the crisis, as shown in similar research by Arimany-Serrat and Sgorla (2024), Arimany-Serrat and Coenders (2025a), Dao et al. (2024), and Saus-Sala et al. (2024).

3. Methods

This section outlines the methodology employed in this study, focusing on the CoDa approach and how it is applied for clustering financial data of agricultural and food production companies in Spain.

The financial data used in this study was obtained from the Sistema de Análisis de Balances Ibéricos (SABI, accessible at https://sabi.bvdinfo.com) database. The focus was placed on companies classified under the following primary codes of the NACE 2009: the cultivation of cereals (excluding rice), legumes, and oilseeds (code 0111); the manufacture of vegetable and animal oils and fats (code 104); the production of milling products, starches, and starch products (code 106); and the manufacture of bakery and farinaceous products (code 107).

In addition to sectoral classification, companies were required to have a minimum of ten employees to ensure the inclusion of firms with sufficient operational activity. Only companies registered within Spain were considered, covering various legal forms such as private and public limited companies, and other business structures.

After the initial data extraction, companies with zero values in key financial indicators such as total assets, operating income, and operating expenses for any of the three study years (2021, 2022 and 2023) were removed, as these zero values indicated periods of inactivity during the specified years. The remaining zero values were handled according to the procedures outlined in Section 3.4 and in Coenders and Arimany-Serrat (2025b).

The final dataset comprised 140 companies involved in cereal cultivation (sector 0111), 95 companies operating in the manufacture of vegetable and animal oils and fats (sector 104), 65 companies in the milling products and starches sector (sector 106), and 897 companies engaged bakery and farinaceous products (sector 107), for a total of 1197 companies and 3591 cases for the three-year period under study. These 1197 companies account for 18.1 % of the selected sectors in numbers, and 59.2 % in revenue (data for 2023).

3.1. Compositional financial statement analysis

In the CoDa methodology, a composition is defined as a set of D strictly positive numbers (parts) where only the relative magnitude of parts to one another is of interest (Aitchison, 1982; Coenders et al., 2023; Filzmoser et al., 2018; Greenacre, 2018; Pawlowsky-Glahn et al., 2015; Van den Boogaart and Tolosana-Delgado, 2013). In scientific fields such as chemistry, compositions often sum to a constant value, but in financial analysis this is not required:

$$\mathbf{x} = (x_1, x_2, \ldots, x_D) \text{ with } x_j > 0,\ j = 1,2,\ldots,D \tag{1}$$

There are two main rules for applying the CoDa methodology to financial data (Coenders and Arimany-Serrat, 2025b; Creixans-Tenas et al., 2019):

- Avoiding negative values, as they can lead to misinterpretation and discontinuities in ratios (e.g., a positive return on equity when both profit and net worth are negative).
- Avoiding overlapping parts. For example, using both total assets and non-current assets is problematic, as the latter is part of the former. Only the full amalgamation (e.g., total assets) or the individual parts (e.g., non-current and current assets) should be used, not both.

In this article, the $D = 6$ positive and non-overlapping financial statement categories x_j were selected to align with this study's focus on liquidity, solvency, operational efficiency, and profitability (Creixans-Tenas et al., 2019; Coenders and Arimany-Serrat, 2025a). Excessive categorization into a high number D of accounting figures risks data sparsity, such as frequent zero value entries, particularly in samples containing small firms. The first four categories correspond to balance sheet items, while the last two are aggregate values from the profit and loss account:

- x_1=non-current assets,
- x_2=current assets,
- x_3=non-current liabilities,
- x_4=current liabilities,
- x_5=revenue (net sales),
- x_6=expenses (operating expenses).

The ratios used in this study are those outlined by in Arimany-Serrat and Coenders (2025a), Dao et al. (2024), Jofre-Campuzano and Coenders (2022), and Saus-Sala et al. (2024) in articles clustering firms according to their financial resilience in front of crises. They are based on the previous six key financial-statement figures and include:

Turnover ratio:

$$x_5 / (x_1 + x_2). \tag{2}$$

Current-asset turnover ratio:

$$x_5 / x_2. \tag{3}$$

Profit margin ratio:

$$(x_5 - x_6) / x_5. \tag{4}$$

Leverage ratio:

$$(x_1 + x_2) / (x_1 + x_2 - x_3 - x_4). \quad (5)$$

Return on Assets (ROA):

$$(x_5 - x_6) / (x_1 + x_2), \quad (6)$$

which can also be derived by multiplying the margin by the turnover ratio.

Return on Equity (ROE):

$$(x_5 - x_6) / (x_1 + x_2 - x_3 - x_4), \quad (7)$$

which can also be obtained by multiplying the ROA by the leverage ratio.

Debt ratio:

$$(x_3 + x_4) / (x_1 + x_2). \quad (8)$$

Short-term debt ratio:

$$x_4 / (x_1 + x_2). \quad (9)$$

Long-term solvency ratio:

$$(x_1 + x_2) / (x_3 + x_4). \quad (10)$$

Short-term solvency ratio a.k.a. liquidity ratio and current ratio:

$$x_2 / x_4. \quad (11)$$

Asset tangibility ratio:

$$x_1 / x_2. \quad (12)$$

Debt maturity ratio:

$$x_3 / x_4. \quad (13)$$

3.2. Centered log-ratios

To apply the CoDa methodology, financial data must first be transformed into a Euclidean space using log-ratio transformations, a standard approach in CoDa analysis (Aitchison, 1986). The specific transformation known as centred log-ratios (CLR) (Aitchison, 1983) retains the relative distances between data points, thereby enabling the use of traditional distance-based statistical methods, such as cluster analysis, on the transformed data. The CLR transformation for each accounting figure in Equation 1 is defined as:

$$CLR_j = \log\left(\frac{x_j}{\sqrt[D]{x_1 x_2 \dots x_D}}\right) \quad \text{with } j = 1,2,\dots,D. \quad (14)$$

In financial statement analysis, this transformation involves comparing each accounting figure x_j to the geometric mean of all for a given firm. This transformation solves the

challenges of non-linearity, asymmetry, and outliers encountered in traditional financial ratios (Arimany-Serrat and Coenders, 2025a; Arimany-Serrat and Sgorla, 2024; Carreras-Simó and Coenders, 2020; Saus-Sala et al., 2021; 2023; 2024).

3.3. Cluster analysis

Cluster analysis is a multivariate statistical technique aimed at grouping firms based on the similarity of their financial structures. In the CoDa context, this method identifies clusters of companies with comparable financial profiles, which is particularly useful for understanding sectoral resilience (Arimany-Serrat and Coenders, 2025a; Arimany-Serrat and Sgorla, 2024; Dao et al., 2024; Saus-Sala et al., 2024).

By applying CLR transformations, traditional Euclidean distances correspond to Aitchison's distances, which are the standard in CoDa (Aitchison, 1983; Aitchison et al., 2000). Consequently, the distance between two firms, m and l, is calculated as:

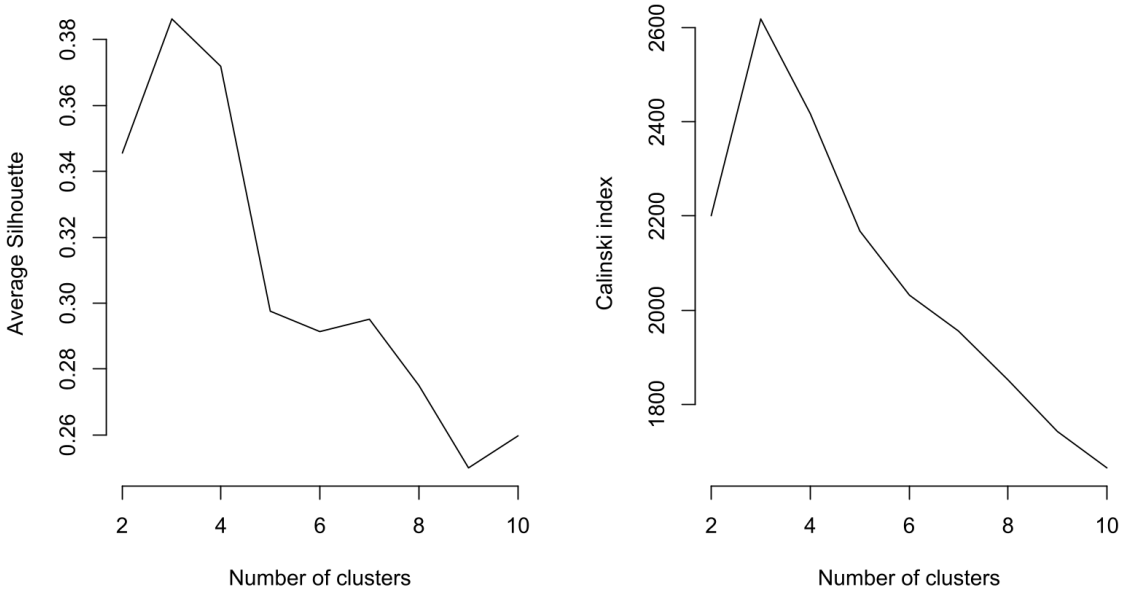
$$d_{ml} = \sqrt{(CLR_{1m} - CLR_{1l})^2 + (CLR_{2m} - CLR_{2l})^2 + \cdots + (CLR_{Dm} - CLR_{Dl})^2} \quad (15)$$

This transformation solves the commonest problems of standard financial ratios in cluster analysis, which tend to form very large and very small clusters and even clusters composed by just one or two outliers (Dao et al., 2024; Feranecová and Krigovská, 2016; Jofre-Campuzano and Coenders, 2022; Linares-Mustarós et al., 2018; Molas-Colomer et al., 2024; Sharma et al., 2016). Moreover, the clusters obtained do not depend on the particular ratios chosen in Equations 2 to 13, but only on the D x_j financial statement categories. They are thus immune to ratio redundancy, which would give more weight to the redundant ratios in the final classification.

This approach allows for the use of common clustering algorithms in financial performance analysis, such as Ward's method (Ward jr, 1963) and k-means (MacQueen, 1967). In this study, the k-means algorithm, as implemented in CoDaPack, is applied, following the methodology described by Coenders and Arimany-Serrat (2025a; 2025b) to classify firms based on their financial profiles. Clustering is made on the pooled data over all three years jointly, as is standard practice in related research (Arimany-Serrat and Coenders, 2025a; Arimany-Serrat and Sgorla, 2024; Dao et al., 2024; Saus-Sala et al., 2023; 2024) to ensure comparability of the cluster structures over time, and the meaningfulness of firm migration from one cluster to another.

Figure 1 illustrates the evolution of both the average silhouette width (Kaufman and Rousseeuw, 1990) and the Caliński-Harabasz (Caliński and Harabasz, 1974) indices across different values of k (numbers of clusters). In this case, a three-cluster solution maximizes both criteria, indicating the most appropriate grouping for the present analysis.

Figure 1. Evaluation of clustering solutions using the average silhouette width and the Caliński-Harabasz indices



3.4. Handling zero values

A common limitation of both compositional and standard financial ratios is their inability to handle zero values in accounting data, as ratios involving zero are undefined (Martín-Fernández et al., 2011). However, the CoDa methodology offers advanced tools for zero imputation before log-ratio computation, which ensures valid analysis.

The most widely used imputation method in compositional financial analysis is the Expectation-Maximization (EM) algorithm for log-ratios, developed by Palarea-Albaladejo and Martín-Fernández (2008). This method predicts zero values based on the existing data under standard statistical assumptions while constraining them to be below a small value selected by the user (e.g., the 5th percentile of non-zero values).

For this study, only one accounting figure had zeros (non-current liabilities for 14.9 % of cases), which were imputed with the method just described. The issue is discussed in depth in Coenders and Arimany-Serrat (2025b).

The zero replacement, classification and further analyses were carried out with CoDaPack2.03.06 (Comas-Cufí and Thió-Henestrosa, 2011; Thió-Henestrosa and Martín-Fernández, 2005). CoDaPack is freely available at https://ima.udg.edu/codapack/. See Coenders and Arimany-Serrat (2023; 2025a) for an introduction to the use of CoDaPack in financial statement analysis in English and Spanish, respectively.

4. Results

4.1. Sector ratio averages

A straightforward way to use financial ratios statistically is to determine average ratios within a sector. In compositional data analysis, this is achieved by calculating the *compositional centre* (Aitchison, 1997). This centre is defined as the array of

geometric means of all firms for each individual part, normalized so that the values sum to one (Table 1).

This is not to be mistaken with the geometric mean of all parts for each individual firm, which are used to compute the CLR. By employing the compositional centre, the geometric-mean approach under the CoDa framework makes it possible to compute standard sector-level financial ratios (Arimany-Serrat and Coenders, 2025a; Arimany-Serrat and Sgorla, 2024; Saus-Sala et al., 2021; 2023; 2024).

Table 1. Compositional centre (geometric means normalized to unit sum) for the selected agricultural and food production sectors

		2021	2022	2023
x_1	Non-current assets	0.0730	0.0712	0.0696
x_2	Current assets	0.1237	0.1145	0.1175
x_3	Non-current liabilities	0.0200	0.0155	0.0129
x_4	Current liabilities	0.0728	0.0711	0.0696
x_5	Revenue	0.3638	0.3712	0.3773
x_6	Expenses	0.3467	0.3565	0.3531

One notable advantage of using geometric means is their property that the ratio of geometric means between two parts equals the geometric mean of their ratios. Let $g(x_i)$ be the geometric mean of the ith accounting figure over a sample of firms:

$$g(x_i / x_j) = g(x_i) / g(x_j) \tag{16}$$

This contrasts with arithmetic means, which do not share this property. Using arithmetic means of the accounting figures and then computing ratios at the sector level can produce results that contradict those obtained by first calculating ratios at the firm level and then averaging them (Saus-Sala et al., 2021).

Using the geometric mean property, the mean sectorial current-asset turnover ratio for 2021 (Equation 3) can be expressed as:

$$g(x_5) / g(x_2) = 0.3638 / 0.1237 = 2.940 \tag{17}$$

Similarly, the margin ratio (Equation 4) for the same year is:

$$(g(x_5) - g(x_6)) / g(x_5) = (0.3638 - 0.3467) / 0.3638 = 0.047 \tag{18}$$

The mean sectoral financial ratios thus computed (Table 2) reveal that firms experienced financial strain during the initial period of the war. In 2022, the ROA, and ROE ratios dropped significantly compared to 2021. Importantly, the decline in these profitability measures was not due to inefficient asset utilization or to leverage—as both the turnover ratio and the current-asset turnover ratio increased while long-term solvency remained virtually identical—but rather can be attributed to decreased margin. However, by 2023 a notable recovery was observed; these profitability measures not only returned to pre-war levels but even surpassed the 2021 figures. These findings suggest that while the initial economic shock triggered by the onset of the war set off significant structural changes, firms demonstrated remarkable resilience, ultimately emerging in a stronger and more financially efficient position.

Table 2. Annual mean financial ratios for the selected agricultural and food production sectors

	2021	2022	2023
Turnover ratio	1.849	1.998	2.016
Current-asset turnover ratio	2.940	3.241	3.211
Profit margin ratio	0.047	0.039	0.064
Leverage ratio	1.893	1.873	1.788
ROA	0.086	0.079	0.129
ROE	0.164	0.148	0.231
Debt ratio	0.471	0.466	0.440
Short-term debt ratio	0.370	0.382	0.371
Long-term solvency ratio	2.120	2.144	2.268
Short-term solvency ratio	1.699	1.610	1.688
Asset tangibility ratio	0.590	0.621	0.592
Debt maturity ratio	0.274	0.218	0.185

A second axis of analysis relates to debt structure. The debt maturity ratio experienced a consistent reduction over the three-year period. This decline was particularly pronounced from 2021 to 2022. This behaviour is also observed in the short-term debt ratio. The initial increase in 2022 suggests a reactive financial adjustment to the pressures of the war, where access to long-term debt may have been restricted. This change in the debt structure had a direct impact on liquidity. The short-term solvency ratio (liquidity ratio) declined from 2021 to 2022, suggesting a temporary deterioration in financial stability. However, from 2022 to 2023, short-term solvency showed a recovery. This is associated with the rebound in key profitability indicators (margin, ROA, and ROE), as well as improved turnover ratios. In other words, while the war initially weakened firms' solvency due to their increased reliance on short-term debt and declining profitability, the financial recovery in 2023 appears to have mitigated these risks.

Table 3 provides a more nuanced analysis by disaggregating the financial ratios on an annual basis by sector, a perspective that contrasts with the global approach of Table 2. In Table 3, the evolution of profitability ratios (profit margin, ROA, and ROE) between 2021 and 2022 reveals that sectors 106 and 0111 benefited from slight improvements in margin, ROA and ROE. This stability in profitability indicators suggests that, despite the economic shock induced by the Ukraine-Russia war, these sectors managed to maintain or even enhance their operational performance, possibly by keeping cost pressures at bay or by adapting their pricing strategies in a turbulent market environment.

In contrast, sector 107, which comprises a much larger number of companies (897 firms operating in the bakery and farinaceous products sector), was the only one to suffer a pronounced deterioration in profitability during the same period. The data indicate that from 2021 to 2022, the profit margin, ROA, and ROE ratios in sector 107 fell significantly. This decline is likely due to the competitive nature of the sector, where profit margins tend to be narrow, and even minor increases in input costs—stemming from supply chain disruptions or heightened commodity prices—can erode profitability. However, it is notable that from 2022 to 2023, sector 107 experienced the largest rebound in these ratios, a classic rebound effect: the deeper the initial fall, the more pronounced the recovery once market conditions begin to stabilize. Sector 104, representing companies involved in the manufacture of vegetable and animal oils and fats, also

displayed an interesting pattern, with hardly any change in profitability between 2021 and 2022.

Table 3. Annual mean financial ratios by NACE code (104: oils and fats; 106: milling products and starches; 107: bakery and farinaceous products; 0111 cultivation of cereals, legumes and oilseeds)

	Code 104			Code 106		
	2021	2022	2023	2021	2022	2023
Turnover ratio	1.908	2.160	1.888	1.902	2.199	2.278
Current-asset turnover ratio	2.003	2.264	1.978	2.004	2.310	2.413
Profit margin ratio	0.067	0.063	0.080	0.038	0.054	0.054
Leverage ratio	2.574	2.499	2.383	2.162	2.085	1.778
ROA	0.128	0.136	0.151	0.073	0.118	0.123
ROE	0.330	0.341	0.361	0.157	0.245	0.218
Debt ratio	0.612	0.600	0.580	0.537	0.520	0.437
Short-term debt ratio	0.520	0.526	0.520	0.459	0.460	0.387
Long-term solvency ratio	1.635	1.667	1.723	1.861	1.922	2.286
Short-term solvency ratio	1.832	1.813	1.836	2.068	2.069	2.440
Asset tangibility ratio	0.050	0.048	0.047	0.054	0.051	0.059
Debt maturity ratio	0.176	0.140	0.116	0.171	0.131	0.131
	Code 107			Code 0111		
	2021	2022	2023	2021	2022	2023
Turnover ratio	1.816	1.934	2.014	0.934	0.962	0.923
Current-asset turnover ratio	3.577	3.954	3.989	1.305	1.356	1.273
Profit margin ratio	0.040	0.028	0.053	0.078	0.089	0.129
Leverage ratio	1.733	1.698	1.647	1.555	1.583	1.562
ROA	0.073	0.054	0.106	0.072	0.085	0.119
ROE	0.127	0.091	0.175	0.113	0.135	0.186
Debt ratio	0.423	0.411	0.393	0.357	0.368	0.360
Short-term debt ratio	0.326	0.333	0.328	0.278	0.299	0.298
Long-term solvency ratio	2.364	2.432	2.547	2.801	2.715	2.779
Short-term solvency ratio	1.556	1.469	1.540	2.571	2.373	2.429
Asset tangibility ratio	0.970	1.045	0.981	0.398	0.410	0.379
Debt maturity ratio	0.296	0.235	0.198	0.283	0.233	0.206

Regarding the debt structure, Table 3 corroborates the findings from Table 2 by showing that the onset of the Ukraine-Russia war prompted all sectors to shift their financing strategies toward short-term debt according to the debt-maturity ratio. However, short term solvency (liquidity) only worsened in 2022 for two sectors: 107 and 0111.

Among the studied sectors, sector 106—comprising 65 companies in the milling products and starches sector—stood out for the most significant adjustment between 2022 and 2023. This sector managed to reduce both its overall debt ratio and short-term debt ratio more than any of the others, thereby achieving the highest short-term solvency by 2023. The relatively smaller number of firms in sector 106 may have allowed for quicker, more

coordinated negotiations with lenders, facilitating a rapid restructuring of their debt profiles in response to the crisis.

In summary, while the aggregated data in Table 2 might suggest a global decline in profitability following the outbreak of the war, the sectoral breakdown in Table 3 reveals that this adverse impact was largely confined to sector 107. The other sectors—104, 106, and 0111—either maintained stable profitability or even improved their financial performance over the period analysed. Additionally, although all sectors experienced a shift toward short-term debt financing, the debt restructuring undertaken by sector 106 in 2023 highlights its superior agility and financial management in a volatile economic landscape. These findings not only illuminate the differential impacts of the war across sectors but also underscore the importance of sector-specific strategies in navigating financial crises.

4.2. Cluster characterization

The cluster analysis identified three distinct financial profiles, each demonstrating a unique strategy for managing solvency, profitability, and operational efficiency amid economic instability. These divergent approaches, detailed in Table 4, confirm that firms adopt distinct financial strategies and have varying resilience.

Table 4. Financial ratios by cluster

	Cluster 1	Cluster 2	Cluster 3
Turnover ratio	0.549	2.606	1.402
Current-asset turnover ratio	3.990	2.790	2.716
Profit margin ratio	0.042	0.057	0.048
Leverage ratio	1.200	9.801	1.276
ROA	0.023	0.150	0.067
ROE	0.027	1.473	0.086
Debt ratio	0.167	0.897	0.216
Short-term debt ratio	0.096	0.611	0.213
Long-term solvency ratio	5.985	1.113	4.619
Short-term solvency ratio	1.420	1.528	2.412
Asset tangibility ratio	6.259	0.070	0.937
Debt maturity ratio	0.722	0.469	0.012

Cluster 1 (34 % of observations) represents firms characterized by a heavy reliance on tangible assets. By maintaining a leverage ratio that reveals a preference for equity over debt, and a debt maturity that reveals a preference for long-term debt, these firms exhibit a conservative financial structure. Their high asset tangibility ratio suggests significant investments in non-current assets, such as machinery or property, which may indicate capital-intensive operations. However, this conservative approach comes at a cost: these firms exhibit the lowest profitability metrics, with a ROA of 0.023 and ROE of 0.028, signalling inefficiency in converting assets or equity into profits.

Cluster 2 (42 % of observations) comprises high-risk firms with extreme leverage, relying heavily on debt to finance operations. This aggressive strategy artificially inflates their ROE through leverage magnification, masking underlying vulnerabilities. However, the

turnover figure leads to a satisfactory ROA. Their debt ratio reveals that nearly 90 % of assets are debt-financed. Paired with a high short-term debt ratio, it exposes them to refinancing risks and insolvency. Their asset-light structure (tangibility ratio) suggests operations dependent on volatile inputs.

The firms in Cluster 3 (24 % of observations) adopted a balanced financial strategy, combining moderate leverage with robust liquidity (short-term solvency ratio), enabling agility amid volatility. Their turnover ratio and profitability (ROA: 0.067, ROE: 0.086) are acceptable. While leveraging short-term debt (maturity ratio) for flexibility, they avoided Cluster 2's excessive risk and Cluster 1's rigidity and low profitability.

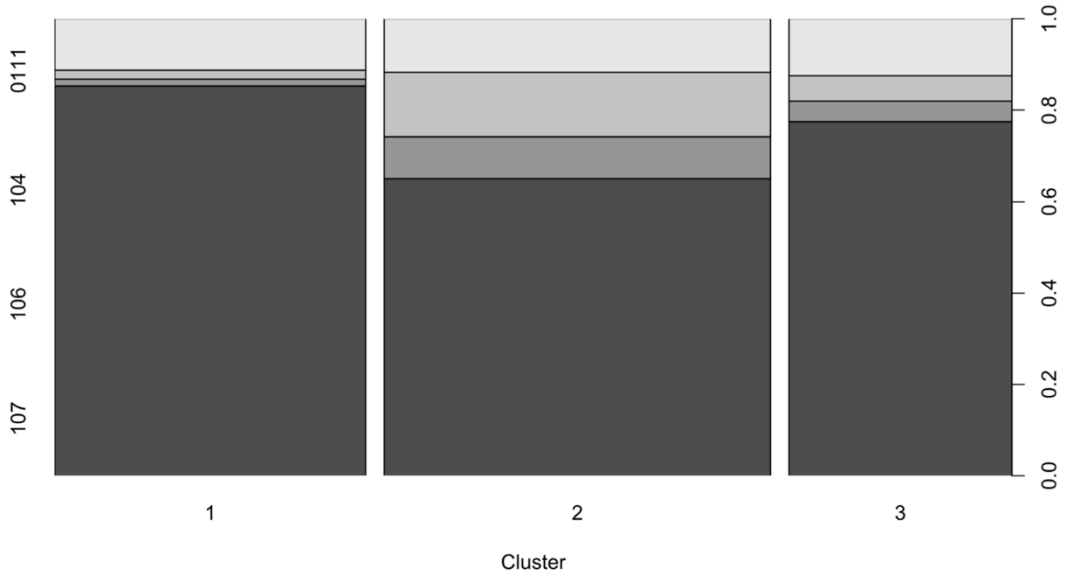
Cluster 3 is by far the best, most balanced and most resilient. It has both profitability and solvency to spare, while the other clusters are deficient in one of these two characteristics. A slight shock in prices or costs could bring the ROA and ROE of Cluster 1 into loss figures. The high leverage of Cluster 2 could translate a slightly negative margin into a large negative ROE, and, if prolonged for a few years, into bankruptcy.

4.3. Relation between cluster and other variables

This section explores the relationship between the three identified clusters and other variables including NACE code, legal structure, year, trade activities (imports and exports), number of employees, and region.

The mosaic plot in Figure 2 illustrates the association between the clusters and the NACE codes. The height of each bar indicates the percentage of companies from each NACE sector within a cluster, while the width of the bars represents the size of the clusters. The majority of firms are concentrated in Cluster 1 and Cluster 2, which together account for over 75 % of the sample. Cluster 3, associated to higher resilience, is the smallest.

Figure 2. Mosaic plot between cluster and NACE code (0111 cultivation of cereals, legumes and oilseeds; 104: oils and fats; 106: milling products and starches; 107: bakery and farinaceous products)

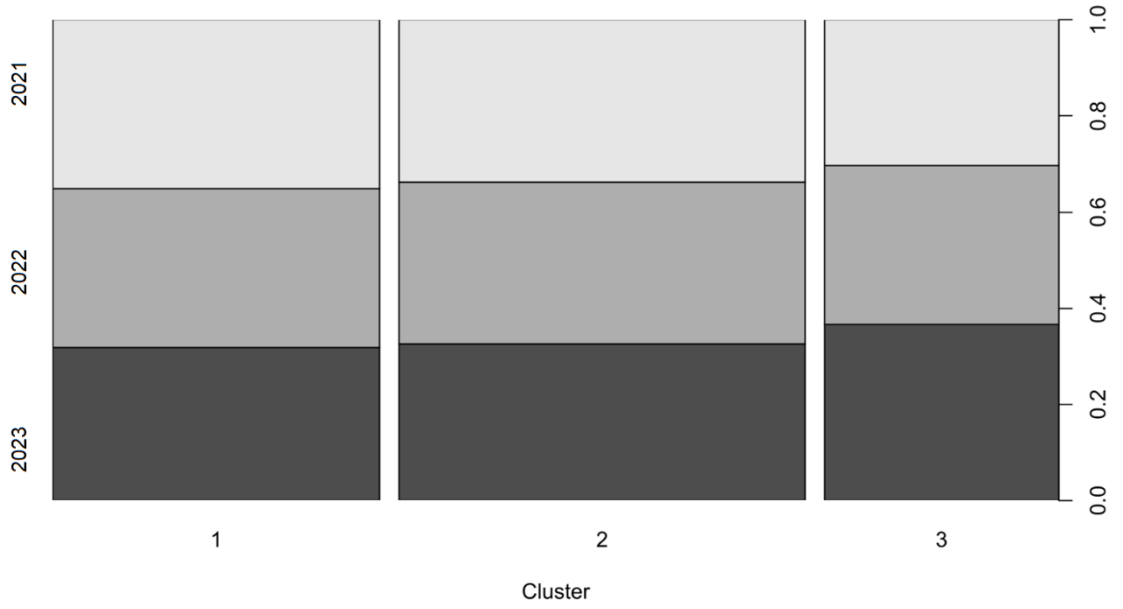


Cluster 1 is associated with sector 107 (bakery and farinaceous products), aligning with its conservative financial structure and reliance on tangible assets. There is virtually no

presence of sectors 106 and 104 in Cluster 1. Cluster 2 is linked to sectors 104 and 106 (vegetable and animal oils/fats, milling and starches), reflecting its high-risk leverage strategy and profitability. Cluster 3 exhibits no clear sectoral dominance, reflecting its heterogeneous composition.

Figure 3 illustrates the relationship between the clusters and the three years of the analysed period. The number of companies in Cluster 3 increases in 2023, which indicates that as firms adapted to the prolonged effects of the conflict, they tended to shift to a better-performing cluster. However, unlike the findings in Arimany-Serrat and Sgorla (2024), Dao et al. (2024), and Saus-Sala et al. (2024), there is no shrinkage of this cluster during 2022, marking the start of the crisis.

Figure 3. Mosaic plot between cluster and year

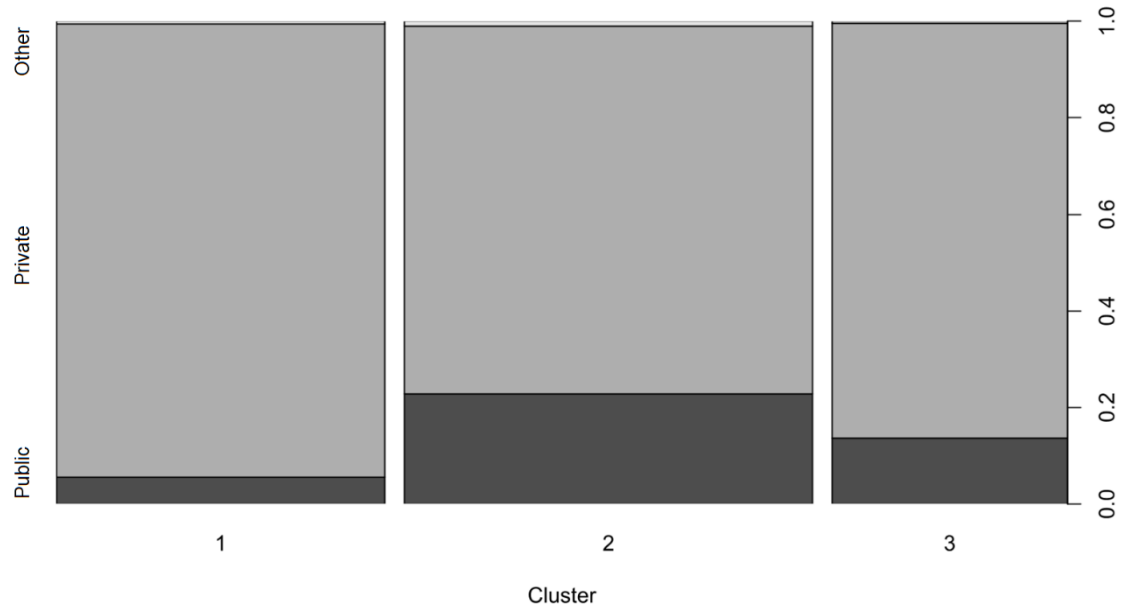


If we look at the transitions of individual firms from and to Cluster 3, altogether, the net gain for Cluster 3 is 25 firms in 2022 and 56 in 2023:

- In 2022 35 companies moved from Cluster 1 to Cluster 3 and 21 the other way around.
- In 2022 21 companies moved from Cluster 2 to Cluster 3 and 10 the other way around.
- In 2023 37 companies moved from Cluster 1 to Cluster 3 and 16 the other way around.
- In 2023 28 companies moved from Cluster 2 to Cluster 3 and 18 the other way around.

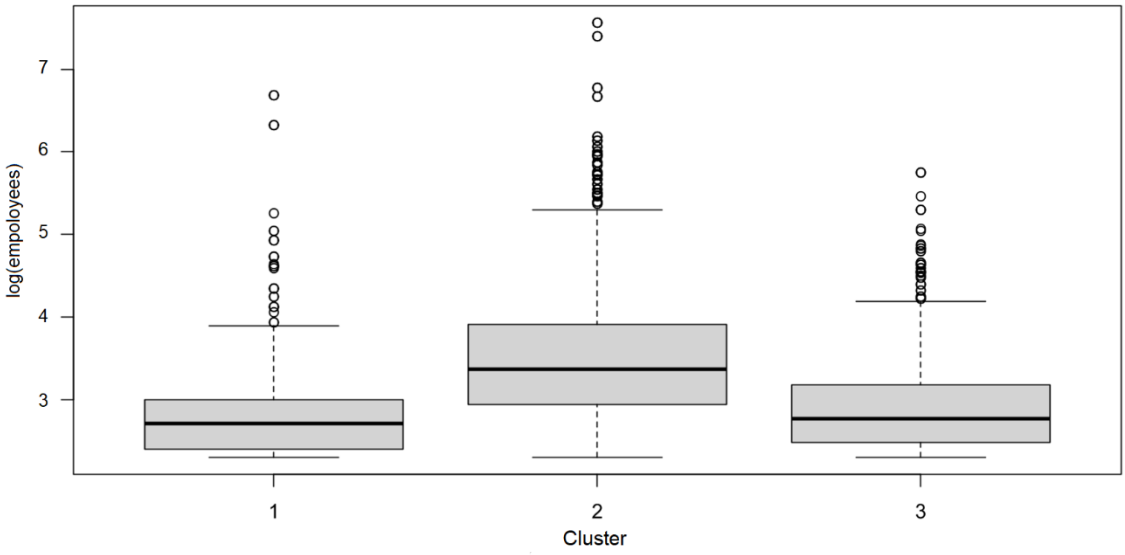
Figure 4 shows that Cluster 1 is the cluster with the lowest proportion of public limited companies and Cluster 2 is the one with the highest proportion. This may be because public companies, with greater access to capital markets and higher investor expectations, tend to adopt more aggressive, debt-driven financial strategies, resulting in the high-risk profile observed in Cluster 2. Conversely, private limited companies often follow more conservative approaches and have less access to debt, aligning them with the characteristics of Cluster 1. There are virtually no companies of other legal forms in any of the clusters.

Figure 4. Mosaic plot between cluster and legal form



A similar conclusion can be drawn from Figure 5, which illustrates the distribution of employee numbers across clusters. Interpreting employee count as an indicator of operational capacity, it can be observed that Cluster 2 is characterized by firms with the highest number of employees. This reinforces the pattern observed in Figure 4: firms with greater operational scale, such as public limited companies with access to broader capital markets, are more likely to adopt aggressive, risk-laden financial strategies. The most resilient Cluster 3 is characterized by a small median number of employees.

Figure 5. Boxplots of employees by cluster



Figures 6 and 7 illustrate the association between clusters and trade activity. Cluster 1, characterized by conservative, asset-intensive firms, exhibits the highest import/export activity. In contrast, Cluster 2, comprised of high-risk, leverage-driven firms, shows the lowest trade activity; their asset-light structure and dependency on volatile inputs make them more vulnerable to trade fluctuations.

Figure 6. Mosaic plot between cluster and imports

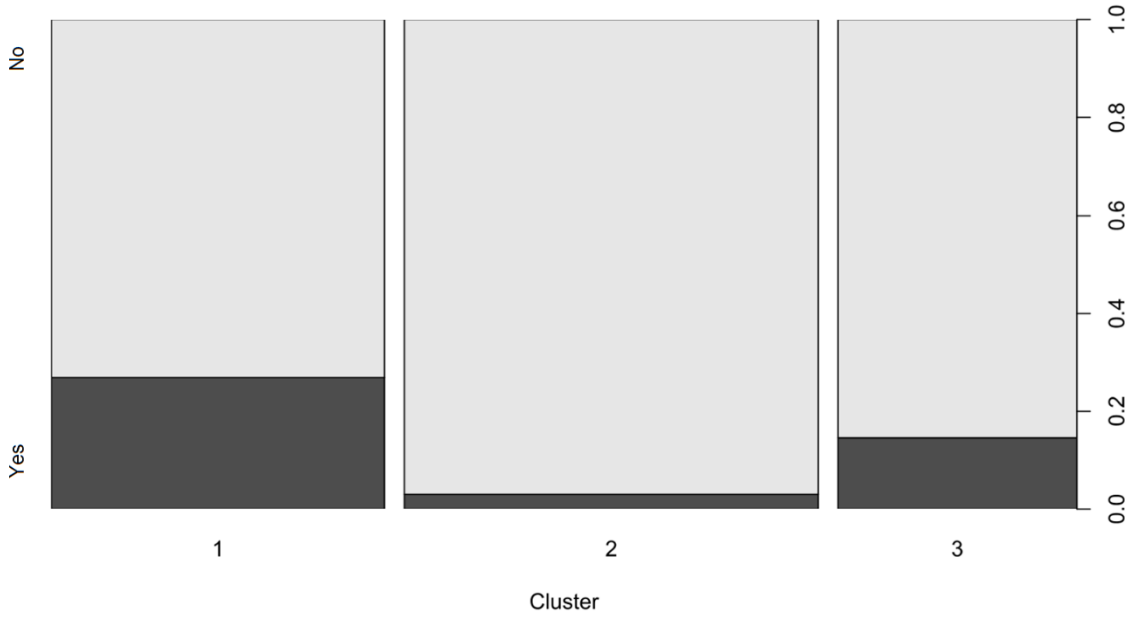


Figure 7. Mosaic plot between cluster and exports

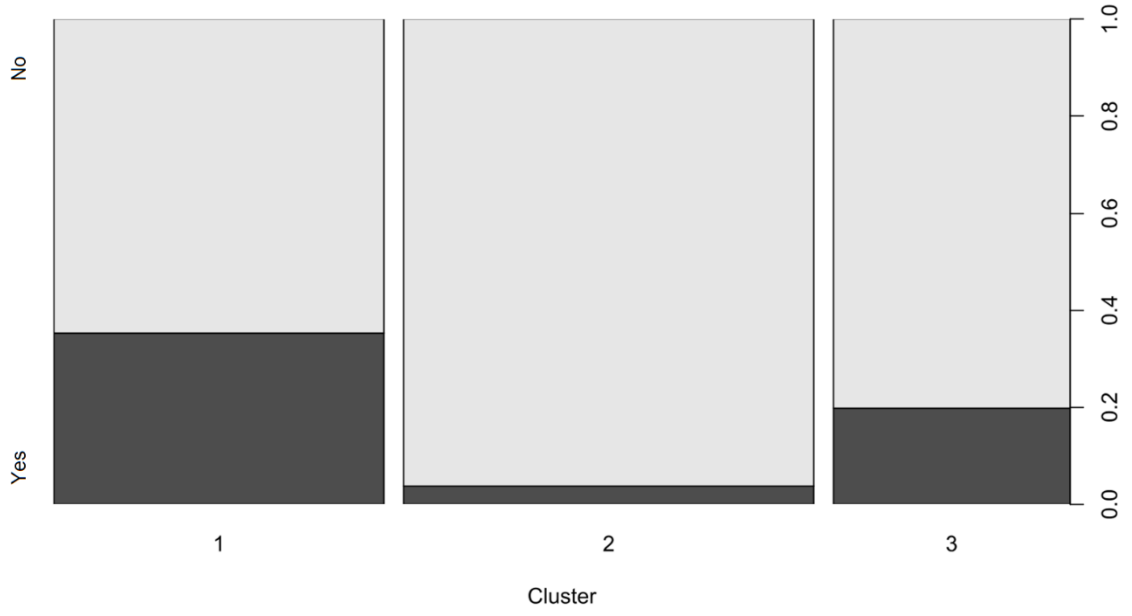


Figure 8. Mosaic plot between cluster and autonomous community (AN: Andalusia, AR: Aragon, CL: Castille-Leon, CM: Castille-la Mancha, CN: Cantabria, CT: Catalonia, GA: Galicia, MA: Madrid, MU: Murcia, OT: Other, PV: Basque country, VA: Valencian community)

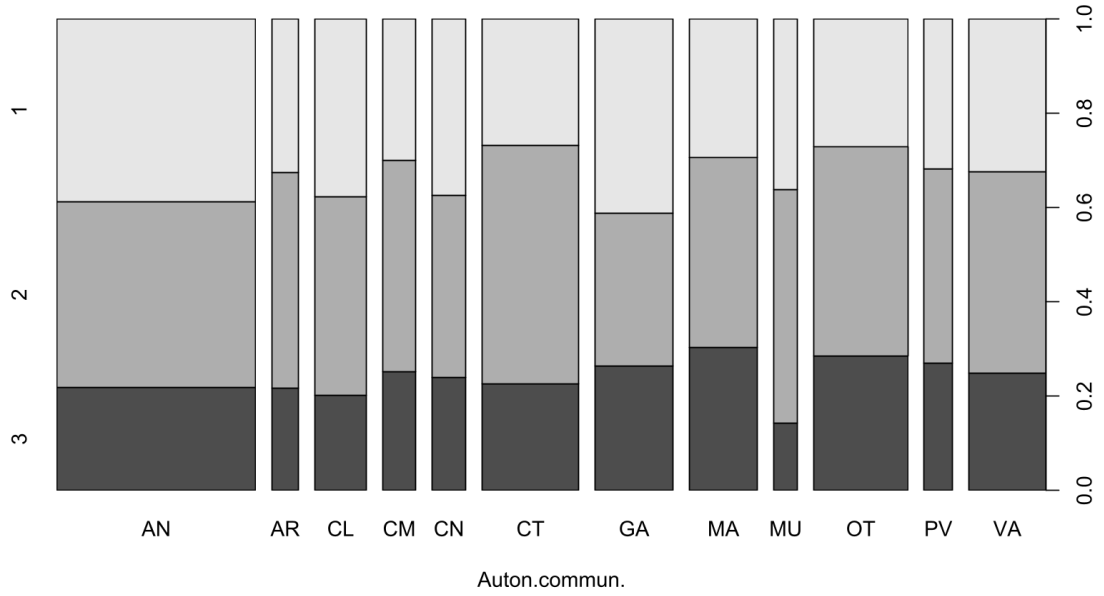


Figure 8 shows the importance of each cluster by regions (autonomous communities in Spain). The least profitable cluster 1 tends to concentrate in Andalusia, Castille-Leon, Cantabria and Galicia. Catalonia stands out for the most indebted cluster 2. The more resilient cluster 3 appears in Madrid and in the other communities (communities with fewer than 40 firms in the sample were grouped together).

5. Conclusion and discussion

The analysis of financial ratios reveals that, although firms in some of the sectors experienced financial strain in 2022 with a drop in profitability measures, they demonstrated remarkable resilience, leading to recovery and even surpassing pre-war performance levels by 2023. This recovery indicates the sector's ability to adapt and overcome the economic disruptions caused by the conflict.

The study also highlights the heterogeneity within the sector. While some sectors, such as the milling products and starches sector (106) and the cereal cultivation sector (0111) maintained or slightly improved their profitability, others, such as the bakery and farinaceous products sector (107), faced a pronounced deterioration in profitability in 2022. For instance, sector 106's rapid debt restructuring—facilitated by its smaller size—demonstrates the benefits of agile financial management.

A k-means cluster analysis of the standard financial ratios in Equations 2 to 13 resulted in a cluster containing 99.64 % of observations and two clusters containing only outliers (0.33 % and 0.03 % of observations respectively). Conversely, as in Arimany-Serrat and Coenders (2025a), Arimany-Serrat and Sgorla (2024), Dao et al. (2024), and Saus-Sala et al. (2024), compositional cluster analysis successfully reveals clusters of well-balanced sizes differing in resilience towards a crisis. The cluster analysis identified three distinct financial profiles: conservative (Cluster 1), high-risk leveraged (Cluster 2), and balanced (Cluster 3). Cluster 3 is the most resilient. Cluster 1 has less than ideal returns. Cluster

2's overreliance on debt illustrates how aggressive leverage can magnify returns while also increasing the risk of insolvency. Unlike our expectations supported by similar research, Cluster 3 did not shrink during 2022. Its growth observed during 2023 does reinforce the idea that prolonged crises encourage firms to adopt more resilient strategies. This finding underscores the importance of diversified financing and adaptive governance to mitigate the impact of geopolitical disruptions.

Furthermore, the analysis revealed that cluster 1 is linked to the bakery sector (107), private firms, and high import/export activity, while Cluster 2 aligns with vegetable/animal oils (104), public limited companies, and low trade engagement. Cluster 3 lacks sectoral dominance, features smaller firms, and grew in the third year supporting a better adaptation of some firms to the conflict. This trajectory could signal that the sector may be better prepared for future crises, provided incentives for balanced strategies—such as those observed in Cluster 3—are sustained or strengthened. Some regional differences also emerged.

While this study focuses on financial resilience, broader systemic policies could amplify these adaptive capacities. For instance, Ben Hassen and El Bilali (2022) emphasize that building resilient food systems is critical to weathering disruptions, a principle echoed in the growth of Cluster 3's diversified financial approaches. Similarly, Abay et al. (2023) propose policy measures such as maintaining open trade flows for agricultural inputs, avoiding export restrictions, and targeting subsidies to vulnerable stakeholders. While the focus of this study is not on these policies, understanding their context can provide valuable insights for strategic planning in the agricultural sector. These systemic considerations must be paired with critical reforms in corporate governance. Notably, the prevalence of public limited companies in cluster 2 raises critical questions about corporate governance priorities. The dominance of high-risk, debt-driven strategies among publicly traded firms may reflect a systemic short-termism driven by shareholder pressure to maximize returns, even at the expense of long-term sustainability. This aligns with the ethical dilemma inherent in shareholder primacy models: balancing profitability demands with the need for operational resilience, particularly in essential sectors such as food production.

The main limitations of this research include firstly the restricted sample derived from the SABI database, which only encompasses companies with a corporate structure, thereby excluding micro-enterprises and individual businesses common in Spain's agricultural and food production sectors, as their financial data are not publicly disclosed. While the sample size of the four analysed subsectors is admittedly very different, it reflects the population structure for the aggregated results.

Secondly, the three-year timeframe (2021–2023) limits the assessment of long-term resilience trajectories. 2023 was the last available year of data at the time the article was submitted. Future research should remedy this limitation.

Thirdly, the study is descriptive. No causal inference can be made. Other relevant shocks during the study period could have affected the results at the same time as the Ukraine-Russia war, chief among them being the severe drought wave. The average rainfall in Spain for the 1991-2020 period was 649 mm., which dropped to a mere 514 in 2021-2022 and 592 in 2022-2023 (source: Spanish meteorological agency). The royal decree 4/2023 issued in May 2023 severely limited watering the fields and water supply to the farms, but for the sheer survival of trees and animals. Causal inference requires using statistical

models in conjunction with the CoDa approach (Farreras-Noguer et al., 2025). For modelling panel data such as we have in this article, see for instance Carreras-Simó and Coenders (2021) and Escaramís and Arbussà (2025).

Fourthly, the study is limited to k-means clustering. Other clustering methods have successfully been adapted to CoDa and could be explored, including hierarchical clustering (Linares-Mustarós et al., 2018), weighted clustering (Jofre-Campuzano and Coenders, 2022), fuzzy clustering (Molas-Colomer et al., 2024) and latent-class analysis (Ferrer-Rosell et al., 2016).

Fifthly, the findings are context-specific to the analysed subsectors (cereal cultivation, oils/fats manufacturing, milling products, and bakery/farinaceous production) and should not be generalized to other sectors without further validation.

Finally, the exclusion of other accounting figures and financial statements such as the cash-flow statement narrows the financial analysis, omitting insights into liquidity dynamics critical for crisis adaptation (Arimany-Serrat et al., 2022).

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AUTHOR CONTRIBUTIONS

Conceptualization: MHR and GC; methodology: GC; formal analysis: MHR and GC; data curation: MHR; writing—original draft: MHR; writing—review & editing: GC; Supervision: GC; funding acquisition: GC.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY

The curated data are available from the corresponding author upon reasonable request.

USE OF ARTIFICIAL INTELLIGENCE (AI)

AI tools were used for language editing only.

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