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Research article

The relationship between asset and capital structure: a compositional approach with panel vector autoregressive models

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Abstract: The companies' investment and financing policies are dynamically interrelated and there is no general consensus about the direction of this relationship. There are theoretical arguments and empirical evidence supporting both possible directions, which makes panel vector autoregressive models an appropriate tool. However, the financial ratios normally used to assess this relationship empirically tend to be asymmetric, and to have extreme outliers and non-linear relationships. The aim of this article is to propose a methodological approach to address these issues by complementing panel vector autoregressive models with compositional data analysis. The usefulness of the proposed methodology is illustrated with real data of Spanish retail companies, while a reanalysis with standard financial ratios is inconclusive.

Keywords: compositional data analysis (CoDa); panel VAR models; accounting ratios; asset structure; capital structure; retail sector

JEL Codes: C33, C49, G30, G32

Abbreviations: CoDa: Compositional Data; EM: Expectation Maximization; GMM: Generalized Method of Moments; SBP: Sequential Binary Partition; VAR: Vector Auto Regressive

1. Introduction

The study of the relationship between asset structure (investment structure) and capital structure (financial structure) has been carried out within the scope of research on theories of capital structure (Frank and Goyal, 2003; Harris and Raviv, 1991; or Kumar et al., 2017). This type of study faces several major challenges. On the one hand, the relationship is dynamic and potentially bidirectional, requiring panel models in which both variables are potentially dependent, such as panel vector autoregressive (panel VAR) models. Indeed, while there is a consensus that the capital and the asset structures are dynamically interrelated, there is no consensus on the direction of this relationship (Childs et al., 2005; Lambrecht and Myers, 2017). On the other hand, distributional problems are invariably reported in financial ratios, which are used as variables to study this relationship, including skewness, non-linearity and outliers (Linares-Mustarós et al., 2018). In this article we put forward a method aimed at solving both problems based by combining compositional data (CoDa) methods with panel VAR models.

Regarding directionality of the relationship, many authors focus on highlighting the collateral that the asset structure represents for the debt. The liquidation value of a company depends on its asset structure (asset tangibility or liquidity). Therefore, companies that invest in a more tangible or more liquid asset structure, in turn, have greater ability to issue debt securities (Shleifer and Vishny, 1992) and are in a better position to take advantage of financial leverage (capital trade off theory—Harris and Raviv, 1991). Moreover, the option of debt as a financial resource presents a better position from the perspective that sources of financing may be a priority for companies with a more tangible and liquid asset structure (pecking order theory—Frank and Goyal, 2003; Myers, 1984). Therefore, these approaches propose that the structure of the assets in a company conditions the structure of its capital.

However, other alternative approaches consider that the capital structure of companies is what could determine their asset structure. These approaches are based on two arguments of how the financial structure can influence investment policy. The first argument about how a company's capital structure can condition its asset structure is based on financial flexibility (Arslan-Ayaydin et al., 2014; Denis and McKeon, 2012). Financial flexibility refers to the greater ability of a company with lower indebtedness to respond to investment opportunities. The second argument is based on conflicts of interest and information asymmetries between shareholders, debtholders and managers (agency cost). Several authors have presented reasons why the capital structure of a company can act as a mechanism to smooth the conflicts of interest between these agents, and thus reduce agency costs and improve efficiency. Jensen (1986) considers the interest conflict between shareholders and managers. Managers will have incentives to overinvest because of their benefits resulting from a larger dimension of the company. A more leveraged financial structure restricts the ability of managers to use the firms' financial resources discretionally, thus mitigating the agency costs (Grossman and Hart, 1982). Jensen and Meckling (1976) and Myers (1977) describe the agency relationship between shareholders and debtholders. These conflicts arise from the asymmetry in the distribution of profits and risks between shareholders and debtholders, which can lead shareholders to invest sub-optimally. This agency cost problem can also be controlled by an adequate debt policy. Therefore, the asset structure resulting from investment decisions may be conditioned by the capital structure.

Thus, the dynamic relationship between capital and asset structure in companies can run in both directions. However, several authors have assumed a priori a direction of this relationship (e.g.

Aivazian et al., 2005; Billett et al., 2007; Bontempi and Golinelli, 2012; Gebauer et al., 2018; Ramalho and Silva, 2009) while others do not benefit from the fact that the interrelationship is dynamic to help address the bidirectionality issue (Alcock and Steiner, 2017).

Additionally, the methodological approaches used to estimate the relationship between capital and asset structure have been based on financial ratios, also referred to as accounting ratios, which present serious problems in statistical and econometric analyses. Using financial ratios for capital and asset structure as data leads to asymmetry, and hence non-normality; non-linearity; and outliers, which pose a serious threat to statistical modelling (Carreras-Simó and Coenders, 2020; Cowen and Hoffer, 1982; Creixans-Tenas et al., 2019; Deakin, 1976; Frecka and Hopwood, 1983; Linares-Mustarós et al., 2018). Furthermore, accounting ratios tend to be mutually redundant and analysis results depend on the choice of which accounting figure is placed in the numerator and in the denominator (Chen and Shimerda, 1981; Creixans-Tenas et al., 2019; Frecka and Hopwood, 1983; Linares-Mustarós et al., 2018).

The aim of this article is to propose a methodological approach to identify the direction of the dynamic relationship between asset and capital structure, which solves the said distributional problems in accounting ratios. This approach is based on panel VAR models (e.g. Abrigo and Love, 2016; Hahn and Kuehrsteiner, 2002; Love and Zicchino, 2006; Sigmund and Ferstl, 2021) to treat both capital and asset structures as dependent variables, and on the CoDa methodology (Aitchison, 1986; Filzmoser et al., 2018; Greenacre, 2018; Pawlowsky-Glahn et al., 2015; Van den Boogaart and Tolosana-Delgado, 2013) to solve the distributional problems. To the best of our knowledge the CoDa methodology has never been used in the field of capital and asset structures, and has never been used in combination with panel VAR models in any field.

The Spanish retail sector is used to illustrate the applicability of this methodological approach. The illustration analyses the dynamic relationship between the asset structure variations and the capital structure variations of the Spanish retail companies for a long period (from 2000 up to 2017) in order to identify the direction of this relationship. The data provide an ideal framework for analysis for two reasons. On the one hand, the temporal scope of the database allows for an accurate analysis of the relationship between both structures to be carried out considering long-term sectoral dynamics. On the other hand, the wide variety of types of companies in the retail sector makes it possible to identify differences in patterns (Ramalho and Silva, 2009), for instance regarding firm size.

The article is structured as follows. Section 2 presents the foundations of the proposed methodological approach. In section 3, the methodology is applied to the Spanish retail sector as an example to analyze the relationship between asset and capital structure and identify the direction and dynamics of this relationship. The article ends in section 4 with a summary of the main conclusions.

2. Materials and methods

2.1. Compositional data

The CoDa methodology emerged in the fields of geology and chemistry. These disciplines typically focus on the relative importance of the components of the whole rock or substance under analysis, while the size of the rock or chemical sample is deemed irrelevant and usually normalized to a fixed sum, for example percentages adding up to 100. After the seminal work by Aitchison (1986), thirty-five years of development have led to a well-established standard CoDa toolbox that is covered in text books (Filzmoser et al., 2018; Greenacre, 2018; Pawlowsky-Glahn et al., 2015; Van den Boogaart and Tolosana-Delgado, 2013) and can be used whenever the research questions concern the relative importance of magnitudes to one another. CoDa are contemporarily defined in very general terms as arrays of strictly positive numbers for which ratios between them are considered to be relevant (Egozcue and Pawlowsky-Glahn, 2019) without any requirement to have a fixed sum. This broad definition has spurred a widespread usage, and has contributed to CoDa spanning all scientific fields, including the social sciences (Coenders and Ferrer-Rosell, 2020). Recently, CoDa have successfully been applied in financial research like crowdfunding (Davis et al., 2017), financial markets (Kokoszka et al., 2019; Ortells et al., 2016; Wang et al., 2019), municipal budgeting (Voltes-Dorta et al., 2014), investment portfolios (Belles-Sampera et al., 2016; Boonen et al., 2019), product portfolios (Joueid and Coenders, 2018), exchange-rates (Gámez-Velázquez and Coenders, 2020; Maldonado et al., 2019), and insurance pricing (Verbelen et al., 2018).

Financial statement analysis by means of accounting ratios fulfils the CoDa definition to the letter and constitutes a further nascent field of application (Carreras-Simó and Coenders, 2020; Creixans-Tenas et al., 2019; Linares-Mustarós et al., 2018; Saus-Sala et al., 2021).

CoDa are positive vector variables carrying information about the relative size of their D components to one another (Aitchison, 1986):

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

When using compositions for the purpose of financial statement analysis, the x_j components in $\mathbf{x}$ are purposely selected positive accounting figures. With the aim of relating asset and capital structure, we define the following components from the balance sheet:

- x_1: non-current assets
- x_2: current assets
- x_3: net worth
- x_4: non-current liabilities
- x_5: current liabilities

The above accounting figures constitute actually two compositions, one for assets (x_1, x_2) with D = 2 components and one for liabilities and net worth (x_3, x_4, x_5) with D = 3. From them, standard financial ratios to analyze capital and debt structure can be computed, like the debt quality ratio (x_4/x_5), the solvency ratio ($x_3/(x_4+x_5)$), and so on.

The use of standard financial ratios in statistical analyses, especially multivariate, has long been advised against because of commonly reported problems of asymmetry and hence non-normality, outliers, non-linearity, redundancy, and dependence of the results on permutation of the numerator and denominator of the ratio (Carreras-Simó and Coenders, 2020; Cowen and Hoffer, 1982; Creixans-Tenas et al., 2019; Deakin, 1976; Frecka and Hopwood, 1983, Linares-Mustarós et al., 2018). These serious problems have also been reported if ratios are aggregated in composite scores (Tuzcuoğlu, 2020) and in other scientific fields using ratios (Isles, 2020). In order to measure the relative importance of the accounting figures in statistical analysis, the common log-ratio transformations in CoDa can be used instead of standard financial ratios.

As recommended by Egozcue et al. (2003), for each composition D–1 log-ratios are constructed as balance coordinates, henceforth referred to as coordinates. The fact that D–1 log-ratios contain all relative information in D components is a further recognition that any number greater than that can only lead to mutual redundancy. Said coordinates can be easily formed from a sequential binary partition (SBP) of components. To create the first coordinate, the complete composition (x_1, x_2,…,x_D) is split into two groups of components: one for the numerator and the other for the denominator of the log-ratio. In the following step, one of the two groups is further split to create the second coordinate. In any step of the SBP, when the z_j coordinate is created, a group containing $r+s$ components is split into two: r components (x_{n1},…,x_{nr}) are placed in the numerator, and s components (x_{d1},…,x_{ds}) in the denominator. The coordinate is a scaled log-ratio of the geometric means of each group of components:

$$z_j = \sqrt{\frac{rs}{r+s}} \log \frac{\sqrt[r]{x_{n1} \cdots x_{nr}}}{\sqrt[s]{x_{d1} \cdots x_{ds}}} \tag{2}$$

The choice about which components are placed in the numerator or the denominator will not modify any property of the coordinate but the sign, thus leaving statistical relationships unchanged. A positive sign of the coordinate implies greater relative importance of the components in the numerator as compared to those in the denominator. $\sqrt{\frac{r\,s}{r+s}}$ is only a scaling constant to take the number of components into account.

It is advisable to select a SBP which can be interpreted in the light of the research purpose or the common concepts in the field. In the asset case, only one coordinate is needed, and the choice boils down to selecting the numerator and denominator components. Placing non-current assets in the numerator:

$$z_{a_1} = \sqrt{\frac{1 \cdot 1}{1+1}} \log\left(\frac{x_1}{x_2}\right) = \left(\frac{1}{\sqrt{2}}\right) \log\left(\frac{x_1}{x_2}\right) \tag{3}$$

leads to interpreting higher z_{a1} values as a greater fixed-asset share.

In the capital case two coordinates z_{l1} and z_{l2} are required. At the top of the SBP, a fist partition comparing net worth (numerator) and liabilities (denominator) provides an indicator of solvency, in other words, lack of indebtedness or low leverage:

$$z_{l1} = \sqrt{\frac{2 \cdot 1}{2+1}} \log\left(\frac{x_3}{\sqrt[2]{x_4 \cdot x_5}}\right) = \sqrt{\frac{2}{3}} \log\left(\frac{x_3}{\sqrt[2]{x_4 \cdot x_5}}\right) \tag{4}$$

In the next partition, comparing non-current (numerator) and current liabilities provides an indicator of debt quality, in other words, longer debt maturity:

$$z_{l2} = \sqrt{\frac{1 \cdot 1}{1+1}} \log\left(\frac{x_4}{x_5}\right) = \left(\frac{1}{\sqrt{2}}\right) \log\left(\frac{x_4}{x_5}\right) \tag{5}$$

2.2. Panel vector autoregressive models

Vector autoregressive (VAR) models have successfully been extended to panel data with repeated measures of a sample of individuals and are an increasingly popular approach to deal with dynamic relationships when there is more than one dependent variable (e.g. Abrigo and Love, 2016; Carlino and Drautzburg, 2020; Hahn and Kuehrsteiner, 2002; Larsson and Lyhagen, 2007; Love and Zicchino, 2006; Mumtaz and Sunder-Plassmann, 2021; Sigmund and Ferstl, 2021), which will always be the case in compositions, represented by several coordinates.

As conventional VAR models, panel VAR models treat all variables as dependent (in our case changes in asset structure may precede changes in capital structure or the other way around), and provide effect estimates of dynamic relationships among variables in all directions. To this end, each variable depends on its own lagged value and on the lagged values of all other variables. As conventional panel models, panel VAR models account for non-observed inter-individual (inter-firm) heterogeneity, thus making time-invariant control variables unnecessary.

VAR models have also successfully been extended to compositional time series data by simply using the vector of coordinates (Boonen et al., 2019; Kynčlová et al., 2015). To the best of our knowledge, in this article we combine both extensions for the first time.

The panel VAR model is thus specified for firm i, period t and maximum lag p as:

$$\begin{pmatrix} z_{a1} \\ z_{l1} \\ z_{l2} \end{pmatrix}_{i,t} = \sum_{k=1}^{p} \mathbf{A}_k \begin{pmatrix} z_{a1} \\ z_{l1} \\ z_{l2} \end{pmatrix}_{i,t-k} + \begin{pmatrix} \mu_{a1} \\ \mu_{l1} \\ \mu_{l2} \end{pmatrix}_{i} + \begin{pmatrix} \varepsilon_{a1} \\ \varepsilon_{l1} \\ \varepsilon_{l2} \end{pmatrix}_{i,t} \tag{6}$$

where the elements in μ stand for the firm-specific panel fixed effects, ε for the independent and identically distributed idiosyncratic errors, and $\mathbf{A}$ for the autoregressive parameter matrices for each lag k from 1 to p.

As in conventional VAR models, besides the model estimates, the impulse-response function computed from the inversion into a moving-average representation, provides a further interpretational tool and shows the manner in which shocks in each variable spread into future changes of the same variable and of other variables. In formal terms, the impulse-response function is expressed as $\mathbf{I}_1$, $\mathbf{I}_2$, $\ldots\mathbf{I}_\infty$ in the moving-average representation:

$$\begin{pmatrix} z_{a1} \\ z_{l1} \\ z_{l2} \end{pmatrix}_{i,t} = \begin{pmatrix} \mu_{a1} \\ \mu_{l1} \\ \mu_{l2} \end{pmatrix}_{i} + \sum_{k=1}^{\infty} \mathbf{I}_k \begin{pmatrix} \varepsilon_{a1} \\ \varepsilon_{l1} \\ \varepsilon_{l2} \end{pmatrix}_{i,t-k} \tag{7}$$

where the elements in $\mathbf{I}_k$ are the effects of each ε shock on each z variable k periods ahead.

Conventional fixed- and random-effects estimators for panel data models are biased for dynamic models such as panel VAR models, and the generalized method of moments (GMM) estimator is a common alternative when the number of cases is large and the number of time points small (Croissant and Millo, 2019). Sigmund and Ferstl (2021) developed the panelvar R library which estimates panel VAR models by GMM with the Windmeijer (2005) correction to standard errors. As recommended by Croissant and Millo (2019), we use the two-step approach to improve efficiency and standard error estimation, the option to collapse moment conditions to prevent the large number of instrumental variables from hampering efficiency, and the forward orthogonal deviation transformation (Arellano and Bover, 1995) rather than the more classical first differences to minimize data losses due to data gaps. As Sigmund and Ferstl (2021), we do not use system instruments (system_instruments = FALSE, transformation = “fod”, steps = “twostep” and collapse = TRUE options in the pvargmm function in the panelvar R library).

The selection of the number of lags is made by means of the Bayesian Information Criterion (BIC) computed according to Andrews and Lu (2001). Stability, in other words, invertibility into a finite moving-average representation (the effects in the impulse-response function $\mathbf{I}_k$ become smaller as k increases), is checked by the modulus of each eigenvalue of the estimated model (Lütkepohl, 2007). The generalized impulse-response function is computed as in Pesaran and Shin (1998) and

Kapetanios (2008) with confidence bands drawn with the cross-sectional bootstrap method (Andrews_Lu_MMSC, stability, girf and bootstrap_irf functions in the panelvar R library).

3. Results

3.1. An illustration: the Spanish retail trade sector 2000–2017

The Spanish retail sector, motor vehicles and motorcycles excepted, is one of the most important sectors in the Spanish economy and is used as illustration of the proposed method. According to the Instituto Nacional de Estadística (Spanish Statistics Institute), the turnover was 240 billion EUR with an added value of 46.3 billion EUR and 1.7 million full-time employees in 2018, which represented 3.8% of gross domestic product and 9.7% of employment in Spain. This sector is a fruitful area to apply the proposed methodology. On the one hand, the type of companies operating in the sector is very heterogeneous. In 2018 there were 425,284 companies operating in this sector, of which 983 had 50 employees or more and 196,587 had between 2 and 9 employees. The flexibility of the business model that companies can use in this sector enables different asset and capital structures to be observed (Ramalho and Silva, 2009). For example, some companies may choose to own the establishments they manage, and others may choose to manage these establishments on a rental basis. These different models may be motivated by the capital structure of the companies or may condition their capital structure.

3.2. Data collection and preprocessing

The data 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. The data spanned 18 years, from 2000 to 2017. Selection criteria were activity during 8 consecutive years witnessed by positive revenue, positive current assets, positive non-current assets, and positive number of employees, and belonging to the retail trade sector except motor vehicles and motorcycles (Statistical classification of economic activities in the European Community rev. 2 codes 4711, 4719, 4721–4726, 4729–4730, 4741–4743, 4751–4754, 4759, 4761–4762, 4764–4765, 4771–4779, 4781–4782, 4791 and 4799). If additional non-consecutive periods showed activity according to the above criteria, only consecutive periods were used. This resulted in 12,135 cases from 857 firms, which corresponds to 14.16 years with data per firm, on average.

The accounting figures of interest may contain no zero values in order for log ratios to be computed (Martín-Fernández et al., 2011). The same holds for standard financial ratio analysis regarding the account in the denominator. Unlike the case in standard financial ratio analysis, CoDa include an advanced toolbox for zero imputation prior to log ratio computation, with Palarea-Albaladejo and Martín-Fernández (2008) and Martín Fernández et al. (2011) being key references. This makes financial statement analysis possible even when some accounting figures of interest equal zero. In this article we use the modified EM algorithm in Palarea-Albaladejo and Martín-Fernández (2008) as implemented in the zCompositions (Palarea-Albaladejo and Martín-Fernández, 2015) R library (lrEM function with default options). Non-current liabilities (x_4) and current liabilities (x_5) had 17.41% and 0.05% zero values respectively, which makes them suitable for EM replacement (Palarea-Albaladejo and Martín-Fernández, 2008).

CoDa also have implications for outlier detection. Given the fact that components cannot be considered in isolation, multivariate outlier detection methods are called for. Squared Mahalanobis distances can be computed on coordinates which, under multivariate normality and for large samples, follow approximately a χ^2 distribution (Filzmoser et al., 2018). An appropriate percentile for this distribution (e.g. $0.95^{(1/n)}$ to take multiple testing into account with a global significance level 0.05) can be used as cut-off criterion for outlier detection (Coenders and Saez, 2000). The number of identified outliers was 14 cases, corresponding to 8 firms, which were removed from the sample entirely, leaving 849 firms and 12,001 cases, with 14.14 years per case on average.

After zero replacement and outlier pruning, data were well behaved in terms of asymmetry and kurtosis and graphs showed no further extreme outliers or non-linear patterns (Table 1, Figures 1 and 2). Section 3.5 shows the same results for standard financial ratios, which are non-linear, asymmetric, hence non-normal, and plagued with extreme outliers to such an extent that makes them completely unsuitable for parametric statistical modelling.

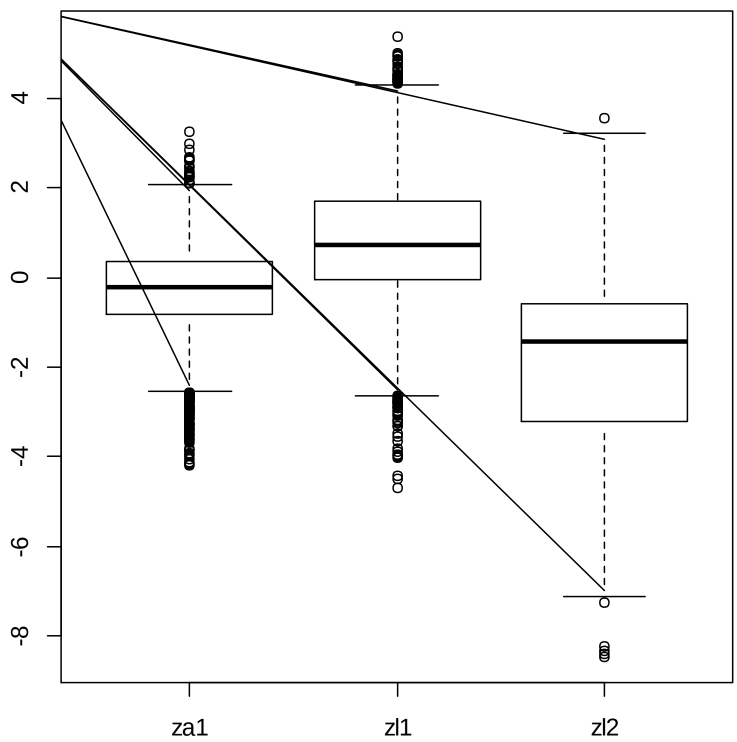

Figure 1. Box plots of asset (za1) and capital (zl1 and zl2) coordinates.

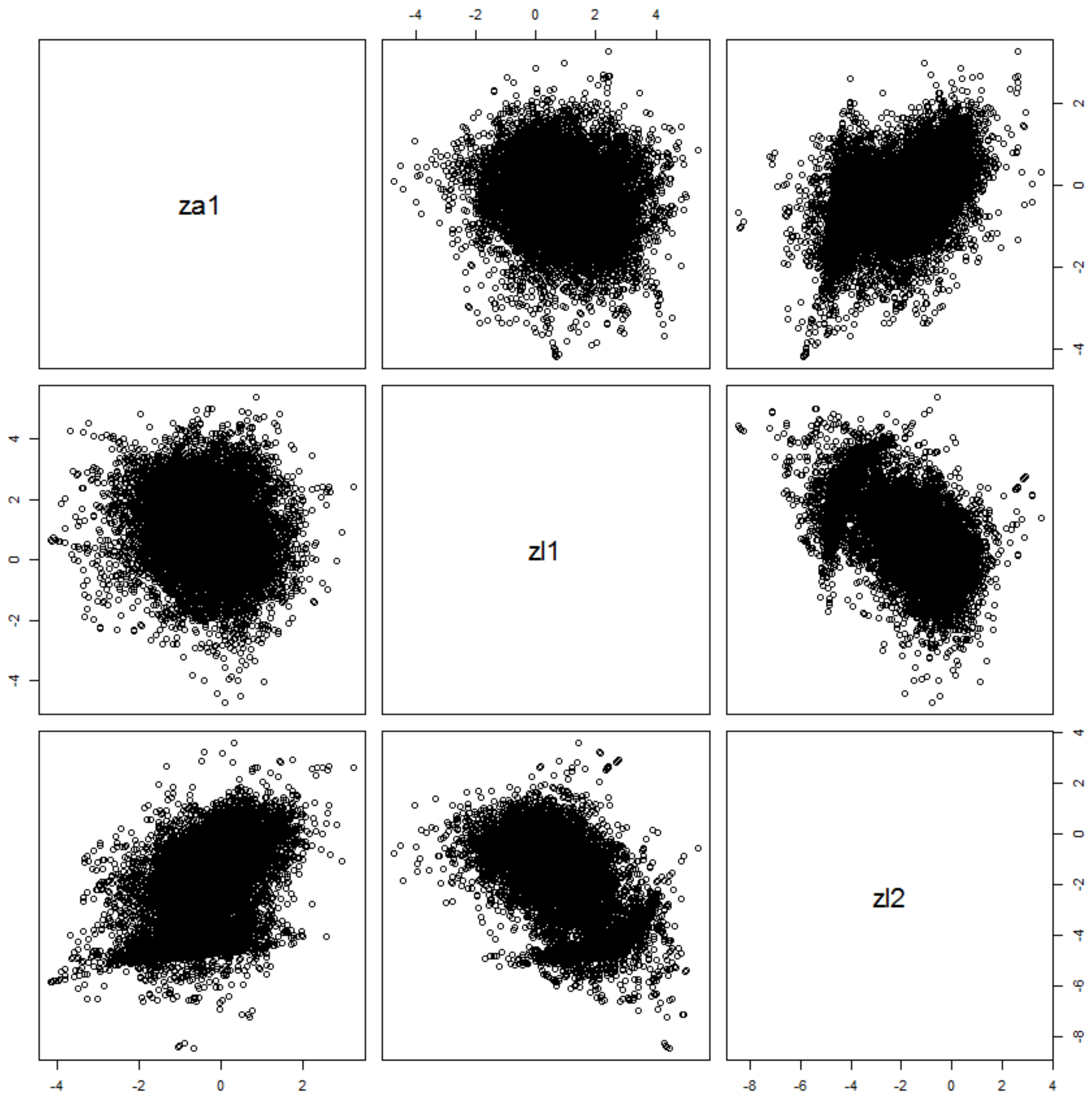

Figure 2. Scatterplots of asset (za1) and capital (zl1 and zl2) coordinates.

Table 1. Descriptive statistics of asset (z_{a1}) and capital (z_{l1} and z_{l2}) coordinates.

	mean	sd	skewness	kurtosis	min	Q1	Q2	Q3	max
z_{a1}	−0.271	0.892	−0.370	0.574	−4.179	−0.822	−0.214	0.338	3.257
z_{l1}	0.835	1.292	0.144	−0.014	−4.705	−0.039	0.715	1.694	5.378
z_{l2}	−1.860	1.683	−0.445	−0.682	−8.464	−3.203	−1.443	−0.588	3.559

When we consider only static relationships, both raw correlations and partial correlations controlling by firm (Table 2) show that increasing the share of non-current assets (z_{a1}) is associated to increases of debt quality (z_{l2}) and decreases of solvency (z_{l1}). Static correlations still do not answer the research question about whether changes in companies' asset structure lead to future changes in their capital structure, or the other way around.

Table 2. Zero-order Pearson correlations (below the diagonal) and partial correlations controlling by firm (above the diagonal).

	z_{a1}	z_{l1}	z_{l2}
z_{a1}	1.000	−0.169***	0.316***
z_{l1}	−0.160***	1.000	−0.685***
z_{l2}	0.467***	−0.604***	1.000

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

3.3. Panel VAR estimates

The BIC shows the lag−1 panel VAR model (−1116.53) to fit better than the lag−2 model (−1107.597). In any case lag−2 effects of z_{a1} on z_{l1} and z_{l2}, and of z_{l1} and z_{l2} on z_{a1} are not statistically significant and the impulse−response functions of the lag−1 and lag−2 models are virtually identical. Only the lag−1 model is shown (Table 3). The three eigenvalue moduli lie inside the unit circle at 0.831, 0.707 and 0.707, thus supporting the model's stability.

Table 3. Panel VAR model estimates. Effects from lagged (rows) to present (columns) coordinates. Standard errors within parentheses.

	z_{a1}	z_{l1}	z_{l2}
Lag(z_{a1})	0.784***	−0.106*	0.232***
	(0.027)	(0.043)	(0.064)
Lag(z_{l1})	−0.031	0.752***	−0.094
	(0.018)	(0.035)	(0.049)
Lag(z_{l2})	−0.006	−0.018	0.709***
	(0.010)	(0.023)	(0.038)

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

It must be noted that the interpretation of relationships among coordinates belonging to the same composition (z_{l1} and z_{l2} in our case) requires specific analytical tools (Erb, 2020; Filzmoser et al., 2018). For this reason, we interpret only the lagged effects of z_{a1} on z_{l1} and z_{l2}, and the lagged effects of z_{l1} and z_{l2} on z_{a1}. This constitutes no drawback as it is in full agreement with the research questions of relating capital and asset structure. The diagonal of Table 3 shows the relationships of coordinates to their own lagged values, and are not directly related to the research questions either.

The results are then interpreted as follows. Increasing the lagged share of non-current assets (z_{a1}) leads to significant increases of present debt quality (z_{l2}) and decreases of present solvency (z_{l1}), in other words, it increases debt maturity and indebtedness. Conversely, the lagged structure of liabilities and net worth (z_{l1} and z_{l2}) does not significantly affect the present share of non-current assets (z_{a1}).

Figure 3 shows the impulse-response functions with their 95% confidence bands. The results show that shocks in the share of non-current assets (z_{a1}) lead to significant future increases of debt quality (z_{l2}), and to significant future decreases of solvency (z_{l1}) up to 5 periods ahead, as the confidence bands do not include 0 for lags 1 to 5 in panels "za1 on zl1" and "za1 on zl2".

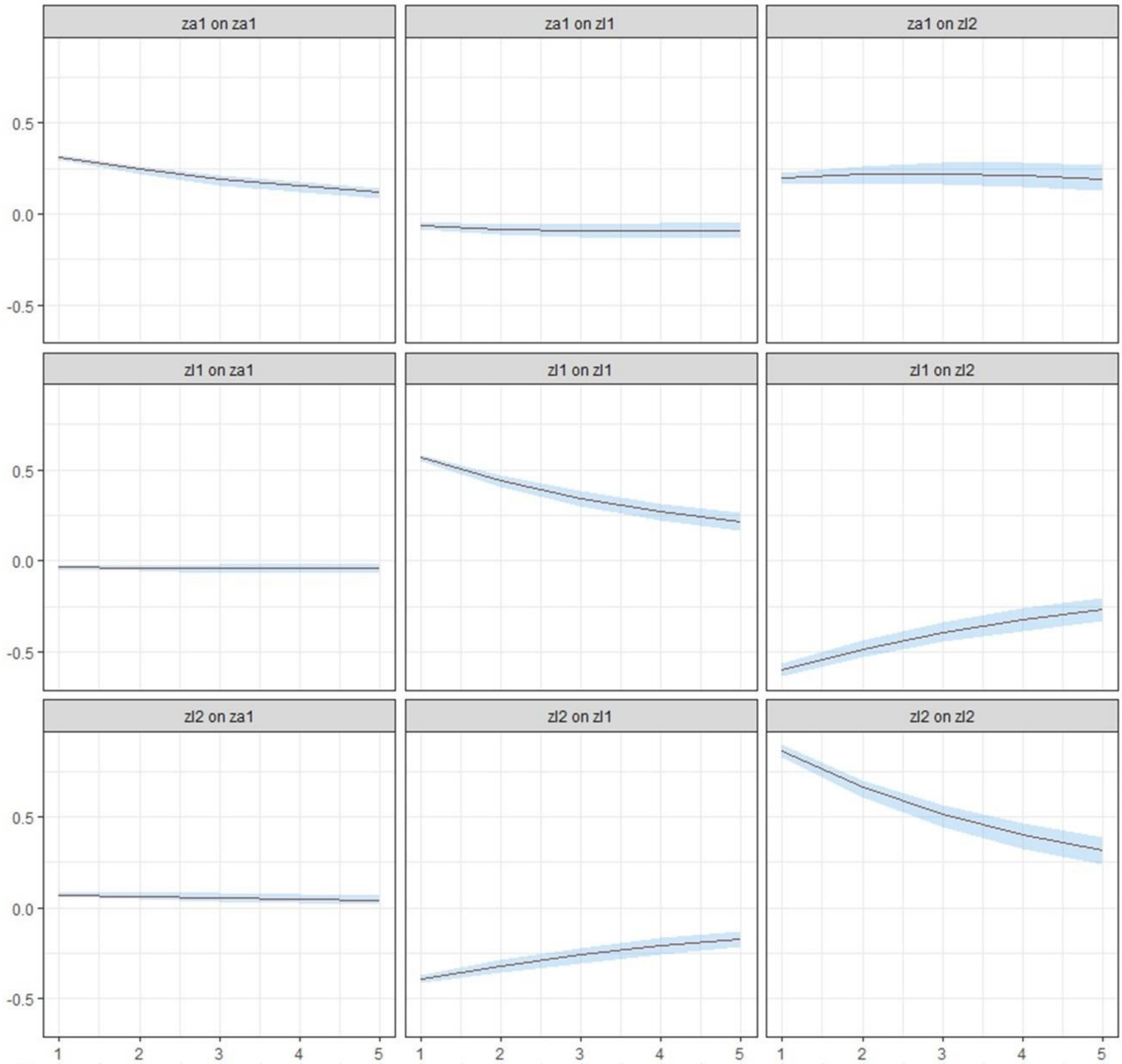

Figure 3. Impulse-response functions of the panel VAR model (lines) and 95% confidence bands (shadowed areas) for lags 1 to 5.

Therefore, the analysis results show that, in general, in the Spanish retail sector the asset structure has conditioned the capital structure of companies over the study period. In detailed terms, a more tangible asset structure has allowed Spanish retail companies to use more debt and to have a higher share of longer-term debt to finance their investments. This result is aligned with the evidence found by Maudos and Fernández (2020) on the evolution of investment and indebtedness of Spanish companies. They confirm that in the last decades, Spanish companies showed a positive relationship between the increase in fixed assets (greater tangibility of assets) and the increase in debt. However, our results suggest that this relationship is in the opposite direction to that one proposed by Maudos and Fernández (2020). The increase in the tangibility of assets is what explains why Spanish retail companies have been financed by increasing their future debt, while it has not been the case that the increase in debt has financed their future investment in a greater tangibility of their assets.

As a robustness check we also estimate two separate panel VAR models, with z_{a1} and z_{l1}, and with z_{a1} and z_{l2} respectively. The results once more show that the lagged structure of liabilities and net worth (z_{l1} and z_{l2}) does not significantly affect the present share of non-current assets (z_{a1}). The effects of the lagged share of non-current assets (z_{a1}) on present solvency (z_{l1}) and on present debt quality (z_{l2}) are very similar to those in Table 3; respectively −0.118 (s.e. 0.040) and 0.190 (s.e. 0.060).

Section 3.5 shows the results for standard financial ratios, which are markedly different and barely significant.

3.4. The moderating effect of company size on the relationship between asset and capital structure

Even if panel VAR models account for inter-firm heterogeneity through the firm-specific panel fixed effects, besides main effects of firm characteristics, moderating effects could also be present. The suggested methodology easily lends itself to studying the moderating effect of any firm attribute by means of subgroup analysis.

It is generally accepted that capital structure, and its relationship with asset structure, may depend on company-specific characteristics, which can condition aspects such as ease of access to capital markets or debt. In this sense, the main company-specific factor considered is size (i.e. Frank and Goyal, 2003; Harris and Raviv, 1991; Ramalho and Silva, 2009; Titman and Wessels, 1988; Shleifer and Visnhy, 1992). In order to identify if the relationship between the asset and capital structures follows a different pattern depending on the size of the companies, the database has been divided in two equal-sized subsets. The first subset includes the companies that have a total asset value higher than the median value (6.49 million EUR), in terms of the average of total assets over the study period (6,091 cases from 424 firms). The second subset includes the companies with total assets lower than or equal to the median (5,910 cases from 425 firms). The analyses in Section 3.3 have been rerun separately for both subsets. In both, the BIC values show the lag-1 model to fit better than the lag−2 model and the eigenvalue moduli lie inside the unit circle.

The results in Table 4 show that there are differences in the strength of the relationship between the asset and capital structures when company size is considered. In the case of the larger companies, there is stronger evidence that the capital structure is conditioned by the asset structure. The results are similar to those of the general case, but relationships are tighter. The larger the size of the company, the easier it is usually to access debt. Moreover, the fact that the asset tangibility constitutes collateral for the debt can explain the interest of larger Spanish retail companies in leveraging their capital structure and in indebtedness to a longer time horizon.

In the case of smaller companies, the results are also similar to the global sample, but the relationship is weaker and only reaches statistical significance for debt quality (z_{l2}). The effects of the lagged value of z_{a1} on z_{l1} are significantly different between large and small firms according to a Wald test (p-value = 0.041) while no significant difference is observed in the effects of the lagged value of z_{a1} on z_{l2} (p-value = 0.091). It must be recalled that the significant relationship between coordinates belonging to the same composition (z_{l1} and z_{l2}) in small firms is not to be interpreted.

Table 4. Panel VAR model estimates by firm size. Effects from lagged (rows) to present (columns) coordinates. Standard errors within parentheses.

Firm size		z_{a1}	z_{l1}	z_{l2}
	Lag(z_{a1})	0.860***	−0.229***	0.400***
		(0.032)	(0.065)	(0.084)
Large	Lag(z_{l1})	−0.027	0.723***	−0.107
		(0.023)	(0.053)	(0.072)
	Lag(z_{l2})	−0.003	−0.036	0.726***
		(0.013)	(0.035)	(0.052)
	Lag(z_{a1})	0.721***	−0.056	0.203*
		(0.035)	(0.054)	(0.082)
Small	Lag(z_{l1})	−0.036	0.752***	−0.110*
		(0.025)	(0.044)	(0.053)
	Lag(z_{l2})	−0.013	0.013	0.620***
		(0.014)	(0.030)	(0.047)

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

The greatest difficulties and the worst conditions for smaller Spanish retail companies to access debt may explain why overall debt is harder to predict from asset structure. However, a higher share of fixed assets continues to be influential on debt quality, regardless of the overall indebtedness.

3.5. Reanalysis with standard financial ratios

As reported in the literature, descriptive results with standard financial ratios for asset structure:

$$s_{a_1} = \frac{x_1}{x_2} \tag{8}$$

solvency:

$$s_{l1} = \frac{x_3}{x_4+x_5} \tag{9}$$

and debt quality:

$$s_{l2} = \frac{x_4}{x_5} \tag{10}$$

show severe non-normality (asymmetry and kurtosis) and non-linearity, which make them unsuitable for panel VAR models (Table 5, Figures 4 and 5). Besides, many new and very extreme outliers emerge. It must be noted that the data in Table 5 and Figures 4 and 5 are shown after removal of the outliers as explained in Section 3.2. Thus, the new outliers are caused by the use of standard ratios and not by unusual combinations of firm characteristics.

Table 5. Descriptive statistics of asset (s_{a1}) and capital (s_{l1} and s_{l2}) standard ratios.

	mean	sd	skewness	kurtosis	min	Q1	Q2	Q3	max
s_{a1}	1.405	2.558	11.805	287.394	0.003	0.313	0.739	1.612	100.040
s_{l1}	1.331	4.640	39.539	2428.768	0.001	0.262	0.578	1.253	332.890
s_{l2}	0.509	2.656	30.084	1279.649	0.000	0.011	0.130	0.435	153.334

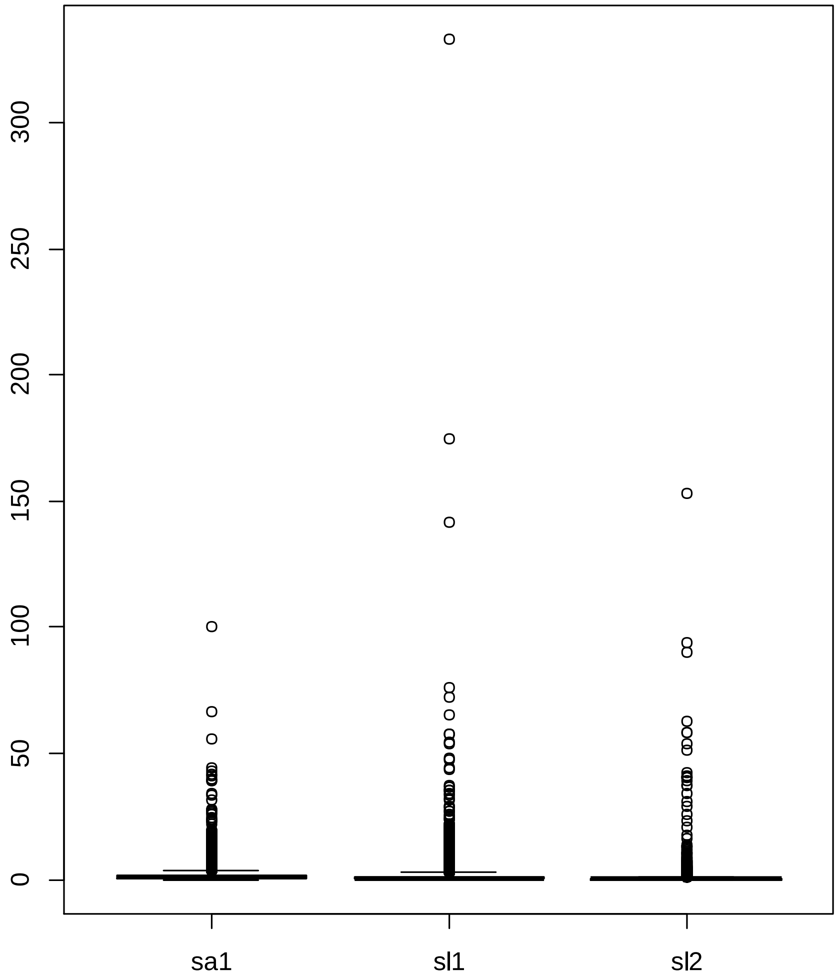

Figure 4. Box plots of asset (sa1) and capital (sl1 and sl2) standard ratios.

Far from being a statistical refinement, these problems have serious practical consequences. Table 6 shows the results of the panel VAR model to be completely different from those in Table 3 and barely significant. In some cases, standard accounting ratios are even not significantly related to their own lagged values.

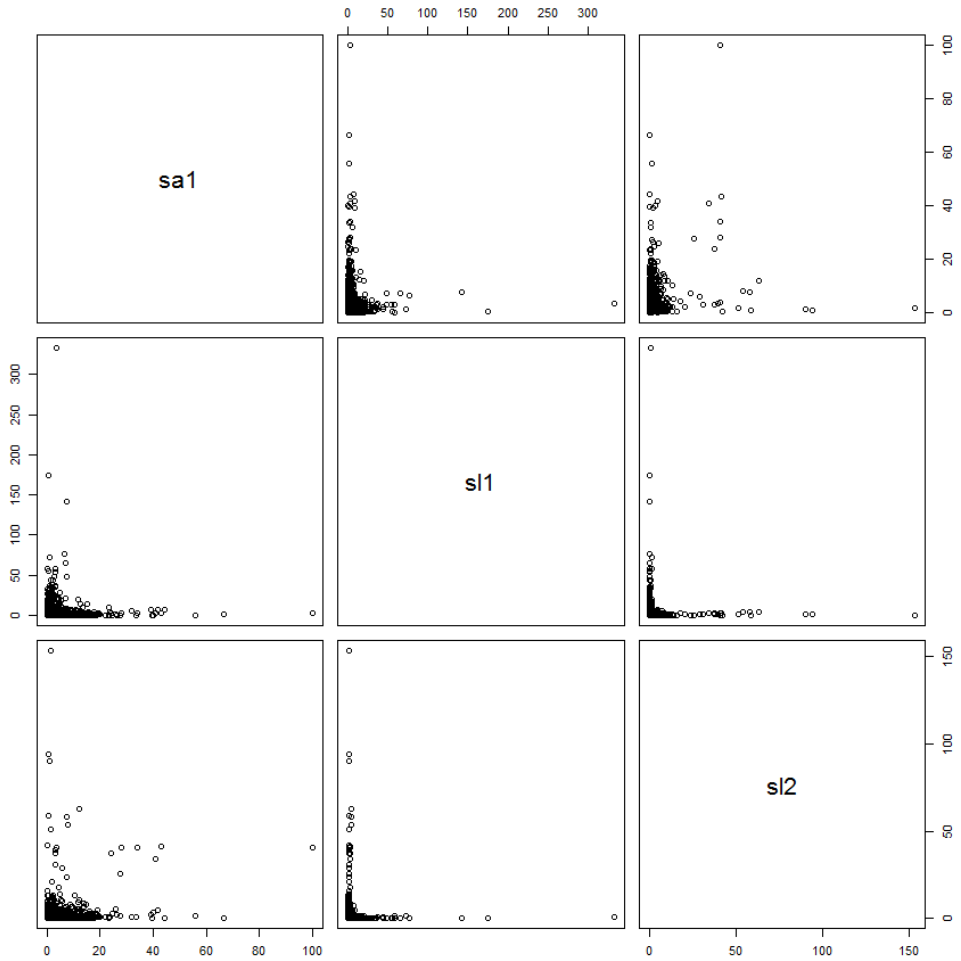

Figure 5. Scatterplots of asset (sa1) and capital (sl1 and sl2) standard ratios.

Table 6. Panel VAR model estimates for standard ratios. Effects from lagged (rows) to present (columns) values. Standard errors within parentheses.

	s_{a1}	s_{l1}	s_{l2}
Lag(s_{a1})	0.504***	−0.106*	−0.008
	(0.122)	(0.042)	(0.071)
Lag(s_{l1})	−0.030	0.135	−0.029
	(0.019)	(0.127)	(0.020)
Lag(s_{l2})	0.039	−0.010	0.089
	(0.045)	(0.010)	(0.058)

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

4. Conclusions

The company investment (asset structure) and financing (capital structure) policies are interrelated. The capital structure may condition the investment opportunities that a company will be able and willing to take advantage of in the future, and the asset structure may condition access to future sources of financing. There have been various theoretical approaches and empirical tests that have aimed to characterize the relationship between corporate asset and capital structure. However, there is no general consensus about the direction of this relationship and there are both strong theoretical arguments and ample empirical evidence supporting both. This relationship is affected by company-specific, sectoral, country-specific, general and external factors which make it difficult to generalize the direction of this relationship. The objective of this article is to enrich the methodological tools that make it possible to address the analysis of the relationship between the asset structure and the capital structure of companies.

The proposed methodological approach avoids making a priori assumptions about the direction of the relationship, controls for time-invariant company unobservables, makes it possible to plot the dynamic relationship between investment and financing structure using panel data, and avoids the common skewness, outliers and non-linearity in standard accounting ratios when used as variables in statistical models. This methodological approach is based on CoDa and panel VAR models. To the best of our knowledge, panel VAR models have never been used on CoDa. The use of CoDa as a way of making accounting figures statistically treatable is recent and, in the opinion of the authors, has a great potential. As shown in Section 3.5, to use standard or compositional accounting ratios is not a matter of statistical refinement but does make a difference in the results. The relationships reported in this article would not have been uncovered with standard ratios. Having said this, a commonly mentioned limitation of CoDa is that results are not robust if the percentage of entries with zero values is large (Martín Fernández et al., 2011; Palarea-Albaladejo and Martín-Fernández, 2008). This may impede dividing assets and liabilities into 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 study sample contains very small companies, as in our example.

The methodological approach has been illustrated with the Spanish retail sector. The database is made up of a panel of heterogeneous companies and covers the period from 2000 to 2017. The results have shown that, in general, the capital structure of the Spanish retail companies has been conditioned by their past asset structure. A more tangible asset structure has allowed Spanish retail companies to use more debt and a larger share of longer-term debt. However, this relationship is weaker in the case of smaller companies. The greater difficulties and the worst conditions for smaller companies to access debt may explain why their solvency is relatively independent of their long-term investment policy. As is logical, the results must be interpreted taking into account the characteristics of the retail sector in Spain. Most of the firms are private limited companies and there is a great deal of management by ownership. Therefore, the conflicts arising from the agency relationship between ownership and management are very limited. This could explain why it is not necessary to use the capital structure as a mechanism to control agency costs and, in this way, the capital structure is more the result of collateral offered by the asset structure. In any case, the data used have to be considered as an example, and there should be no intent to generalize the findings in other contexts.

Several extensions are possible, both from methodological and applied perspectives. From an applied perspective, the analysis has only considered company size as a moderating factor of the relationship between asset and capital structure. A natural extension of this research is to expand the moderating factors to analyze the influence of other company-specific, sectoral or macroeconomic variables on the relationship between asset and capital structure. Another possible extension is to include other components from the balance sheet, provided that they have few zeros. Finally, panel VAR models in combination with the CoDa methodology can be used to assess the dynamic relationships among any financial ratios, not necessarily linked to the problem of asset and capital structures.

From a methodological perspective, some recent developments in the CoDa methodology can be combined with the approaches presented in this article. Greenacre et al. (2021) present the so-called amalgamation log-ratio balances. These balances revert to using sums of components rather than their geometric means and may be easier to link to the accounting practice, although their statistical merits are for the most pending research evidence. Thomas-Agnan and Morais (2021) present an alternative interpretation of the parameters of a statistical model in terms of the shares of the components rather than log-ratios, i.e., in terms of percentages of non-current and current assets, net worth, and non-current and current liabilities. To this end, the so-called simplicial derivatives have to be computed.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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