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MULTIVARIATE PARTIAL ADJUSTMENT OF FINANCIAL RATIOS: A BAYESIAN HIERARCHICAL APPROACH*

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SUMMARY

In this paper we propose a multivariate extension of the partial adjustment model of financial ratios. To that end, we use a dynamic factor model which assumes that financial ratios measuring, essentially, the same economic–financial dimension of the firm evolve in a similar way, reflecting the evolution of the common factor. The proposed model is hierarchical with three levels. The first describes the relationship between each ratio and its common factor; the second describes the evolution of the common factors over time by means of Lev's (1969) partial adjustment model; and the third analyzes the similarity of firms' adjustment coefficients, taking into account their characteristics. The methodology is applied to the analysis of a set of financial ratios related to the business and financial structure of the firm. Copyright © 2008 John Wiley & Sons, Ltd.

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1. INTRODUCTION

Financial ratios are analytical tools for the study of a range of concepts such as the activity, profitability or productivity of a firm. They are widely used as explanatory variables in accounting research with applications ranging from the determinants of an auditor's compensation to explaining the firm's investment decisions and the determinants of capital structure (Ioannidis *et al.*, 2003).

From a strictly statistical point of view, moreover, the use of these ratios enables the data to better satisfy the assumptions underlying statistical tools such as regression analysis, weakening the influence of certain characteristics such as the firm's size. For these reasons, it is interesting to characterize their dynamic evolution process. One of the models most commonly employed to analyse this process is the partial adjustment model, which was first proposed for dividend policy by J. Lintner (1956) and for financial ratio analysis by Lev (1969). Subsequently, it has been applied in a range of contexts by Lee and Wu (1988), Peles and Schneller (1989), Davis and Peles (1993), Wu and Ho (1997), Gallizo *et al.* (2002) and Gallizo and Salvador (2003), among others.

The original adjustment model postulates that for each financial ratio firms have a constant adjustment coefficient that measures the speed at which one ratio returns to an equilibrium value from unbalanced positions produced by shocks that affect management activity. Most of the works published in the literature analyse the problem from a univariate standpoint, assuming

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that each ratio evolves independently of the others. This hypothesis is clearly unrealistic, given that there exist sets of ratios that measure what is essentially the same financial dimension or aspect of the firm (indebtedness, profitability, solvency, productivity, etc.) and, furthermore, that these dimensions are usually interrelated, reflecting the financial situation of the firm from various points of view. Additionally, the adjustment speeds of firms operating in similar conditions are very similar, as various papers have shown (Gallizo and Salvador, 2003).

For all these reasons it seems logical to assume sets of ratios measuring the same financial dimension should evolve in a similar manner when applied to firms operating under approximately the same conditions. Similarly, it could be argued that the partial adjustment model should be able to describe the joint evolution of the firm's various financial dimensions and show the any interdependences between them. Consequently, it is necessary to adopt a multivariate approach to the problem, allowing us, in particular, to capture any similarities between the financial ratio adjustments in firms. This paper proposes a Bayesian hierarchical dynamic factor model that is defined in three levels. The first describes the relationship between each ratio and its common factor; the second describes the evolution of the common factors over time by means of Lev's (1969) partial adjustment model; and the third analyses the similarity of firms' adjustment coefficients, taking into account their characteristics.

Since the model proposed has numerous parameters and the analysis is not analytically tractable, it uses Monte Carlo Markov chain (MCMC) methods and, more specifically, Gibbs sampling, which is particularly effective for problems of this kind (Gallizo *et al.*, 2000, 2002) given the conditional conjugacy of the full conditional distributions of the posterior distribution of the parameters of the model. The methodology is applied to the analysis of a set of financial ratios measuring four key economic dimensions of the activity of a firm (Foster, 1986; Nikkinen and Sahlström, 2004). These are profitability, financial leverage, liquidity and efficiency. Meanwhile, the sector of activity and size of the firm are used to explain similarities between the adjustment coefficients of these dimensions. We have used a sample of European manufacturing firms drawn from the AMADEUS database. The results confirm the validity of the partial adjustment model hypothesis for each of the factors. Furthermore, the analysis reveals certain interdependences between the joint evolution of these factors, which a traditional one-dimensional analysis of the problem would be unable to capture.

The rest of the paper is organized as follows. In Section 2, we describe the multivariate partial adjustment model used in the paper and the parameter estimation process by means of MCMC methods. In Section 3, the proposed methodology is applied to the data drawn from the AMADEUS database. Finally, Section 4 concludes with a brief review of the main conclusions and an indication of our future research lines. Finally, we have included an Appendix with the algorithm used to make inferences about the model parameters described in Section 2.

2. SETTING UP THE PROBLEM

Let $\mathbf{Y} = (Y_1, \ldots, Y_p)'$ be the set of financial ratios measured in a set of N firms in T periods of time. Let $(F_1, \ldots, F_K)'$ be the set of common factors that represent the financial dimensions considered in the analysis.

Let $\{\mathbf{Y}_t^i; t = 1 \ldots, T; i = 1, \ldots, N\}$ be the observed values of these variables with $\mathbf{Y}_t^i = (Y_{1t}^i, \ldots, Y_{pt}^i)'$, where Y_{jt}^i is the value of the jth financial ratio corresponding to the ith firm in period t with $j = 1, \ldots, p$; $i = 1, \ldots, N$; $t = 1, \ldots, T$.

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Finally, let $\{\mathbf{X}^{i} = (X_1^i, \ldots, X_q^i)' i = 1, \ldots, N\}$ be the observed value of q covariates $\mathbf{X} = (X_1, \ldots, X_q)'$ that describe the characteristics of the firm assumed to be relevant to explaining the similarities that exist between the adjustment coefficients.

The proposed model is given by the following expressions:

$$Y_{jt}^i = \alpha_j + \beta_j F_{k(j),t}^i + \varepsilon_{jt}^i \quad \varepsilon_{jt}^i \sim N(0, \sigma_{\varepsilon_j}^2) \tag{1}$$

$$F_{kt}^i = \sum_{\ell=1}^{K} \gamma_{k\ell}^i F_{\ell,t-1}^i + w_{kt}^i \quad w_{kt}^i \sim N(0, \sigma_{w_k^i}^2) \tag{2}$$

$$\gamma_{k\ell}^i = \rho_{k\ell} + \sum_{h=1}^{q} \psi_{k\ell}^h X_h^i + v_{k\ell}^i \quad v_{k\ell}^i \sim N(0, \sigma_{v_{k\ell}}^2) \tag{3}$$

with $k(j) \in \{1, \ldots, K\}$; $i = 1, \ldots, N$; $t = 1, \ldots, T$; $k, \ell = 1, \ldots, K$, and where it is assumed that the error series

$$\{\varepsilon_{jt}^i; j = 1, \ldots, p; i = 1, \ldots, N; t = 1, \ldots, T\},$$
$$\{w_{kt}^i; k = 1, \ldots, K; i = 1, \ldots, N; t = 1, \ldots, T\} \text{ and}$$
$$\{v_{k\ell}^i; k = 1, \ldots, K; \ell = 1, \ldots, K; i = 1, \ldots, N\}$$

are independent white noise.

Therefore, the model has three hierarchical levels:

1. The first, given by equations (1), relates each financial ratio Y_j to the economic–financial dimension of the firm that it measures. This is represented by the factor $F_{k(j)}$ with $k(j) \in \{1, \ldots, K\}$. By way of identifiability we will assume that if J_k denotes the set of financial ratios related to the factor F_k, i.e., $J_k = \{j \in \{1, \ldots, p\} : k(j) = k\}$ and if $J_k = \{j_{k_1} < j_{k_2} < \ldots < j_{k_{\ell_k}}\}$ then $\beta_{j_{k_1}} \geq 0$.
2. The second level is given by equations (2) and describes the joint evolution over time of each common factor by means of a multivariate partial adjustment model, which assumes that each factor influences not only itself but also the remaining factors, where the coefficient $\gamma_{k\ell}^i$ determines the sign and the magnitude of this influence.
3. The third level is given by equations (3) and describes the existing similarities between the adjustment coefficient $\gamma_{k\ell}^i$, in terms of the explanatory covariates $\mathbf{X}$. The coefficients $\{\psi_{k\ell}^h; h = 1, \ldots, q\}$ determine the sign and magnitude of these influences, while the coefficient $\rho_{k\ell}$ is the expected value of $\gamma_{k\ell}^i$ for firms with characteristics $\mathbf{X} = \mathbf{0}$.

2.1. Prior Distribution

Given that we use a Bayesian approach, it is necessary to describe the prior distribution of the parameters of the model (1)–(3). These distributions are the following:

$$\beta_j \sim N(0, 1) \text{ truncated at } [0, \infty) \text{ if } j \in A \text{ and } \beta_j \sim N(0, 1); \text{otherwise} \tag{4}$$

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where $A = \{j \in \{1, \ldots, p\} : \beta_j > 0\}$.

$$\alpha_j \sim N(0, \sigma^2_{\alpha_j}); j = 1, \ldots, p; i = 1, \ldots, N \tag{5}$$

$$\rho_{k\ell} \sim N(0, 1); k = 1, \ldots, K; \ell = 1, \ldots, K \tag{6}$$

$$\psi^h_{k\ell} \sim N(0, 1); k = 1, \ldots, K; h = 1, \ldots, q; \ell = 1, \ldots, K \tag{7}$$

$$\tau_{\varepsilon_j} = \frac{1}{\sigma^2_{\varepsilon_j}} \sim \text{Gamma}\left(\frac{n_\varepsilon}{2}, \frac{d_\varepsilon}{2}\right); j = 1, \ldots, p \tag{8}$$

$$\tau_{w^i_k} = \frac{1}{\sigma^2_{w^i_k}} \sim \text{Gamma}\left(\frac{n_w}{2}, \frac{d_w}{2}\right); k = 1, \ldots, K; i = 1, \ldots, N \tag{9}$$

$$\tau_{v_{k\ell}} = \frac{1}{\sigma^2_{v_{k\ell}}} \sim \text{Gamma}\left(\frac{n_v}{2}, \frac{d_v}{2}\right); k = 1, \ldots, K; \ell = 1, \ldots, K \tag{10}$$

$$F^i_{k0} \sim N(0, 1); k = 1, \ldots, K; i = 1, \ldots, N \tag{11}$$

where $\text{Gamma}(p, a)$ denotes the gamma distribution with form and scale parameters p and a, respectively. All these distributions are standard and are assumed to be independent. In particular, it is assumed that coefficients $\{\beta_j; j = 1, \ldots, p\}$ and $\{\gamma^i_{k\ell}; k = 1, \ldots, K; \ell = 1, \ldots, K; i = 1, \ldots, N\}$ will very likely take values between -1 and 1. Furthermore, if σ^2_α is large and $\{n_i \to 0, d_i \to 0; i \in \{\varepsilon, w, v\}\}$, distributions (5) and (8)–(10) are non-informative. Finally, in order to avoid identifiability problems, in (11) it is supposed that $\{F_k; k = 1, \ldots, K\}$ are standardized in period 0.

2.2. Posterior Distribution

Let

$$\boldsymbol{\theta} = \left((\alpha_j, \beta_j)^p_{j=1}, (\gamma^i_{k\ell})^{K,K,N}_{k,\ell=1,i=1}, (\rho_{k\ell})^{K,K}_{k,\ell=1}, (\psi^h_{k\ell})^{K,K,q}_{k,\ell=1,h=1}, (\tau_{\varepsilon_j})^p_{j=1}, (\tau_{w^i_k})^{K,N}_{k=1,i=1}, (\tau_{v_{k\ell}})^{K,K}_{k,\ell=1}\right)$$

be the vector of the static parameters and let $\mathbf{F}_T = \left((F^i_{kt})^{K,N,T}_{k=1,i=1,t=1}\right)$ be the vector of the dynamic parameters of the model (1)–(3).

Let $D = \{Y^i_t; t = 1., T; i = 1, \ldots, N\}$ the data set.

The posterior distribution is given by

$$\begin{aligned}
&[\boldsymbol{\theta}, \mathbf{F}_T|D] \propto [D|\mathbf{F}_T, \boldsymbol{\theta}][\mathbf{F}_T|\boldsymbol{\theta}][\boldsymbol{\theta}] \\
&\propto \prod_{i=1}^{N}\prod_{j=1}^{p}\prod_{t=1}^{T} \tau^{1/2}_{\varepsilon_j} \exp\left[-\frac{\tau_{\varepsilon_j}}{2}(Y^i_{jt} - \alpha_j - \beta_j F^i_{k(j),t})^2\right] \\
&\times \prod_{i=1}^{N}\prod_{k=1}^{K}\prod_{t=1}^{T} \tau^{1/2}_{w^i_k} \exp\left[-\frac{\tau_{w^i_k}}{2}\left(F^i_{kt} - \sum_{\ell=1}^{K} \gamma^i_{k\ell} F^i_{\ell,t-1}\right)^2\right] \prod_{i=1}^{N}\prod_{k=1}^{K} \exp\left[-\frac{1}{2}(F^i_{k0})^2\right] \\
&\times \prod_{i=1}^{N}\prod_{k=1}^{K}\prod_{\ell=1}^{K} \tau^{1/2}_{v_{k\ell}} \exp\left[-\frac{\tau_{v_{k\ell}}}{2}\left(\gamma^i_{k\ell} - \rho_{k\ell} - \sum_{h=1}^{q} \psi^h_{k\ell} X^i_h\right)^2\right]
\end{aligned}$$

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$$\times \prod_{j\in A} \exp\left[-\frac{1}{2}\beta_j^2\right] I_{[0,\infty)}(\beta_j) \prod_{j\in\{1,\ldots,p\}-A} \exp\left[-\frac{1}{2}\beta_j^2\right] \prod_{j=1}^{p} \exp\left[-\frac{1}{2}\frac{(\alpha_j)^2}{\sigma_\alpha^2}\right]$$
$$\times \prod_{k=1}^{K}\prod_{\ell=1}^{K} \exp\left[-\frac{1}{2}\rho_{k\ell}^2\right] \prod_{h=1}^{q}\prod_{\ell=1}^{K}\prod_{k=1}^{K} \exp\left[-\frac{1}{2}(\psi_{k\ell}^h)^2\right]$$
$$\times \prod_{j=1}^{p} \tau_{\varepsilon_j}^{\frac{n_\varepsilon}{2}-1} \exp\left[-\frac{d_\varepsilon}{2}\tau_{\varepsilon_j}\right] I_{[0,\infty)}(\tau_{\varepsilon_j}) \prod_{i=1}^{N}\prod_{k=1}^{K} \tau_{w_k^i}^{\frac{n_w}{2}-1} \exp\left[-\frac{d_w}{2}\tau_{w_k^i}\right] I_{[0,\infty)}(\tau_{w_k^i})$$
$$\times \prod_{k=1}^{K}\prod_{\ell=1}^{K} \tau_{v_{k,\ell}}^{\frac{n_v}{2}-1} \exp\left[-\frac{d_v}{2}\tau_{v_{k,\ell}}\right] I_{[0,\infty)}(\tau_{v_{k,\ell}}) \tag{12}$$

where I_B denotes the indicator function of the set B.

Given that distribution (12) is not analytically tractable, we will employ MCMC methods (Robert and Casella, 1999) and, more specifically, Gibbs sampling, as the estimation method for the model parameters (see Appendix).

3. EMPIRICAL ANALYSIS

3.1. The data

The data used in this paper are drawn from the AMADEUS database, one of the most important accountant databases of European firms. This database includes information from 5 million private and publicly owned non-financial firms in 34 European countries. The data are standardized through a local source in each country which is usually the official records of the firms. It consists of 22 items of the balance sheet and 22 items of the profit and loss account.

In order to capture stable behaviours in time and to avoid the possible influence of outliers, our analysis is based on a balanced panel sample of 395 European consolidated firms from the manufacturing sector taken from the above-mentioned database.

Table I shows the financial ratios analysed, which measure four key dimensions of the commercial activity and the financial structure of the firm: profitability, financial leverage, liquidity and efficiency (Foster, 1986; Nikkinen and Sahlström, 2004). The analysed period corresponds to 1994–2003.

The profitability ratios are return on investment (ROI), return on equity (ROE) and operating profit margin (OPM). These three ratios refer to a company's overall ability to generate earnings and, by extension, cash flows (Haskins *et al*., 1996: 133).

The financial leverage ratios are debt to equity (DE) and equity to total capital (EC). The DE ratio indicates the debt of the firm for each monetary unit invested in its proper funds. The prime function of own funds is to underwrite risk in the event of loss and therefore to reduce the danger of insolvency for external lenders of funds. The EC ratio provides a means of assessing the financial solidity of a firm and hence its solvency. This ratio indicates to what extent an firm's shareholders underwrite its risks (European Commission,1996). Therefore, firms that are highly (resp. low) levered are expected to take high (resp. low) values in DE and low (resp. high) values in EC.

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Table I. Financial ratios

Factor	Financial ratios (expected sign of β_j)	Expression
Profitability	Return on investment (+)	$Y_1 = \text{ROI} = \frac{\text{Profit before taxation}}{\text{Total assets}}$
	Return on equity (+)	$Y_2 = \text{ROE} = \frac{\text{Profit before taxation}}{\text{Total shareholder funds}}$
	Operating profit margin (+)	$Y_3 = \text{OPM} = \frac{\text{Turnover} - \text{Operating expenses}}{\text{Turnover}}$
Financial leverage	Debt to equity (+)	$Y_4 = \text{DE} = \frac{\text{Current liabilities + Non - current liabilities}}{\text{Total shareholder funds}}$
	Equity to total capital (−)	$Y_5 = \text{EC} = \frac{\text{Equity}}{\text{Total shareholder funds + Liabilities}}$
Liquidity	Current ratio (+)	$Y_6 = \text{CR} = \frac{\text{Stocks + Debtors + Other current assets}}{\text{Loans + Creditors + Other current liabilities}}$
	Quick ratio (+)	$Y_7 = \text{QR} = \frac{\text{Cash + Receivables + Other current assets}}{\text{Total shareholder funds + Liabilities}}$
Efficiency	Turnover to total assets (+)	$Y_8 = \text{TA} = \frac{\text{Turnover}}{\text{Total assets}}$

Current ratio (CR) and quick ratio (QR) measure the ability of a firm to meet its short-term financial obligations when and as they are due. Therefore, firms with a high (resp. low) level of liquidity are expected to take high (resp. low) values in these ratios.

The turnover to total assets ratio (TA) is a proxy for the efficiency. It measures the sales obtained for each investment unit. Thus, efficient (resp. inefficient) firms tend to take high (resp. low) values in this ratio.

Table II shows the evolution of the mean value of the ratios analysed over time. In most of these ratios we may observe a highly stable evolution and, indeed, the only exception is found in ratios related with the profitability factor, which decline after 1998 due to the economic crisis suffered in the countries analysed, which had an immediate impact on corporate profits.

We also have information about the size of each firm and the sectors in which they conduct their activity. Table III shows the composition of the sample. It has been shown that a firm's size is a defining characteristic of its financial structure. This matter was studied by Petersen and Rajan (1994), who confirmed that limited access to funding is a significant impediment to growth and is reflected in the balance sheet. It is also well known that European small and medium entepresises (SME) have more debt, in relative terms, than large firms, while their staff costs are also higher in terms of sales and added value, depending on the industrial sector (Serrano *et al.*, 2005). Meanwhile, financial weaknesses are more prevalent in SMEs than in large concerns and, according to EUROSTAT data, the number of insolvencies has been consistently higher in small than in large firms. This only underscores the importance of the characteristics mentioned.

Table II. Evolution of the mean value of the ratios analysed

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
ROI	0.0826	0.0887	0.0920	0.0934	0.0820	0.0689	0.0572	0.0443	0.0460	0.0438
ROE	0.2161	0.2197	0.2033	0.2348	0.1909	0.1851	0.0938	0.1000	0.0685	0.0424
OPM	0.0626	0.0687	0.0719	0.0708	0.0671	0.0578	0.0505	0.0388	0.0411	0.0349
DE	2.3763	2.0500	1.8655	1.8038	1.8080	1.7925	2.1029	1.9628	1.8893	1.9850
EC	0.4265	0.4335	0.4442	0.4487	0.4583	0.4600	0.4537	0.4544	0.4605	0.4634
CR	1.6414	1.6321	1.6571	1.6783	1.7185	1.7265	1.6671	1.7464	1.8148	1.8974
QR	0.4906	0.4864	0.4892	0.5047	0.4860	0.4792	0.4694	0.4733	0.4824	0.4937
TA	1.4705	1.5112	1.5279	1.4897	1.4394	1.3837	1.3761	1.3982	1.3930	1.4201

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Table III. Composition of the sample of firms by size and sector

Sector		Size[a]		Total
		Small/medium	Large	
Wood and paper	Count	44	45	89
	% of total	11.14%	11.39%	22.53%
Chemistries and petroleum products	Count	55	52	107
	% of total	13.92%	13.16%	27.09%
Minerals and machinery	Count	96	103	199
	% of total	24.30%	26.08%	50.38%
Total	Count	195	200	395
	% of total	49.37%	50.63%	100.00%

[a] We consider a large firm as one in which the median number of employees in 1994–2003 was $\geq$445.

3.2. Statistical Analysis

In this case, we have $N = 395$, $T = 10$, $p = 8$ and $K = 4$. In addition, and according to the notation of Table I, $J_1 = \{1, 2, 3\}$, $J_2 = \{4, 5\}$, $J_3 = \{6, 7\}$ and $J_4 = \{8\}$.

A logarithmic transformation of the ratios DE, EC, CR, QR and TA was applied in order to closely approximate our assumption of conditional normality. Finally, the condition was imposed that the factor loadings β_j of the ratios ROI, DE and CR should be positive and that the coefficient of the ratio TA should be equal to 1 in order to avoid identifiability problems.

As explanatory variables of the coefficients γ_{ij} we have taken the size of the firm and the sector in which it operates. The size of the firm was codified as a binary variable (small–medium/large), where a firm is defined as small–medium sized if it has fewer than 445 employees (the median size of the firms of the sample), and large otherwise. Three sector categories were established for firms with similar activities. These are the wood and paper sector (SIC codes 20, 21 and 22), the chemical and petroleum products sector (SIC codes 23, 24 and 25) and metallic and non-metallic products (SIC codes 26, 27, 28 and 29).

Four models, given by the expressions (1)–(2), were fitted. The models differ in the hypothesis adopted at the third level:

- The model $\mathbf{M}_0$ supposes that the adjustment coefficients are given by

$$\gamma_{k\ell}^{i} = \rho_{k\ell} + \upsilon_{k\ell}^{i}$$

  That it is to say, it supposes that there are no systematic differences in the adjustment of the ratios, whether by sector or by size.
- The model $\mathbf{M}_{\text{size}}$ supposes that these coefficients are given by

$$\gamma_{k\ell}^{i} = \rho_{k\ell} + \psi_{k\ell}^{1}\text{size}^{i} + \upsilon_{k\ell}^{i}$$

  This assumes that there are differences in the adjustment of the ratios, which can be explained by the size of the firm, size^i.
- The model $\mathbf{M}_{\text{sector}}$ supposes that these coefficients are given by

$$\gamma_{k\ell}^{i} = \rho_{k\ell} + \psi_{k\ell}^{2}\text{sector}^{i} + \upsilon_{k\ell}^{i}$$

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This assumes that there are differences in the adjustment of the ratios that can be explained by the sector, sector^i, in which the firm conducts its business.

- The model $\mathbf{M}_{\text{size}-\text{sector}}$ supposes that these coefficients are given by

$$\gamma_{k\ell}^i = \rho_{k\ell} + \psi_{k\ell}^1 \text{size}^i + \psi_{k\ell}^2 \text{sector}^i + v_{k\ell}^i$$

That it is to say, it supposes that there are differences in the adjustment of the ratios, which can be explained both by the size of the firm and by the sector in which it operates.

In order to choose a diffuse prior, the parameters of the prior distribution for each of the models compared were $n_v = n_w = n_\varepsilon = d_v = d_w = d_\varepsilon = 0.1$ and $\sigma_{\alpha_j}^2 = 1; j = 1, \ldots, 9$. However, it is worth noting that the results obtained are scarcely influenced by the prior distribution due to the very large number of series analysed. The algorithm described in the previous section was initiated with a sample of the prior distribution (4) - (11) and it was executed for 10,000 iterations. The study of convergence was carried out for each model by visual inspection of the series for the model parameters and using the Geweke (1992) method. By means of these models, convergence was found to be obtained after 5000 iterations. The results we present in the next section are based on the last 5000 iterations, taking samples every five iterations with the aim of weakening the serial dependence of the sample observations.

3.3. Results Obtained

Tables IV–IX show the results obtained in the estimation of the parameters of all the models compared. In particular, we have calculated the posterior median and the limits of the 95% Bayesian credibility intervals, built from the quantiles 2.5 (Q2.5) and 97.5 (Q97.5) of the sample of the posterior distribution (12) obtained from the algorithm described in the Appendix.

Tables IV and V show the estimations of the coefficients α_j and β_j obtained from equations (1) of the first level of the model for each model compared. The estimations are very similar for all the fitted models and, in particular, the signs of the coefficients β_j coincide with the expected signs (see Table I), confirming that each financial ratio analysed does measure the factors listed in Table I.

Tables VI–IX show the estimations of the expected adjustment coefficients:

$$\overline{\gamma}_{k\ell}^i = E[\gamma_{k\ell}^i | X_h^i, \rho_{k\ell}, \{\psi_{k\ell}^h; h = 1, \ldots, q\}] = \rho_{k\ell} + \sum_{h=1}^{q} \psi_{k\ell}^h X_h^i$$

for each model compared. In all cases the results obtained are compatible with the postulates of the partial adjustment model, given that the adjustment coefficients $\{\overline{\gamma}_{\ell\ell}^i; \ell = 1, \ldots, 4\}$ are positive and less than 1. It also appears that the profitability factor adjusts faster than the others. Thus, using the posterior median of these coefficients, the speed of adjustment of profitability is estimated as $100(1 - 0.5229)\% = 47.71\%$ compared to $100(1 - 0.8768)\% = 12.32\%$ for liquidity, $100(1 - 0.9013)\% = 9.87\%$ for financial leverage and $100(1 - 0.9024)\% = 9.76\%$ for efficiency (see Table VI), the last three of which show considerable stability over time. This confirms the first impressions gleaned from analysis of the evolution of the average values for the ratios analysed, as shown in Table II. Consequently, factors that are more sensitive to temporary circumstances (in this case, profitability) have a higher speed of adjustment than structural factors (financial leverage, liquidity and efficiency), the evolution of which is more stable over time.

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Table IV. Estimations and 95% credibility intervals of the coefficients α_j

Models	$\mathbf{M}_0$			$\mathbf{M}_{size}$			$\mathbf{M}_{sector}$			$\mathbf{M}_{size-sector}$		
Ratios	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5
ROI	0.0680	0.0710	0.0739	0.0685	0.0712	0.0739	0.0686	0.0714	0.0742	0.0682	0.0710	0.0737
ROE	0.1472	0.1649	0.1802	0.1545	0.1659	0.1790	0.1551	0.1679	0.1805	0.1526	0.1650	0.1784
OPM	0.0547	0.0570	0.0593	0.0548	0.0571	0.0594	0.0550	0.0571	0.0594	0.0547	0.0570	0.0593
DE	0.3100	0.3499	0.3908	0.3230	0.3588	0.3990	0.2585	0.3087	0.3418	0.3083	0.3361	0.3770
EC	−0.9904	−0.9675	−0.9447	−0.9960	−0.9730	−0.9521	−0.9639	−0.9447	−0.9164	−0.9834	−0.9599	−0.9438
CR	0.3191	0.3630	0.3895	0.3317	0.3693	0.4078	0.3508	0.3693	0.3863	0.3480	0.3754	0.4041
QR	−0.8641	−0.8426	−0.8238	−0.8604	−0.8400	−0.8197	−0.8545	−0.8393	−0.8248	−0.8537	−0.8359	−0.8184
TA	0.1342	0.7706	4.3437	0.1526	0.7907	4.1562	0.1409	0.7940	4.3301	0.1536	0.8253	4.2052

Table V. Estimations and 95% credibility intervals of the coefficients β_j

Models	$\mathbf{M}_0$			$\mathbf{M}_{size}$			$\mathbf{M}_{sector}$			$\mathbf{M}_{size-sector}$		
Ratios	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5
ROI	0.0611	0.0647	0.0687	0.0612	0.0648	0.0683	0.0607	0.0642	0.0681	0.0607	0.0642	0.0685
ROE	0.5211	0.5433	0.5705	0.5197	0.5437	0.5613	0.5194	0.5379	0.5624	0.5189	0.5380	0.5661
OPM	0.0307	0.0334	0.0364	0.0307	0.0334	0.0361	0.0305	0.0332	0.0361	0.0304	0.0331	0.0362
DE	0.5979	0.6162	0.6660	0.6272	0.6451	0.6632	0.6199	0.6489	0.6745	0.6177	0.6392	0.6759
EC	−0.3740	−0.3456	−0.3353	−0.3722	−0.3618	−0.3515	−0.3783	−0.3637	−0.3478	−0.3792	−0.3587	−0.3460
CR	0.2765	0.2885	0.2986	0.2708	0.2823	0.2963	0.2703	0.2832	0.2951	0.2700	0.2810	0.2953
QR	0.1106	0.1203	0.1295	0.1090	0.1181	0.1280	0.1089	0.1183	0.1278	0.1083	0.1177	0.1277
TA	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Table VI. Estimations and 95% credibility intervals of the expected adjustment coefficients $\overline{\gamma}_{k\ell}$ for the model $\mathbf{M}_0$[a]

$\overline{\gamma}_{k\ell}$	Profitability			Leverage			Liquidity			Efficiency		
	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5
Profitability	**0.4804**	**0.5229**	**0.5643**	**0.0168**	**0.0318**	**0.0477**	−0.0040	0.0077	0.0203	−0.0106	0.0092	0.0308
Leverage	**−0.1076**	**−0.0533**	**−0.0044**	**0.8752**	**0.9013**	**0.9263**	−0.0252	−0.0054	0.0143	**0.0328**	**0.0644**	**0.0999**
Liquidity	−0.0468	−0.0017	0.0427	**−0.0672**	**−0.0427**	**−0.0168**	**0.8471**	**0.8768**	**0.9016**	−0.0663	−0.0253	0.0083
Efficiency	−0.0850	−0.0419	0.0052	**0.0028**	**0.0225**	**0.0471**	−0.0143	0.0082	0.0288	**0.8509**	**0.9024**	**0.9604**

[a] Significant coefficients in bold.

Table VII. Estimations and 95% credibility intervals of the expected adjustment coefficients $\overline{\gamma}_{k\ell}$ for the model $\mathbf{M}_{\text{size}}$[a]

$\overline{\gamma}_{k\ell}$	Profitability			Leverage			Liquidity			Efficiency		
	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5
Small/medium												
Profitability	**0.4279**	**0.4858**	**0.5450**	**0.0180**	**0.0390**	**0.0589**	−0.0040	0.0120	0.0292	−0.0083	0.0203	0.0462
Leverage	**−0.1384**	**−0.0725**	**−0.0032**	**0.8719**	**0.9084**	**0.9445**	−0.0350	−0.0086	0.0182	**0.0519**	**0.1018**	**0.1650**
Liquidity	−0.0718	0.0014	0.0645	**−0.0903**	**−0.0520**	**−0.0112**	**0.8420**	**0.8783**	**0.9175**	−0.1047	−0.0311	0.0189
Efficiency	−0.0467	0.0095	0.0839	**0.0132**	**0.0439**	**0.0768**	−0.0088	0.0188	0.0505	**0.7985**	**0.8720**	**0.9496**
Large												
Profitability	**0.4930**	**0.5509**	**0.6047**	**0.0044**	**0.0284**	**0.0503**	−0.0122	0.0037	0.0206	−0.0217	0.0015	0.0278
Leverage	−0.1075	−0.0376	0.0270	**0.8463**	**0.8787**	**0.9111**	−0.0290	−0.0045	0.0215	−0.0058	0.0301	0.0665
Liquidity	−0.0806	−0.0122	0.0601	−0.0682	−0.0330	0.0021	**0.8381**	**0.8754**	**0.9076**	−0.0583	−0.0132	0.0274
Efficiency	**−0.1555**	**−0.0916**	**−0.0318**	−0.0111	0.0193	0.0516	−0.0215	0.0045	0.0318	**0.8635**	**0.9195**	**0.9746**

[a] Significant coefficients in bold.

Table VIII. Estimations and 95% credibility intervals of the expected adjustment coefficients $\overline{\gamma}_{k\ell}$ for the model $\mathbf{M}_{\text{sector}}$[a]

$\overline{\gamma}_{k\ell}$	Profitability			Leverage			Liquidity			Efficiency		
	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5
Wood and paper												
Profitability	**0.3519**	**0.4322**	**0.5185**	**0.0361**	**0.0701**	**0.1037**	**0.0049**	**0.0311**	**0.0589**	−0.0257	0.0097	0.0459
Leverage	−0.0334	0.0611	0.1598	**0.8363**	**0.8885**	**0.9448**	−0.0517	−0.0125	0.0319	−0.0026	0.0507	0.1091
Liquidity	−0.1136	−0.0281	0.0624	**−0.1291**	**−0.0713**	**−0.0087**	**0.8256**	**0.8765**	**0.9300**	−0.0483	0.0153	0.0864
Efficiency	−0.1431	−0.0609	0.0111	−0.0054	0.0452	0.0903	−0.0011	0.0379	0.0764	**0.8304**	**0.9111**	**0.9725**
Chemistries and petroleum												
Profitability	**0.4712**	**0.5482**	**0.6241**	**0.0036**	**0.0323**	**0.0633**	−0.0236	0.0011	0.0238	−0.0286	0.0009	0.0337
Leverage	−0.1372	−0.0540	0.0295	**0.8293**	**0.8740**	**0.9155**	−0.0616	−0.0273	0.0112	**0.0056**	**0.0550**	**0.1121**
Liquidity	−0.1326	−0.0393	0.0481	−0.0551	−0.0065	0.0468	**0.8413**	**0.8888**	**0.9374**	−0.0913	−0.0256	0.0338
Efficiency	−0.1364	−0.0487	0.0433	−0.0211	0.0201	0.0632	−0.0252	0.0116	0.0487	**0.8538**	**0.9183**	**0.9794**
Minerals and machinery												
Profitability	**0.4826**	**0.5425**	**0.5990**	**0.0045**	**0.0251**	**0.0449**	−0.0137	0.0035	0.0200	−0.0133	0.0137	0.0412
Leverage	**−0.1598**	**−0.0986**	**−0.0363**	**0.8751**	**0.9102**	**0.9438**	−0.0211	0.0044	0.0295	**0.0211**	**0.0640**	**0.1137**
Liquidity	−0.0408	0.0262	0.0904	**−0.0882**	**−0.0543**	**−0.0210**	**0.8318**	**0.8669**	**0.9003**	−0.0954	−0.0389	0.0041
Efficiency	**−0.0756**	**−0.0174**	**0.0431**	**−0.0172**	**0.0100**	**0.0391**	**−0.0359**	**−0.0112**	**0.0143**	**0.8333**	**0.8978**	**0.9646**

[a] Significant coefficients in bold.

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Table IX. Estimations and 95% credibility intervals of the expected adjustment coefficients $\overline{\gamma}_{k\ell}$ for the model $\mathbf{M}_{\text{size-sector}}$[a]

$\overline{\gamma}_{k\ell}$	Profitability			Leverage			Liquidity			Efficiency		
	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5	Q2.5	Median	Q97.5
Small—Wood and paper												
Profitability	**0.1891**	**0.3017**	**0.4231**	**0.0337**	**0.0913**	**0.1480**	**0.0107**	**0.0534**	**0.0998**	−0.0521	0.0075	0.0615
Leverage	−0.0648	0.0786	0.2116	**0.7297**	**0.8182**	**0.9123**	**−0.1305**	**−0.0660**	**−0.0018**	**0.0415**	**0.1306**	**0.2485**
Liquidity	−0.2034	−0.0788	0.0500	−0.1315	−0.0313	0.0758	**0.8171**	**0.9072**	**0.9944**	−0.2106	−0.0600	0.0496
Efficiency	−0.0981	0.0225	0.1249	−0.0107	0.0639	0.1343	−0.0224	0.0425	0.1041	**0.7514**	**0.8679**	**0.9666**
Small—Chemistries and petroleum												
Profitability	**0.4381**	**0.5475**	**0.6513**	−0.0120	0.0323	0.0707	−0.0301	0.0062	0.0414	−0.0441	0.0055	0.0528
Leverage	−0.2185	−0.0814	0.0534	**0.8334**	**0.8970**	**0.9586**	−0.0641	−0.0180	0.0354	**0.0388**	**0.1162**	**0.2165**
Liquidity	−0.1346	−0.0172	0.1113	−0.0984	−0.0268	0.0452	**0.8123**	**0.8859**	**0.9535**	−0.1758	−0.0674	0.0340
Efficiency	−0.1197	−0.0183	0.0974	−0.0094	0.0514	0.1171	−0.0139	0.0392	0.0954	**0.7851**	**0.8870**	**0.9741**
Small—Minerals and machinery												
Profitability	**0.4358**	**0.5152**	**0.6007**	**0.0018**	**0.0308**	**0.0590**	−0.0182	0.0057	0.0304	−0.0074	0.0297	0.0690
Leverage	**−0.2402**	**−0.1413**	**−0.0496**	**0.8856**	**0.9354**	**0.9813**	−0.0236	0.0104	0.0456	**0.0134**	**0.0835**	**0.1796**
Liquidity	−0.0600	0.0433	0.1269	**−0.1135**	**−0.0658**	**−0.0208**	**0.8209**	**0.8683**	**0.9155**	−0.1028	−0.0053	0.0743
Efficiency	−0.0628	0.0200	0.1070	−0.0055	0.0334	0.0771	−0.0319	0.0036	0.0399	**0.7884**	**0.8723**	**0.9520**
Large—Wood and paper												
Profitability	**0.4295**	**0.5450**	**0.6572**	**0.0086**	**0.0551**	**0.0980**	−0.0148	0.0197	0.0541	−0.0447	0.0043	0.0578
Leverage	−0.0997	0.0277	0.1629	**0.8509**	**0.9249**	**0.9915**	−0.0300	0.0264	0.0815	−0.0876	0.0032	0.0892
Liquidity	−0.1147	0.0200	0.1426	**−0.1657**	**−0.0923**	**−0.0174**	**0.7823**	**0.8535**	**0.9284**	−0.0235	0.0736	0.1845
Efficiency	**−0.2696**	**−0.1458**	**−0.0241**	−0.0141	0.0545	0.1171	−0.0107	0.0424	0.0914	**0.8299**	**0.9094**	**0.9854**
Large—Chemistries and petroleum												
Profitability	**0.4330**	**0.5381**	**0.6381**	−0.0145	0.0299	0.0793	−0.0387	−0.0061	0.0308	−0.0496	−0.0066	0.0364
Leverage	−0.1743	−0.0530	0.0743	**0.7738**	**0.8378**	**0.9032**	−0.0850	−0.0317	0.0151	−0.0599	0.0112	0.0746
Liquidity	−0.1790	−0.0603	0.0606	−0.0509	0.0268	0.0960	**0.8151**	**0.8827**	**0.9437**	−0.0745	0.0069	0.0959
Efficiency	−0.2087	−0.0752	0.0654	−0.0474	0.0138	0.0790	−0.0495	0.0011	0.0547	**0.8447**	**0.9241**	**0.9948**
Large—Minerals and machinery												
Profitability	**0.4835**	**0.5570**	**0.6313**	−0.0139	0.0163	0.0448	−0.0245	−0.0008	0.0232	−0.0323	−0.0016	0.0292
Leverage	−0.1513	−0.0593	0.0313	**0.8385**	**0.8812**	**0.9256**	−0.0356	0.0013	0.0380	−0.0021	0.0448	0.0991
Liquidity	−0.0960	−0.0034	0.1007	−0.0939	−0.0432	0.0112	**0.7998**	**0.8581**	**0.9052**	−0.1280	−0.0554	0.0025
Efficiency	−0.1549	−0.0685	0.0287	−0.0386	0.0030	0.0471	−0.0594	−0.0189	0.0219	**0.8379**	**0.9074**	**0.9703**

[a] Significant coefficients in bold.

Analysis of the results taking the sector and/or size of the firm into account also reveals significant differences in the speed of adjustment of profitability depending on the size of the firm and the sector in which it operates. Specifically, the evolution of this factor fluctuates most widely in the wood and paper sector (see Table VIII) and particularly in small firms (see Table IX) with an estimated average speed of adjustment equal to 69.83% for enterprises in this group. This implies that these firms are able to quickly correct the management of their business in order to raise profits from one year to the next, though this adjustment is evidently also influenced by the evolution of the general state of the markets in which they operate. When a firm finds that circumstances are favourable, it will seek to take advantage of rising demand to improve earnings, while declining reserves in times of recession will make it more difficult to meet profitability objectives. In some sectors, trading margins are so low that any oscillation in the price of the factors of production will have a direct impact on profitability. This is the case in the wood and paper industry, where the cost of raw materials are set in international markets and fluctuate constantly, affecting business profits.

This faster speed of reaction towards higher profits is no accident: the phenomenon reflects the greater flexibility of a small organization, allowing it to adapt to changes in production by cutting operating and marketing costs quickly, in contrast to large firms, which find it more difficult to reduce variable costs.

The evolution of leverage is also observed to fluctuate more strongly in large firms operating in the chemicals sector (see Table IX), with a speed of adjustment of 16.22%, although the difference is not significant at a level of credibility of 95%. This correction percentage indicates that the financial structure of these firms is more stable over time than any of the other factors examined or, to put it another way, there is little variation in the level of indebtedness of these firms from one year to the next. Basically, these firms base their activity on a significant volume of debt and could not compete in the market without such borrowing, which explains the scant correction of corporate debt to equity (shareholders' funds). No significant differences were observed in the evolution of the other factors either by sector or size of the firm.

In contrast to the conventional univariate models described in the literature, however, the evolution of each of the above factors is influenced by the others. This allows us to address certain questions that cannot be answered using existing models. For example, an analyst might wonder to what extent the past evolution and current position of the factors analysed will affect the financial situation of the firm in the coming years. To answer this question, we need to observe the following relations:

(a) *Higher profitability* $\Rightarrow$ *lower leverage*

The most profitable firms today tend to be those with the lowest leverage tomorrow (see Table VI). This makes perfect sense: firms that have succeeded in generating higher profits per monetary unit invested apply a part of these earnings to self-financing. The policy of retaining earnings within the firm allows profitable concerns to reduce borrowing requirements without forsaking growth. This effect is significant in small firms, which have more limited access to funding and are therefore obliged to make greater use of self-financing in their growth strategies (see Table VII). It is also apparent in the metallurgical and capital equipment industries due to the capital-intensive structure of the balance sheet with high levels of investment compared to the volume of business (see Table VII), particularly in smaller firms (see Table IX).

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(b) *Higher leverage* $\Rightarrow$ *higher profitability and lower liquidity (and greater efficiency in small enterprises and vice versa)*

Highly leveraged firms tend to achieve higher profitability, although they have lower liquidity (see Table VI). This is because the interest at which firms are able to borrow is frequently lower than their profitability rate. In this situation, the firm generates a 'leverage' effect where debt helps raise profits and profitability at a financial cost that is acceptable given the cost structure. However, indebtedness is reflected in a decline in liquidity, which means leveraged firms must allow for a reduction in their solvency levels.

The effect is clearly apparent in small firms (see Table VII) and in the wood and paper and metallurgical and capital goods sectors (see Table VIII). It is particularly significant in small metal-bashing firms and machine tool manufacturers, as well as in large wood and paper concerns (see Table IX). A direct two-way relationship between efficiency and leverage is also observable in small enterprises operating in all sectors (see Tables VII, VIII and IX).

This is, of course, a reflection of the influence of low interest rates, not to mention the economic boom which took place during the period analysed, which has allowed firms to take on short-term debt at low cost and invest to raise profitability. In the case of small firms, it has also boosted efficiency despite the decline in liquidity because of the presence of current debt in the denominators of the relevant ratios. The phenomenon is especially powerful in small firms, which have the highest growth potential. In this case, the most efficient firms are generally better able to access the debt market, and they therefore tend to raise their levels of financial leverage in order to exploit this potential. A part of the profits generated are applied to repay the loans, which explains the inverse influence of the profitability factor on leverage.

(c) *In large firms higher (lower) profitability* $\Rightarrow$ *lower (higher) efficiency* (see Table VII)

High-margin enterprises tend to have low asset turnover and vice versa. This means that certain firms require high levels of investment compared to revenues due to the nature of the business, and they must sell significant volumes if prices are low in their markets. This situation arises in sectors where the structure of production costs is very rigid relative to revenues, resulting in narrow margins. This phenomenon is particularly significant in large firms operating in the wood and paper industry (Table IX) due to the inverse relationship between sales and trading margins existing in the majority of these concerns. The sector is defined by fierce international competition with high prices for imported raw materials that cannot be passed on through price hikes and low sale prices, which makes it necessary to sell significant volumes and expand into new areas of business and markets to survive (see *Interchina Consulting*, 22 March 2005, http//:www.casaasia.es/documentos/200505china07.pdf).

3.4. Comparison of Models

The statistical significance of the differences observed in the evolution of factors depending on size of the firm and the sector in which it operates was analysed through a comparison of the models estimated. We applied the pseudo-Bayes factor (Geisser and Eddy, 1979) given by the

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following expression for this purpose:

$$\mathrm{BF}(\mathbf{M}, \mathbf{M}_{\mathrm{ref}}) = \prod_{i=1}^{N} \frac{[\mathbf{Y}^i|\mathbf{M}, \mathbf{Y}^{(-i)}, \mathbf{X}]}{[\mathbf{Y}^i|\mathbf{M}_{\mathrm{ref}}, \mathbf{Y}^{(-i)}, \mathbf{X}]} \tag{13}$$

where $\mathbf{M}_{\mathrm{ref}}$ is the benchmark model used in the comparison, which in this study is $\mathbf{M}_{\mathrm{size-sector}}$, $\mathbf{M} \in \{\mathbf{M}_0, \mathbf{M}_{\mathrm{size}}, \mathbf{M}_{\mathrm{sector}}\}$, $\mathbf{Y}^i = \{\mathbf{Y}_t^i; t = 1, \ldots, T\}$ are the values of the series for the ith firm, $\mathbf{Y}^{(i)} = \{\mathbf{Y}_T^j; t = 1, \ldots, T; j \neq i\}$ are the values for the remaining series, $\mathbf{X} = \{\mathbf{X}^i; i = 1, \ldots, N\}$ are the values of the model covariables, and

$$[\mathbf{Y}^i|\mathbf{M}, \mathbf{Y}^{(-i)}, \mathbf{X}] = \int [\mathbf{Y}^i|\mathbf{M}, \mathbf{Y}^{(-i)}, \mathbf{X}, \mathbf{F}_T, \theta][\mathbf{F}_T, \theta|\mathbf{M}, \mathbf{Y}^{(-i)}, \mathbf{X}]\mathrm{d}\mathbf{F}_T\mathrm{d}\boldsymbol{\theta} \tag{14}$$

is the predictive density of the data in respect of the ith firm using the information provided by the remaining firms in the sample. The calculation of (13) was performed on the basis of the sample obtained in (12) using the algorithm described in the Appendix, and applying the procedure described in Gelfand's (1996: 155) expression (9.6) for calculating the value of the predictive distributions (14) for each model. The results obtained are shown in Table X. The model that best fits the data is $\mathrm{M}_{\mathrm{size-sector}}$, and we may therefore conclude that the differences described above depending on the size of the firm and the sector are significant.

4. CONCLUSIONS

In this paper we have proposed a multivariate extension of Lev's (1969) partial adjustment model, in which it is assumed that the adjustment of ratios measuring basically the same economic–financial dimension of a firm evolves in a similar way, reflecting the dynamic of the dimension concerned. To this end, we have used a hierarchical Bayesian multivariate model with three levels. The first describes the relationship between each ratio and the dimension it measures; the second describes the evolution of each dimension over time using Lev's (1969) partial adjustment model, as well as the interrelationships inherent in their common evolution; and the third analyses the similarity of the adjustment coefficients of the firms taking into account their characteristics.

The methodology is applied to analyse the evolution of a set of financial ratios conventionally used to measure four key dimensions of firms' commercial activities and financial structure (profitability, financial leverage, liquidity and efficiency) for a sample of European manufacturing firms using information drawn from the AMADEUS database.

Table X. Pseudo-Bayes[a] factors for the models compared in the paper

Model	Pseudo-Bayes factor
$\mathbf{M}_0$	0.0000
$\mathbf{M}_{\mathrm{size}}$	0.0239
$\mathbf{M}_{\mathrm{sector}}$	0.0559

[a] Benchmark model: $\mathbf{M}_{\mathrm{size-sector}}$.

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The results obtained confirm the postulates of the partial adjustment model, revealing that the speed of adjustment is greater for those factors that are sensitive to temporary circumstances and lower for structural factors. In contrast to the conventional univariate analyses described in the literature, meanwhile, it may be observed that the common evolution of these dimensions involves interrelationships that depend on the size of the firm and the sector in which it conducts its business. More specifically, it may be observed that more highly leveraged firms tend to increase their profitability and efficiency, although their liquidity declines. This phenomenon is particularly significant in the case of small firms. The reason for this is the influence of low interest rates, not to mention the economic boom which took place during the period analysed, which has allowed firms to take on short-term debt at low cost and invest to raise profitability. In the case of small firms, it has also boosted efficiency despite the decline in liquidity because of the presence of current debt in the denominators of the relevant ratios. The phenomenon is especially powerful in small firms, which have the highest growth potential.

These results highlight the need to take a multivariate approach to the problem of the adjustment of financial ratios if we want to consider all of the existing interrelationships in the economic and financial dimensions of the firm.

In this paper we have used a balanced panel of firms in order to avoid the influence of outliers. It would be interesting to extend this analysis, for example, by including a larger number of firms (unconsolidated firms, with missing data, etc.) or other areas of business activity (investment and R&D outlay, productivity and so on). Furthermore, the reliability and realism of this analysis could be enhanced by taking into account the intrinsic dynamism of some characteristics of a firm such as its size or its age. These questions provide ample opportunities for future lines of research.

APPENDIX

In this appendix we calculate the full conditional distributions of the posterior distribution (12) necessary for Gibbs sampling, and we describe the algorithm used to obtain a sample of this distribution, from which it is possible to make inferences about the parameters of the model described in the paper.

A.1. Full Conditional Distributions

(D1) ***Distribution*** $\mathbf{F}_T|\theta, \{\mathbf{Y}_t^i; t = 1, \ldots, T; i = 1, \ldots N\}$

In order to obtain this distribution, let us begin by observing that the equations of the model (1)–(3) and the prior distribution (11) can be written as follows:

$$
\begin{aligned}
&\mathbf{U}_t^i = \mathbf{Y}_t^i - \boldsymbol{\alpha} = \mathbf{A}_1\mathbf{F}_t^i + \boldsymbol{\varepsilon}_t^i \quad \boldsymbol{\varepsilon}_t^{\mathrm{i}} \sim N_{\mathrm{p}}(\mathbf{0}, \boldsymbol{\Sigma})\\
&\mathbf{F}_t^i = \mathbf{A}_2^i\mathbf{F}_{t-1}^i + \mathbf{w}_t^i \quad \mathbf{w}_t^i \sim N_{K+p}(\mathbf{0}, \mathbf{W}^i)\\
&\mathbf{F}_0^i \sim N_K(\mathbf{0}_K, \mathbf{I}_K)
\end{aligned}
\tag{A.1}
$$

where $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_p)'$, $\mathbf{F}_t^i = (F_{1t}^i, \ldots, F_{Kt}^i)'$, $\mathbf{A}_1 = (b_{jk})$ matrix $p \times K$, such that $b_{jk} = \beta_j$ if $j \in J_k$ and otherwise 0, $\mathbf{A}_2^i = (\gamma_{k\ell}^i)$, $\boldsymbol{\Sigma} = \mathrm{diag}(\sigma_{\varepsilon_j}^2)$ and $\mathrm{W}^i = \mathrm{diag}(\sigma_{w_k^i}^2)$ for $i = 1, \ldots, N$.

The expressions (A.1) correspond, for each $i = 1, \ldots, N$, to a linear state-space model for which the forward-filtering-backward-sampling algorithm proposed by Carter and Kohn (1994) and Früchwirth-Schnatter (1994, 1995) can be used. This algorithm consists of the following two stages:

Stage 1: Forward-filtering
In this step, the values of the mean vectors $\{\mathbf{m}_t^i; t = 1, \ldots, T\}$ and the variance and covariance matrices $\{\mathbf{C}_t^i; t = 1, \ldots, T\}$ of the distributions $\{\mathbf{F}_t^i | D_t^i, \boldsymbol{\theta}; t = 1, \ldots, T\}$, here $D_t^i = \{\mathbf{Y}_j^i; j = 1, \ldots, t\}$, are determined by way of the Kalman flter, using the following recurrent relationship:

$$\begin{aligned}
\mathbf{a}_t^i &= \mathbf{A}_2^i \mathbf{m}_{t-1}^i \\
\mathbf{R}_t^i &= \mathbf{A}_2^i \mathbf{C}_{t-1}^i \mathbf{A}_2^{i'} + \mathbf{W}^i \\
\mathbf{f}_t^i &= \mathbf{A}_1 \mathbf{a}_t^i \\
\mathbf{Q}_t^i &= \mathbf{A}_1 \mathbf{R}_t^i \mathbf{A}_1' + \boldsymbol{\Sigma} \\
\mathbf{m}_t^i &= \mathbf{a}_t^i + \mathbf{R}_t^i \mathbf{A}_1' (\mathbf{Q}_t^i)^{-1} (\mathbf{Y}_t^i - \mathbf{f}_t^i) \\
\mathbf{C}_t^i &= \mathbf{R}_t^i (\mathbf{I}_{\mathrm{p+K}} - \mathbf{A}_1' (\mathbf{Q}_t^i)^{-1} \mathbf{A}_1 \mathbf{R}_t^i)
\end{aligned}$$

$t = 1, \ldots, T$ and taking $\mathbf{m}_0^i = \mathbf{0}_K$ and $\mathbf{C}_0^i = \mathbf{I}_K$ as initial values.

Stage 2: Backward-sampling
This sampling is carried out in two steps:

(i) Draw $\mathbf{F}_t^i$ from $N_K(\mathbf{m}_t^i, \mathbf{C}_t^i)$
(ii) For $t = T-1, T-2, \ldots, 0$ draw $\mathbf{F}_t^i$ from

$$\mathbf{F}_t^i | \mathbf{F}_{t+1}^i, D_t^i, \boldsymbol{\theta} \sim N_K(\mathbf{med}_t^i, \mathbf{Var}_t^i)$$

with

$$\begin{aligned}
\mathbf{med}_t^i &= \{\mathbf{I}_{K+p} - \mathbf{C}_t^i \mathbf{A}_2^{i'} (\mathbf{R}_{t+1}^i)^{-1} \mathbf{A}_2^i\} \mathbf{m}_t^i + \mathbf{C}_t^i \mathbf{A}_2^{i'} (\mathbf{R}_{t+1}^i)^{-1} \boldsymbol{\Theta}_{t+1}^i \\
\mathbf{Var}_t^i &= \{\mathbf{I}_{K+p} - \mathbf{C}_t^i \mathbf{A}_2^{i'} (\mathbf{R}_{t+1}^i)^{-1} \mathbf{A}_2^i\} \mathbf{C}_t^i
\end{aligned}$$

(D2) Distributions $\{(\alpha_j, \beta_j) | \{\tau_{\varepsilon_j}, (F_{kt})_{k=1,t=1}^{K,T}, (Y_{jt}^i)_{t=1,i=1}^{T,N}\}; j = 1, \ldots, p\}$

We now have for $j \in J_k; i = 1, \ldots, N$

$$Y_{jt}^i = \boldsymbol{\xi}_j' \mathbf{X}_t^i(k) + \varepsilon_{jt}^i \text{ with } \varepsilon_{jt}^i \sim N(0, \sigma_{\varepsilon_j}^2) \tag{A.2}$$

where $\boldsymbol{\xi}_j = (\alpha_j, \beta_j)'$ and $\mathbf{X}_t^i(k) = (1, F_{kt}^i)'$. From (4) and (5) it now follows that $\boldsymbol{\xi}_j \sim N_2\left(\mathbf{0}_2, \begin{pmatrix} 1 & 0 \\ 0 & \sigma_{\alpha_j}^2 \end{pmatrix}\right)$ truncated at $B = \mathrm{R}\mathrm{x}[0, \infty)$ if $j \in A$, and $B = \mathrm{R}^2$ otherwise. Taking into account (A.2) by means of standard calculations, we have

$$\boldsymbol{\xi}_j | \{\tau_{\varepsilon_j}, (F_{kt})_{t=1}^T, (Y_{jt}^i)_{t=1,i=1}^{T,N}\} \sim N_2(\mathbf{m}_j, \mathbf{S}_j) \text{ truncated at } B \tag{A.3}$$

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where

$$\mathrm{m}_j = \mathbf{S}_j(\tau_{\varepsilon_j}(\mathbf{X}(k)'\mathbf{y}_j)),\ \mathbf{S}_j^{-1} = \tau_{\varepsilon_j}(\mathbf{X}(k)'\mathbf{X}(k)) + \begin{pmatrix} 1 & 0 \\ 0 & \sigma^2_{\alpha_j} \end{pmatrix}$$

where $\mathbf{X}(k) = (\mathbf{X}_t^i(k)')$, $\mathbf{y}_j = \mathrm{vec}(Y^i_{jt})$. A sample from (A.3) can be drawn by means of the method proposed by Geweke (1991).

(D3) Distributions $\tau_{\varepsilon_j}|\alpha_j, \beta_j, \mathbf{F}_T, \{Y^i_{jt}; t = 1, \ldots, T; i = 1, \ldots, N\}; j = 1, \ldots, p$

If $j \in J_k$, and using (A.2) and (8) by means of standard calculations, it follows that

$$\tau_{\varepsilon_j}|\alpha_j, \beta_j, \mathbf{F}_T, \{Y^i_{jt}; t = 1, \ldots, T; i = 1, \ldots, N\} \sim \mathrm{Gamma}\left(\frac{n_{\varepsilon_{jT}}}{2}, \frac{d_{\varepsilon_{jT}}}{2}\right)$$

where $n_{\varepsilon_{jT}} = n_\varepsilon + NT$ and $d_{\varepsilon_{jT}} = d_\varepsilon + \sum_{i=1}^{N}\sum_{t=1}^{T}(Y^i_{jt} - \alpha_j - \beta_j F^i_{kt})^2$

(D4) Distributions $\left\{\boldsymbol{\gamma}^i|\mathbf{F}^i_T, (\rho_{k\ell})^{K,K}_{k,\ell=1}, (\psi^h_{k\ell})^{K,K,q}_{k,\ell=1;h=1}, (\tau_{w^i_k})^{K,N}_{k=1;i=1}, (\tau_{\upsilon_{k,\ell}})^{K,K}_{k,\ell=1}, \mathbf{X}^i_h; i = 1, \ldots, N\right\}$

Vectorizing the expressions (2) and (3) it follows that

$$\mathbf{F}^i_t = \left((\mathbf{F}^i_{t-1})' \otimes \mathbf{I}_K\right)\boldsymbol{\gamma}^i + \mathbf{w}^i_t \quad \text{with } \mathbf{w}^i_t \sim N_K(\mathbf{0}, \boldsymbol{\Sigma}_{w^i}) \tag{A.4}$$

$$\boldsymbol{\gamma}^i = \boldsymbol{\rho} + \sum_{h=1}^{q}\boldsymbol{\psi}^h \mathrm{X}^i_h + \boldsymbol{\nu}^i \quad \text{with } \boldsymbol{\nu}^i \sim N_{K^2}(\mathbf{0}, \boldsymbol{\Sigma}_\upsilon) \tag{A.5}$$

where $\boldsymbol{\gamma}^i = \mathrm{vec}(\gamma^i_{k\ell})$, $\boldsymbol{\rho} = \mathrm{vec}((\rho_{k\ell}))$, $\boldsymbol{\psi}^h = \mathrm{vec}(\psi^h_{k\ell})$, $\boldsymbol{\Sigma}_{w^i} = \mathrm{diag}(\sigma^2_{w^i_k})$, $\boldsymbol{\nu}^i = \mathrm{vec}((\upsilon^i_{k\ell}))$, $\boldsymbol{\Sigma}_\upsilon = \mathrm{diag}(\sigma_{\upsilon^2_{k\ell}})$.

Using standard calculations from (A.4) and (A.5) it follows that

$$\boldsymbol{\gamma}^i|\mathbf{F}^i_T, (\rho_{k\ell})^{K,K}_{k,\ell=1}, (\psi^h_{k\ell})^{K,K,q}_{k,\ell=1;h=1}, (\tau_{w^i_k})^{K,N}_{k=1;i=1}, (\tau_{\upsilon_{k,\ell}})^{K,K}_{k,\ell=1}, \mathbf{X}^i_h \sim N_{K^2}(\mathbf{med}^i_\gamma, \mathbf{var}^i_\gamma); i = 1, \ldots, N$$

where

$$\mathbf{med}^i_\gamma = \mathbf{var}^i_\gamma\left\{\boldsymbol{\Sigma}_\upsilon^{-1}\left(\boldsymbol{\rho} + \sum_{h=1}^{q}\boldsymbol{\psi}^h\mathbf{X}^i_h\right) + \sum_{t=2}^{T}(\mathbf{F}^i_{t-1} \otimes \mathbf{I}_K)\boldsymbol{\Sigma}^{-1}_{w^i}\mathbf{F}^i_t\right\}$$

$$\mathbf{var}^i_\gamma = \left(\boldsymbol{\Sigma}_\upsilon^{-1} + \sum_{t=2}^{T}((\mathbf{F}^i_{t-1}\mathbf{F}^{i'}_{t-1}) \otimes \boldsymbol{\Sigma}^{-1}_{w^i})\right)^{-1}$$

(D5) Distributions $\{\tau_{w^i_k}|\mathbf{F}^i_{kT}, (\gamma^i_{k\ell})^{K,K}_{k,\ell=1}; k = 1, \ldots, K; i = 1, \ldots, N\}$

By means of standard calculations from (2) and (9) we have

$$\tau_{w^i_k}|\mathbf{F}^i_{kT}, (\gamma^i_{k\ell})^{K}_{k,\ell=1} \sim \mathrm{Gamma}\left(\frac{n_{w^i_k T}}{2}, \frac{d_{w^i_k T}}{2}\right); k = 1, \ldots, K; i = 1, \ldots, N$$

where

$$n_{w_k^i T} = n_w + T - 1$$

$$d_{w_k^i T} = d_w + \sum_{t=2}^{T}\left(F_{kt}^i - \sum_{\ell=1}^{K}\gamma_{k\ell}^i F_{\ell,t-1}^i\right)^2$$

(D6) Distribution $\mathbf{\Delta}|\{\boldsymbol{\gamma}^j; i = 1, \ldots, N\}, \mathbf{X}, \mathbf{\Sigma}_v$ where $\Delta = (\boldsymbol{\rho}, \boldsymbol{\psi}^1, \ldots, \boldsymbol{\psi}^q)$

From (A.5) we have

$$\boldsymbol{\gamma}^j = \left((\mathbf{Z}^i)' \otimes \mathbf{I}_{K^2}\right)\boldsymbol{\delta} + \boldsymbol{v}^i \quad \text{with } \boldsymbol{\nu}^i \sim N_{K^2}(\mathbf{0}, \mathbf{\Sigma}_v) \tag{A.6}$$

where $\mathbf{Z}^i = (1, X_1^i, \ldots, X_q^i)'; i = 1, \ldots, N$ and $\boldsymbol{\delta} = \text{vec}(\mathbf{\Delta})$. Meanwhile, vectorizing (6) and (7) we have $\boldsymbol{\delta} \sim N_{(q+1)K^2}(\mathbf{0}, \mathbf{I}_{(q+1)K^2})$ and therefore by means of standard calculations from (A.6) it follows that

$$\boldsymbol{\delta}|\{\boldsymbol{\gamma}^j; i = 1, \ldots, N\}, \mathbf{X}, \mathbf{\Sigma}_v \sim N_{(q+1)K^2}(\mathbf{med}_\delta, \mathbf{var}_\delta)$$

with

$$\mathbf{med}_\delta = \mathbf{var}_\delta\left(\sum_{i=1}^{N}(\mathbf{Z}^i \otimes \mathbf{I}_{K^2})\mathbf{\Sigma}_v^{-1}\boldsymbol{\gamma}^j\right), \mathbf{var}_\delta = \left(\mathbf{I}_{(q+1)K^2} + \left(\sum_{i=1}^{N}\mathbf{Z}^i(\mathbf{Z}^i)' \otimes \mathbf{\Sigma}_v^{-1}\right)\right)^{-1}$$

(D7) Distributions $\{\tau_{v_{k\ell}}|\{\boldsymbol{\gamma}^j; i = 1, \ldots, N\}, \mathbf{\Delta}, \mathbf{X}; k, \ell = 1, \ldots, K\}$

By using standard calculations from (3) and (10) we have

$$\tau_{v_{k,\ell}}|\{\boldsymbol{\gamma}^j; i = 1, \ldots, N\}, \mathbf{\Delta}, \mathbf{X} \sim \text{Gamma}\left(\frac{n_{v_{k\ell}^T}}{2}, \frac{d_{v_{k\ell}^T}}{2}\right); k = 1, \ldots, K; i = 1, \ldots, N$$

where

$$n_{v_{k\ell}^T} = n_v + N$$

$$d_{v_{k\ell}^T} = d_v + \sum_{i=1}^{N}\left(\gamma_{k\ell}^i - \rho_{k\ell} - \sum_{h=1}^{q}\psi_{k\ell}^h X_h^i\right)^2$$

A.2. Algorithm

The following algorithm describes how the samples from the distribution (12) necessary to make inferences about the parameters of the model (1)–(3) have been obtained.

Step 0: Start
Obtain a sample of the parameter vector $\boldsymbol{\theta}$,

$$\boldsymbol{\theta}^{(0)} = \left((\beta_j^{(0)}, \alpha_j^{(0)})_{j=1}^{p}, (\gamma_{k\ell}^{i(0)})_{k,\ell=1}^{K,K}, (\rho_{k\ell}^{(0)})_{k,\ell=1}^{K,K}, (\psi_{k\ell}^{h(0)})_{k,\ell=1,h=1}^{K,K,q}, (\tau_{\varepsilon_j}^{(0)})_{j=1}^{p}, (\tau_{v_{k\ell}}^{(0)})_{k,\ell=1}^{K,K}, (\tau_{w_k^i}^{(0)})_{k,i=1}^{K,N}\right)$$

using, for example, the distributions (3)–(10). Next, obtain a sample of the parameter vector $\mathbf{F}_T, \mathbf{F}_T^{(0)} = \left((F_{kt}^{i(0)})_{k=1,i=1,t=1}^{K,N,T}\right)$ using the distributions (11) and (2). Fix the number of maximum iterations $\mathrm{IT}_{\max}$ and set it $= 1$.

Step 1
Repeat the following steps for it $= 1, \ldots, \mathrm{IT}_{\max}$

Step 1(a)
Draw $(\mathbf{F}_T^{(\mathrm{it})})$ from $\mathbf{F}_T|\boldsymbol{\theta}^{(\mathrm{it})}, \{\mathbf{Y}_t^i; t = 1, \ldots, T; i = 1, \ldots, N\}$ using the forward-filtering-backward-sampling algorithm described in (D1).

Step 1(b)
Draw $(\alpha_j^{(\mathrm{it})}, \beta_j^{(\mathrm{it})})_{j=1}^p$ using the distributions $\{(\alpha_j, \beta_j)|\tau_{\varepsilon_j}^{(\mathrm{it}-1)}, \mathbf{F}_T^{(\mathrm{it})}, \{Y_{jt}^i; t = 1, \ldots, T; i = 1, \ldots, N\}; j = 1, \ldots, p\}$ calculated in (D2).

Step 1(c)
Draw $(\tau_{\varepsilon_j}^{(it)})_{j=1}^p$ from $\{\tau_{\varepsilon_j}|(\alpha_j^{(\mathrm{it})}, \beta_j^{(\mathrm{it})}), \mathbf{F}_T^{(\mathrm{it})}, \{Y_{jt}^i; t = 1, \ldots, T; i = 1, \ldots, N\}; j = 1, \ldots, p\}$ calculated in (D3).

Step 1(d)
Draw $\{\boldsymbol{\gamma}^{i(it)} = \mathrm{vec}(\gamma_{k\ell}^{i(it)})_{k,\ell=1}^{K,K}; i = 1, \ldots, N\}$ from the distributions $\Big\{\boldsymbol{\gamma}^i|\mathbf{F}_T^{i(\mathrm{it})}, (\rho_{k\ell}^{(\mathrm{it}-1)})_{k,\ell=1}^{K,K}, (\psi_{k\ell}^{h(\mathrm{it}-1)})_{k,\ell=1;h=1}^{K,K,q}, (\tau_{w_k^i}^{(\mathrm{it}-1)})_{k=1;i=1}^{K,N}, (\tau_{v_{k,\ell}}^{(\mathrm{it}-1)})_{k,\ell=1}^{K,K}, \mathbf{X}_h^i\Big\}$ calculated in (D4).

Step 1(e)
Draw $(\tau_{w_k^i}^{(\mathrm{it})})_{k=1,i=1}^{K,N}$ from $\{\tau_{w_k^i}|\mathbf{F}_{kT}^{(\mathrm{it})}, (\gamma_{k\ell}^{i(\mathrm{it})})_{k,\ell=1}^{K,K}; k = 1, \ldots, K; i = 1, \ldots, N\}$ calculated in (D5).

Step 1(f)
Draw $\Delta^{(\mathrm{it})}$ from $\boldsymbol{\Delta}|\{\boldsymbol{\gamma}^{i(\mathrm{it})}; i = 1, \ldots, N\}, \mathbf{X}, \boldsymbol{\Sigma}_v^{(\mathrm{it}-1)}$ calculated in (D6).

Step 1(g)
Draw $(\tau_{v_{k\ell}}^{(\mathrm{it})})_{k,\ell=1}^{K,K}$ from $\{\tau_{v_{k\ell}}|\{\boldsymbol{\gamma}^{i(\mathrm{it})}; i = 1, \ldots, N\}, \boldsymbol{\Delta}^{(\mathrm{it})}, \mathbf{X}; k, \ell = 1, \ldots, K\}$ calculated in (D7).

Once the $\mathrm{IT}_{\max}$ iterations have been completed, we discard the first IT_0 necessary in order to reach convergence with the stationary distribution of the chain for (12). An approximate sample of the posterior distribution (12) will thus be given by $\{\boldsymbol{\theta}^{(\mathrm{it})}; \mathrm{it} = \mathrm{IT}_0 + 1, \ldots, \mathrm{IT}_{\max}\}$with

$$\boldsymbol{\theta}^{(\mathrm{it})} = \Big((\alpha_j^{(\mathrm{it})}, \beta_j^{(\mathrm{it})})_{j=1}^p, (\gamma_{k\ell}^{i(\mathrm{it})})_{k,\ell=1,i=1}^{K,N}, (\rho_{k\ell}^{(\mathrm{it})})_{k,\ell=1}^{K}, (\psi_{k\ell}^{h(\mathrm{it})})_{k,\ell=1,h=1}^{K,q}, (\tau_{\varepsilon_j}^{(\mathrm{it})})_{j=1}^p, (\tau_{w_k^i}^{(\mathrm{it})})_{k=1,i=1}^{K,N}, (\tau_{v_{k,\ell}}^{(\mathrm{it})})_{k,\ell=1}^{K}\Big)$$

We can use this sample to make inferences on the parameters of the model (1)–(3). In particular, we can obtain $100(1-\alpha)\%$ Bayesian credibility intervals using the quantiles 0.5α and $1 - 0.5\alpha$ of the previous sample.

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