PERGAMON

Omega 30 (2002) 185–195

omega
The International Journal of Management Science

www.elsevier.com/locate/dsw

Adjusting financial ratios: a Bayesian analysis of the Spanish manufacturing sector

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Received 20 May 2001; accepted 4 February 2002

Abstract

In this paper, we propose a Bayesian hierarchical model based on the partial adjustment model described by Wu and Ho (Rev. Quant. Finance Acc. 9 (1997) 71). The proposed model allows us to estimate the average adjustment coefficients associated with the error correction component and with the sensitivity of the firm to exogenous factors that have an industry-wide effect. Using the proposed model, we analyse the financial ratios calculated by *The Bank of Spain's Central Balance Sheet Office* (*CBSO*) corresponding to the Spanish manufacturing sector during the period 1986–1997. In almost all the ratios analysed, we find that the error correction component exerts a greater influence, with the Interest Expense to Liabilities ratio demonstrating a greater sensitivity to this effect; by contrast, factors endogenous to the firm have more influence over the Indebtedness ratio. When considered by sectors, we find that it is the Transport sector which enjoys the greatest capacity for manoeuvre in the Profitability and Indebtedness ratios.

Keywords: Financial ratios; Partial adjustment; Bayesian inference; Gibbs sampling; Hierarchical models

1. Introduction

The analysis of financial ratios has traditionally been used to measure the financial situation of a firm through a comparison of its ratios with those of other firms operating in the same sector. Using such information it is possible to forecast bankruptcies, to take decisions on whether or not to grant loans or to carry out auditing evaluations. All these aspects make it interesting to characterise the dynamic economic process of such ratios. One of the models most commonly used to describe this evolution is the partial adjustment model proposed by Lev [1] and analysed by Lee and Wu [2], Davis and Peles [3] and Wu and Ho [4] amongst others.

Recently, Wu and Ho [4] have proposed an error correction model that explains the evolution over time of financial ratios as a consequence of two types of effect. First, a passive adjustment effect, due to exogenous factors that affect the entire industrial sector in which the firm operates and, secondly, an active adjustment effect, whose aim is to achieve a relative position in that sector. The first effect is short-term in nature and is caused by shocks that have an industry-wide effect. By contrast, the second is long-term, and determines the position of the firm in the sector in which this is located. Using this model, Wu and Ho [4] have estimated these two effects, further taking into account the sectorial dependency that exists between the financial ratios of the firms and the non-stationarity observed in many financial series [5].

Against this background, the aim of this paper is to carry out a Bayesian analysis of the problem. To that end, we propose a hierarchical model that allows us to estimate the above-mentioned effects and their forecast errors without having to recur to asymptotic approximations, as well as to select the most appropriate model and estimate its goodness of fit. We make use of the methodology proposed by Chib and Greenberg [6] for the hierarchical analysis of SUR models based on the Monte Carlo Markov chain methods (MCMC) [7]. This methodology has been applied to analyse the evolution of the Spanish manufacturing sector between 1986 and 1997 using data provided by the Bank of Spain's

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0305-0483/02/$ - see front matter
PII: S0305-0483(02)00026-9

Table 1
Financial ratios analysed

Name	Financial ratio	Expression
R1	Net income to total assets	NI/TA
R2	Interest expense to liabilities (with cost)	I/L
R3	Net income to shareholder's equity	NI/SE
R4	Liabilities to total assets	L/TA
R5	Financial leverage	NI/TA-I/L
R6	Operating income to net sales	OI/S

Central Balance Sheet Office (CBSO) with respect to the ratios set-out in Table 1. We find that the error correction component exerts a greater influence in almost all the ratios analysed, with the Interest Expense to Liabilities ratio demonstrating a higher sensitivity to this effect. By contrast, the factors that are exogenous to the firm have a greater influence over the Indebtedness ratio. When considered by sectors, we find that the transport sector stands out by virtue of having greater capacity for manoeuvre in the Profitability and Indebtedness ratios.

The rest of the paper is organised as follows. In Section 2 we briefly describe the model proposed by Wu and Ho [4]. Section 3 is devoted to the hierarchical model that we use in this paper. The problem of estimating the parameters of the model by way of MCMC methods is analysed in Section 4. In Section 5 we consider the problem of selecting the model and also study its goodness of fit. In Section 6 we apply the proposed methodology to the data from the CBSO. Finally, Section 7 closes the paper with a review of the main conclusions and future lines of research. All the demonstrations of the results that appear in the paper have been relegated to the appendix.

2. The partial adjustment model

The partial adjustment model proposed by Lev [1] postulates that the financial ratios of a firm are related with the average ratios of the industrial sector in which it operates, due to investors using these comparisons in order to decide the firms in which they will invest within that sector. However, although subsequent works (for example [2]) have found that this postulate to be a reasonable one, the majority of these studies have not distinguished between passive adjustments to external shocks and the active strategic control of the financial ratios on the part of the firm's management (with a notable exception to this being David and Peles [3]). Recently, Wu and Ho [4] have proposed an error correction model to describe the short and long-term movements in the financial ratios of a firm, with this being given by the equation:

$$\log(Y_{t+1}/Y_t) = g_t + \lambda[\log(X_t/X_{t-1}) - k_{t-1}] + \gamma[\beta - \log(Y_t/X_{t-1})] + \text{error}, \qquad (2.1)$$

where Y_t is the value of the financial ratio of a firm in time t, X_t is the value of the average ratio of the sector in time t, g_t is the expected logarithmic change in the ratio in time t, k_{t-1} is the expected logarithmic change in the average industrial ratio in time $t-1$ and β is the coefficient which determines the relative position of the firm in the sector in the long-term, in such a way that:

$$\lim_{t\to\infty} \log[Y_t/X_{t-1}] = \beta. \qquad (2.2)$$

In this model there are two adjustment coefficients of the deviations of the financial ratio Y_t from its equilibrium position. On the one hand, γ is the adjustment coefficient associated with the component of the error correction. This measures the speed of reaction of the firm's management in each period to shocks that affect the relative long-term position of the firm in the industry. On the other, the adjustment coefficient λ reflects the sensitivity of the firm's ratio to exogenous factors that have an industry-wide effect.

In this way, the second term on the right-hand side of the equality in (2.1) captures the passive response of the financial ratios to unanticipated shocks that affects the entire industrial sector. The third term is the error correction component that moves the current financial ratios towards their long-term equilibrium levels. It represents the endogenous attempts of the firms' management to achieve these equilibrium levels.

With the aim of facilitating the estimation of the adjustment coefficients, Wu and Ho [4] postulate model (2.1) in the form:

$$\log(Y_{t+1}/Y_t) = \alpha + \lambda\log(X_t/X_{t-1}) - \gamma\log(Y_t/X_{t-1}) + \text{error}, \qquad (2.3)$$

imposing heteroskedasticity restrictions, contemporaneous dependency and an AR(1) serial dependency structure in the error terms corresponding to each of the firms being analysed. Using pooling regression and a generalised least squares method, these authors estimate the average values of the α, λ and γ coefficients of the ratios and firms being analysed and relate them with the size and type of industry in which the firm operates.

In the following sections, we will analyse the model proposed by Wu and Ho [4] from a Bayesian perspective when the series being analysed are short (in the example used in this paper, there are 12 data per series). In this context, Bayesian inference provides a natural framework to aggregate the information provided by each of the series and to estimate the average adjustment coefficients, processing such information in an exact manner without recurring to asymptotic results of doubtful validity. Given that the problem does not have a conjugated form, we have used the MCMC methods (see, for example [7]) in order to analyse it.

3. The Bayesian hierarchical model

In this section, we propose the equations of the hierarchical model used in the paper, as well as the prior distributions over its parameters. Similarly, we calculate the likelihood function of the model and the posterior distribution of its parameters. Given that this distribution cannot be treated analytically, it is necessary to use approximate methods that will be described in Section 4.

3.1. The equations of the model

Let $\{R_t=(R_{1t},\ldots,R_{Nt})';\ t=1,\ldots,T\}$ be the observations of the evolution of one financial ratio R in N firms during T periods of time, where R_{it} is the value of the financial ratio R of the nth firm in time t.

Let $\{y_t=(y_{1t},\ldots,y_{Nt})';\ t=1,\ldots,T\}$ with $y_{it}=\log R_{it}$ be the logarithms of the observed financial ratios.

Let x_t be the logarithm of the average ratio of the firms analysed in year t.

The proposed model is based on Eqs. (2.3)–(2.6) of Wu and Ho [4] and describes the dynamic evolution of the series y_t. The model is defined by the equations:

$$\Delta y_{it}=\alpha_i+\lambda_i\Delta x_{t-1}-\gamma_i(y_{i,t-1}-x_{t-1})+u_{it},$$

$$u_{it}=\rho_i u_{it-1}+\varepsilon_{it}\quad \text{with } E[u_{it-1}\varepsilon_{jt}]=0$$

$$i,j=1,\ldots,N;\quad t=2,\ldots,T, \tag{3.1}$$

where the errors $(\varepsilon_{1t},\ldots,\varepsilon_{Nt})'$ are white noise with marginal distribution $\mathrm{N}_N[0_N,\Theta]$.

The normality hypothesis is justified by the fact that the logarithms of the majority of the financial ratios are distributed normally [8].

3.2. The prior distribution

Let $\alpha=(\alpha_1,\ldots,\alpha_N)'$, $\lambda=(\lambda_1,\ldots,\lambda_N)'$, $\gamma=(\gamma_1,\ldots,\gamma_N)'$ and $\rho=(\rho_1,\ldots,\rho_N)'$.

The prior distribution of the parameters of the above model are given by

$$\alpha|\mu_\alpha,\Sigma_\alpha\sim \mathrm{N}_N[\mu_\alpha,\Sigma_\alpha], \tag{3.2}$$

$$\omega|\mu_\omega,\Omega\sim \mathrm{N}_{2N}[1_N\otimes\mu_\omega, I_N\otimes\Omega], \tag{3.3}$$

where $\omega=(\lambda_1,\gamma_1,\ldots,\lambda_N,\gamma_N)'$, $\mu_\omega=(\mu_\lambda,\mu_\gamma)'$, $1_N=(1,\ldots,1)'$ (N times), Ω is a symmetric and defined positive 2×2 matrix and $\otimes$ denotes the Kronecker product:

$$\mu_\omega\sim \mathrm{N}_2(\mathbf{0},\Sigma_\omega), \tag{3.4}$$

$$\Omega^{-1}\sim \mathrm{W}_2(v_\Omega,(v_\Omega\Omega_0)^{-1}), \tag{3.5}$$

$$\Theta^{-1}\sim \mathrm{W}_N(v_\Theta,(v_\Theta\Theta_0)^{-1}), \tag{3.6}$$

$$\rho\sim \mathbf{U}(\mathfrak{I}), \tag{3.7}$$

where μ_α, Σ_α, Σ_ω, v_Ω, Ω_0, v_Θ and Θ are known constants, (3.4)–(3.7) are independents, $\mathrm{W}_N(v,A)$ denotes a Wishart N-dimensional distribution with degrees of freedom and scale matrix A whose density is given by the expression:

$$k\,\frac{|G|^{(v-N-1)/2}}{|A|^{v/2}}\exp\left[-\frac{1}{2}\operatorname{tr}[A^{-1}G]\right]|G|>0 \tag{3.8}$$

with k being a proportionality constant and $\mathbf{U}(\mathfrak{I})$ denoting the uniform distribution in the N-dimensional interval $\mathfrak{I}=(-1,1)\times\cdots\times(-1,1)$.

Note that, by contrast with Wu and Ho [4], we only carry out the pooling in coefficients λ and γ. This is due to the fact that, as we can appreciate from expression (2.1), the coefficients α depend, in particular, on the coefficient β which determines the long-term position of the firm in the industry, and there is no reason for this position to be the same for each of these firms. This gives greater flexibility to the model, permitting a more reliable estimation of the adjustment coefficients λ and γ.

3.3. The likelihood function of the model

In what follows we will use the notation $[X]$ to denote the density of the variable X and $[X\mid Y]$ to denote the density of the variable X conditioned by the variable Y. Let $Y_T=(y_2,\ldots,y_T)$ and $X_T=(x_1,\ldots,x_T)$.

In order to express the likelihood function of the model, we will begin by putting Eq. (3.1) in vectoral form. We have that:

$$\Delta y_t=\alpha+\lambda\Delta x_{t-1}-V_{t-1}\gamma+u_t;\quad t=1,\ldots,T, \tag{3.9}$$

$$u_t=Du_{t-1}+\varepsilon_t \tag{3.10}$$

with $V_t=\operatorname{diag}(y_{1,t}-x_t,\ldots,y_{N,t}-x_t)$, $D=\operatorname{diag}(\rho_1,\ldots,\rho_N)$, $u_t=(u_{1t},\ldots,u_{NT})'$ and $\varepsilon_t\sim \mathrm{N}_N[0_N,\Theta]$.

Using (3.9) and (3.10) it follows that the likelihood function will be given by

$$[\{y_t;\ t=4,\ldots,T\}\,|\,(\Theta^{-1},\alpha,\omega,\rho),\{y_1,y_2,y_3,X_T\}]$$

$$\propto\ |\Theta^{-1}|^{(T-3)/2}\exp\left[-\frac{1}{2}\sum_{t=4}^{T}(\Delta y_t^*-\alpha^*-\Delta x_{t-1}^*\lambda+V_{t-1}^*\gamma)\Theta^{-1}(\Delta y_t^*-\alpha^*-\Delta x_{t-1}^*\lambda+V_{t-1}^*\gamma)\right], \tag{3.11}$$

where $y_t^*=y_t-Dy_{t-1}$, $x_t^*=I_Nx_t-Dx_{t-1}$, $\alpha^*=(I_N-D)\alpha$, $V_t^*=V_t-DV_{t-1}$.

3.4. The posterior distribution

Denoting the vector of parameters of the model by $\psi=(\Theta^{-1},\alpha,\lambda,\gamma,\rho,\mu_\omega,\Omega^{-1})$, and using (3.11) it follows that the density of the posterior distribution of the parameters of the model is given by

$$
\begin{aligned}
&[\psi \mid Y_T, X_T] \\
&\quad \propto [\{y_t;\ t=4,\dots,T\} \mid (\Theta^{-1},\alpha,\omega,\rho),\{y_1,y_2,y_3,X_T\}] \\
&\quad [\alpha \mid \mu_\alpha,\Sigma_\alpha][\omega \mid \mu_\omega,\Omega^{-1}][\mu_\omega \mid \Sigma_\omega][\Omega^{-1} \mid v_\Omega,\Omega_0] \\
&\quad [\Theta^{-1} \mid v_\Theta,\Theta_0][\rho] \\
&\quad \propto |\Theta^{-1}|^{(T-3)/2} \exp\left[-\frac{1}{2}\sum_{t=4}^{T}(\Delta y_t^* - \alpha^* - \Delta x_{t-1}^*\lambda \right. \\
&\qquad \left. + V_{t-1}^*\gamma)'\Theta^{-1}(\Delta y_t^* - \alpha^* - \Delta x_{t-1}^*\lambda + V_{t-1}^*\gamma)\right] \\
&\quad \times\exp\left[-\frac{1}{2}(\alpha-\mu_\alpha)'\Sigma_\alpha^{-1}(\alpha-\mu_\alpha)\right]\ |\Omega^{-1}|^{N/2} \\
&\quad \times\exp\left[-\frac{1}{2}(\omega - 1_N\otimes\mu_w)'(I_N\otimes\Omega^{-1})(\omega - 1_N\otimes\mu_w)\right] \\
&\quad \times\exp\left[-\frac{1}{2}\mu_\omega'\Sigma_\varpi^{-1}\mu_\varpi\right]\ |\Omega^{-1}|^{(v_\Omega-2-1)/2} \\
&\quad \times\exp\left(-\frac{1}{2}\,\mathrm{tr}((v_\Omega\Omega_0)\Omega^{-1})\right) \\
&\quad \times|\Theta^{-1}|^{(v_\Theta-(N+1)-1)/2}\exp\left(-\frac{1}{2}\,\mathrm{tr}((v_\Theta\Theta_0)\Theta^{-1})\right) I_{\Im}(\rho),
\end{aligned}
\tag{3.12}
$$

where $I_{\Im}(\rho)=1$ if $\rho\in\Im$ and 0 otherwise. This distribution cannot be treated analytically, and thus it is necessary to recur to approximate methods in order to calculate the distributions, the moments and the posterior quantiles of the parameters of the model.

4. Estimation of the model

In order to analyse the SUR Bayesian hierarchical models, we use the MCMC methods, and particularly Gibbs sampling, in a manner analogous to that employed in [6].

The aim of the MCMC methods is to obtain a random sample of the posterior distribution. On this basis we can calculate posterior moments and quantiles, as well as to estimate the posterior densities of the parameters of the model by way of non-parametric Kernel type estimators. To that end, we construct Markov chains over the parametric space. The stationary distributions of these chains are the posterior distributions, in such a way that if the chain is executed a sufficiently large number of times so that convergence to the stationary distribution is achieved, then, on the basis of a given iteration, the samples obtained will, in approximate terms, be a sample of the posterior distribution.

The most commonly used MCMC method is undoubtedly the Gibbs sampling, and it is this method that we have chosen to use in this paper. In order to do so, we need to calculate the full conditional distributions of the parameters of the model, whose expressions are given in the following section.

4.1. The full conditional distributions

These distributions are calculated in a way similar to those described in Chib and Greenberg [6] and are given by the following expressions:

(a) $[\Theta^{-1} \mid \psi_{-\Theta^{-1}}, Y_T, X_T]$

$$\sim \mathrm{W}_N\left(T+v_\Theta-2,\left(v_\Theta\Theta_0+\sum_{t=3}^{T}z_tz_t'\right)^{-1}\right), \tag{4.1}$$

where $z_t=\Delta y_t^*-\alpha^*-\Delta x_{t-1}^*\lambda+V_{t-1}^*\gamma;\ t=3,\dots,T.$

(b) $[\alpha,\lambda,\gamma \mid \psi_{-\alpha,-\lambda,-\gamma}, Y_T, X_T]$

$$\sim \mathrm{N}_{3N}\left[\Lambda\left(B^{-1}\kappa+\sum_{t=4}^{T}A_t'\Theta^{-1}\Delta y_t\right)\Lambda\right], \tag{4.2}$$

where $A_t=(I_N - D\ B_t)$, $\kappa=(\mu_\alpha'\ \ 1_N'\otimes\mu_\omega')'$ with $B_t=(b_{i,j})$ being an $N\times 2N$ matrix with

$$b_{i,2i-1}=\Delta x_{it-1}^*;\quad b_{i,2i}=x_{it-1}^*-y_{it-1}^*$$

$$i=1,\dots,N;\ b_{i,j}=0 \text{ para } j\neq 2i-1,2i,$$

$$B^{-1}=\begin{pmatrix}\Sigma_\alpha^{-1} & 0\\ 0 & I_N\otimes\Omega^{-1}\end{pmatrix} \text{ and}$$

$$\Lambda^{-1}=B^{-1}+\sum_{t=4}^{\mathrm{T}}A_t'\Theta^{-1}A_t.$$

(c) $[\mu_\omega \mid \psi_{-\mu_\omega}, Y_T, X_T] \sim \mathrm{N}_2(a_\omega, A_\omega),$ (4.3)

where $A_\omega=(N\Omega^{-1}+\Sigma_\omega^{-1})^{-1}$, $a_\omega=A_\omega(\Omega^{-1}v1_N)$ and $v=\binom{\lambda'}{\gamma'}$.

(d) $[\Omega^{-1} \mid \psi_{-\Omega^{-1}}, Y_T, X_T]$

$$\sim \mathrm{W}_2(N+\upsilon_\Omega,((v-\mu_w\otimes 1_N')(v-\mu_w\otimes 1_N')' + \upsilon_\Omega\Omega_0)^{-1}). \tag{4.4}$$

(e) $[\rho \mid \psi_{-\rho}, Y_T, X_T] \sim \mathrm{N}_N(m_\rho, N_\rho^{-1})$

truncated in the N-dimensional interval $\Im$ (4.5)

where $m_\rho=N_\rho^{-1}f$ with $f=\mathrm{diag}(F_T)$, $F_T=\Theta^{-1}(\sum_{t=4}^{T}s_ts_{t-1}')$, N_ρ is element to element product matrix of Θ^{-1} and $M_T=\sum_{t=4}^{T}s_{t-1}s_{t-1}'$ with $s_t=\Delta y_t-\alpha-\Delta x_{t-1}\lambda+V_{t-1}\gamma$.

4.2. Implementing the Gibbs sampling

Given that all the full conditional distributions have a standard form, it is not complicated to apply the Gibbs sampling. For that purpose, it is sufficient to take the following steps:

Step 0: Begin with an initial sample of the parameters of ψ

$$\{\psi^{(0,j)} = (\alpha^{(0,j)}, \lambda^{(0,j)}, \gamma^{(0,j)}, \rho^{(0,j)}, \Theta^{-1(0,j)}, \mu_\omega^{(0,j)}, \Omega^{-1(0,j)}),\quad j = 1,\ldots,k\},$$

where k is the number of chains executed in parallel. From this point on steps 1–4 are repeated for $j = 1,\ldots,k$; $i = 1,\ldots,M + M + n_0$.

Step 1: Draw $\Theta^{-1(i,j)}$ from $\Theta^{-1} \mid (\alpha^{(i-1,j)}, \lambda^{(i-1,j)}, \gamma^{(i-1,j)})$, $(\,^{Y_T}_{X_T})$ using (4.1).

Step 2: Draw $(\alpha^{(i,j)}, \lambda^{(i,j)}, \gamma^{(i,j)})$ from $(\alpha, \lambda, \gamma) \mid (\Theta^{-1(i,j)}, \mu_\omega^{(i-1,j)}, \Omega^{-1(i-1,j)})$, $(\,^{Y_T}_{X_T})$ using (4.2).

Step 3: Draw $\mu_\omega^{(i,j)}$ from $\mu_\omega \mid (\lambda^{(i,j)}, \gamma^{(i,j)}, \Omega^{-1(i-1,j)})$ using (4.3).

Step 4: Draw $\Omega^{-1(i,j)}$ from $\Omega^{-1} \mid (\lambda^{(i,j)}, \gamma^{(i,j)}, \mu_\omega^{(i,j)})$ using (4.4).

Step 5: Draw $\rho^{(i,j)}$ from $\rho \mid (\alpha^{(i,j)}, \lambda^{(i,j)}, \gamma^{(i,j)}, \Theta^{-1(i,j)})$ using (4.5).

After discarding the first n_0 iterations to achieve convergence, we have at the end of the algorithm an approximate sample of the posterior distribution of ψ, $\{\psi^{(1)},\ldots,\psi^{(M)}\}$, that we can use to calculate moments, quantiles or to estimate posterior densities. Similarly, we can use it to make forecasts or to test the goodness of fit of the model, as we indicate in the following two subsections.

5. Posterior analysis of the model

Having estimated the model, it is appropriate to analyse whether it is possible to simplify it by imposing some type of restrictions over its parameters, as well as to study its goodness of fit to the data.

5.1. Simplification of the model

The simplification of the model is analysed in two directions. On the one hand, we study whether there is any sense in pooling the parameters $\{\lambda_i;\ i = 1,\ldots,N\}$ and $\{\gamma_i;\ i = 1,\ldots,N\}$; on the other, we analyse for the existence of autocorrelation in the residuals u_t.

The way to analyse these two possible simplifications of the model is through the partial Bayes factor [6,9] or the posterior Bayes factor [10]. In order to calculate the former, we take the first t_0 observations as the estimation sample of the model and the remaining $T - t_0 + 1$ as the validation sample. For each one of the compared models, we then calculate the posterior forecast density which is given by

$$[Y_{T-t_0+1} \mid Y_{t_0}, X_T, \mathbf{M}] = \int [Y_{T-t_0+1} \mid Y_{t_0}, X_T, \psi, \mathbf{M}][\psi \mid Y_{t_0}, X_T, \mathbf{M}]\,\mathrm{d}\psi, \quad (5.1)$$

where $Y_{T-t_0+1} = (y_{t_0+1},\ldots,y_T)'$ and $Y_{t_0} = (y_1,\ldots,y_{t_0})'$; $\mathbf{M}$ is the compared model and $[\psi \mid Y_{t_0}, X_T, \mathbf{M}]$ is the posterior distribution of the parameter ψ of the model $\mathbf{M}$ given the estimation sample Y_{t_0}. As demonstrated by Chib and Greenberg [6], a consistent estimator of (5.1) is given by the expression:

$$\frac{1}{N}\sum_{i=1}^{N} [Y_{T-t_0+1} \mid Y_{t_0}, X_T, \psi^{(i)}, \mathbf{M}], \quad (5.2)$$

where $\{\psi^{(i)};\ i = 1,\ldots,N\}$ is a sample of the posterior distribution $\psi|Y_{t_0}, X_T, \mathbf{M}$.

The posterior Bayes factor is calculated using the posterior forecast density of the observed data, and calculated using a similar process where the observed data are taken as the estimation and validation sample.

5.2. Analysis of the predictive goodness of fit

The goodness of fit of the model is studied by analysing its predictive behaviour. To that end, we calculate the posterior p-value of the observed mean squared error (MSE) which is given by

$$P[\mathrm{MSE} \geqslant \mathrm{MSE}_{\mathrm{obs}} \mid Y_{t_0}, X_T, \mathbf{M}], \quad (5.3)$$

where $\mathrm{MSE} = 1/(T - t_1)\sum_{t=t_1}^{T-1} (y_{t+1} - E[y_t \mid \psi, Y_{t-1}, X_t, \mathbf{M}])^2$, $\mathrm{MSE}_{\mathrm{obs}}$ is the value of the MSE for the observed series and $\mathbf{M}$ is the model being considered. This probability is calculated, using the Monte Carlo method, through the expression:

$$\frac{1}{N}\sum_{i=1}^{N} I_{\{\mathrm{MSE} \geqslant \mathrm{MSE}_{\mathrm{obs}}\}}(\psi^{(i)}, Y_T^{(i)}), \quad (5.4)$$

where $\{\psi^{(i)};\ i = 1,\ldots,N\}$ is a sample of the posterior distribution $\psi \mid Y_{t_0}, X_T, \mathbf{M}$ and the function $I_{\{\mathrm{MSE} \geqslant \mathrm{MSE}_{\mathrm{obs}}\}}(\psi, U_T) = 1$ if the value of the MSE, calculated using ψ and U_T generated from ψ, is equal to or greater than the value of the MSE calculated using ψ and the observed series Y_T. The function takes the value 0 in the contrary case.

Similarly, we calculate the coverage of the one step ahead Bayesian forecast intervals constructed for a given posterior probability $1 - \alpha$. These intervals are constructed using the quantiles $\alpha/2$ and $1 - \alpha/2$ of the forecasts made one step ahead for $\{y_t;\ t = t_1,\ldots,T\}$, using the composition sample described in Section 5.2.1 for $T = t$ and $h = 1$. Having calculated such intervals, the coverage is estimated by counting the number of intervals constructed that cover the value of the observed series at each time t.

5.2.1. Calculating the Bayes forecast interval for a time horizon h

If we wish to use the proposed model to forecast the future values of the ratios analysed in each, we must first calculate a forecast of the value of the average ratio. In such forecasts, we must also take into account the uncertainties associated with the estimation of the parameters of the model, with this being quantified by the posterior distribution of the parameters as well as the uncertainty associated with the forecast that is made of the average ratio. All this is taken into consideration in a natural manner by the composition sample described below with respect to the model given by Eq. (3.1).

Let us suppose that we wish to make forecasts on the value of the series analysed h period ahead, that is to say, in the periods $T+1,\dots,T+h$ and that we have a model that describes the behaviour of the average ratio x_t on the basis of which we can obtain forecasts of that ratio. We proceed in the following manner:

Repeat the following steps for $i=1,\dots,L$:

(1) Choose randomly one element of the sample obtained from the posterior distribution of ψ, $\psi^{(i)} = (\alpha^{(i)}, \lambda^{(i)}, \gamma^{(i)}, \rho^{(i)}, \Theta^{-1(i)}, \mu_\omega^{(i)}, \Omega^{-1(i)})$.

(2) Draw $\{\varepsilon_{T+1}^{(i)},\dots,\varepsilon_{T+h}^{(i)}\}$ from $\mathrm{N}_N(0,\Theta^{(i)})$.

(3) Make forecasts of x_t, $\{x_{T+1}^{(i)},\dots,x_{T+h}^{(i)}\}$ in the periods $T+1,\dots,T+h$.

(4) Make forecasts of y_t in the periods $T+1,\dots,T+h$ by way of the recursive formulas:

$$y_{T+j}^{(i)} = \alpha^{(i)} + \lambda^{(i)}\Delta x_{T+j}^{(i)} + y_{T+j-1}^{(i)} - V_{T+j-1}^{(i)}\gamma^{(j)} + u_{T+j}^{(i)}$$

$$j=1,\dots,h,$$

where $u_{T+j}^{(i)}=D^{(i)}u_{T+j-1}^{(i)}+\varepsilon_{T+j}^{(i)}$, $V_{T+j-1}^{(i)}=\mathrm{diag}(y_{T+j-1}^{(i)} - x_{T+j-2}^{(i)}1_N)$, $D^{(i)}=\mathrm{diag}(\rho^{(i)})$ and $y_{T+j}^{(i)}=y_{T+j}$, $u_{T+j}^{(i)}=u_{T+j}$ if $j \leqslant 0$.

As a consequence of this algorithm we have, for each period $\{T+i;\ i=1,\dots,h\}$, L random samples $\{y_{T+i}^{(1)},\dots,y_{T+i}^{(L)}\}$ that can be used to calculate forecasts moments i steps ahead or Bayesian forecast intervals with a given posterior probability using the appropriate quantiles.

6. Analysis of the financial ratios of the CBSO

In this section, we will analyse the evolution over time of six financial ratios in the Spanish manufacturing sector during the period 1986–1997 ($T=12$). The data have an annual character and have been obtained from the Bank of Spain's CBSO. The ratios analysed are set out in Table 1, whilst Table 2 contains the subsectors of the Spanish manufacturing sector that represent the series to be analysed ($N=7$). Similarly, Fig. 1 reflects the evolution of the seven sectors, as well as that of the entire manufacturing sector, with respect to the six ratios.

Table 2
Sub-sectors of the spanish manufacturing sector

Sector	Abbreviation
Food, Drinks and Tobacco	FOOD
Oil Refining and Treatment of Nuclear Fuels	OIL
Chemical Industries	CHEM
Glass, Ceramic and Metal Transformation	GLASS
Electric, Electronic and Optical Material and Equipment Industry	ELEC
Transport Material Manufacture	TRANS
Other Manufacturing Industries	OTHERS

6.1. Statistical analysis

For each ratio, we consider the following models. First, model $\mathbf{M}_0$ which assumes that each of the series oscillates freely, without significant residual correlation and that there needs to be no pooling of the adjustment coefficients of the series being analysed, with the parameters μ_ω, Ω and ρ of the model therefore being eliminated. Secondly, model $\mathbf{M}_1$ which assumes that there must be a pooling and, furthermore, that the residual autocorrelation is null, eliminating the vector of parameters ρ. Finally, model $\mathbf{M}_2$ which also assumes that there must be a pooling and, furthermore, that there is a residual autocorrelation which is not null in the residuals.

In all the models, the prior distribution is that described in Section 3.2. This has been taken concentrating on the maximum likelihood estimators (MLE) of each parameter and with small degrees of freedom in the Wishart distributions, with the aim that it be diffuse, and with the obvious modifications for each model. Thus, the vector μ_α has been taken as equal to the MLE estimator of α and the matrix Σ_α as equal to the matrix of variances and covariances of that estimator. The vector μ_ω has been taken as equal to the averages vector of the MLE estimators of the vectors λ and γ; the matrix Ω_0 as equal to the matrix of variances and covariances of those estimators and $v_\omega=4$; finally, $v_\Theta=N+2$ and Θ_0 as equal to the MLE estimator of Θ. Other choices of the hyperparameters μ_α and μ_ω do not significantly change the results. However, the values of the variances and covariances matrices Σ_α, Ω_0 and Θ_0 do affect the estimations of the parameters, in some cases causing that the shrinkage effect towards the values μ_α and μ_ω is greater, thereby increasing the uncertainty associated with the estimations obtained. This is due to the scarcity of data per series and to the fact that the number of series being analysed is small. Given that the literature does not provide any guide on how to choose these parameters, we have chosen to act in an empirical-Bayesian form, taking the values described earlier.

For each model and each ratio we have executed the algorithm described in Section 4.2 during 5000 iterations and have discarded the first 1000. The final sample has been obtained by choosing a sample every four iterations from the

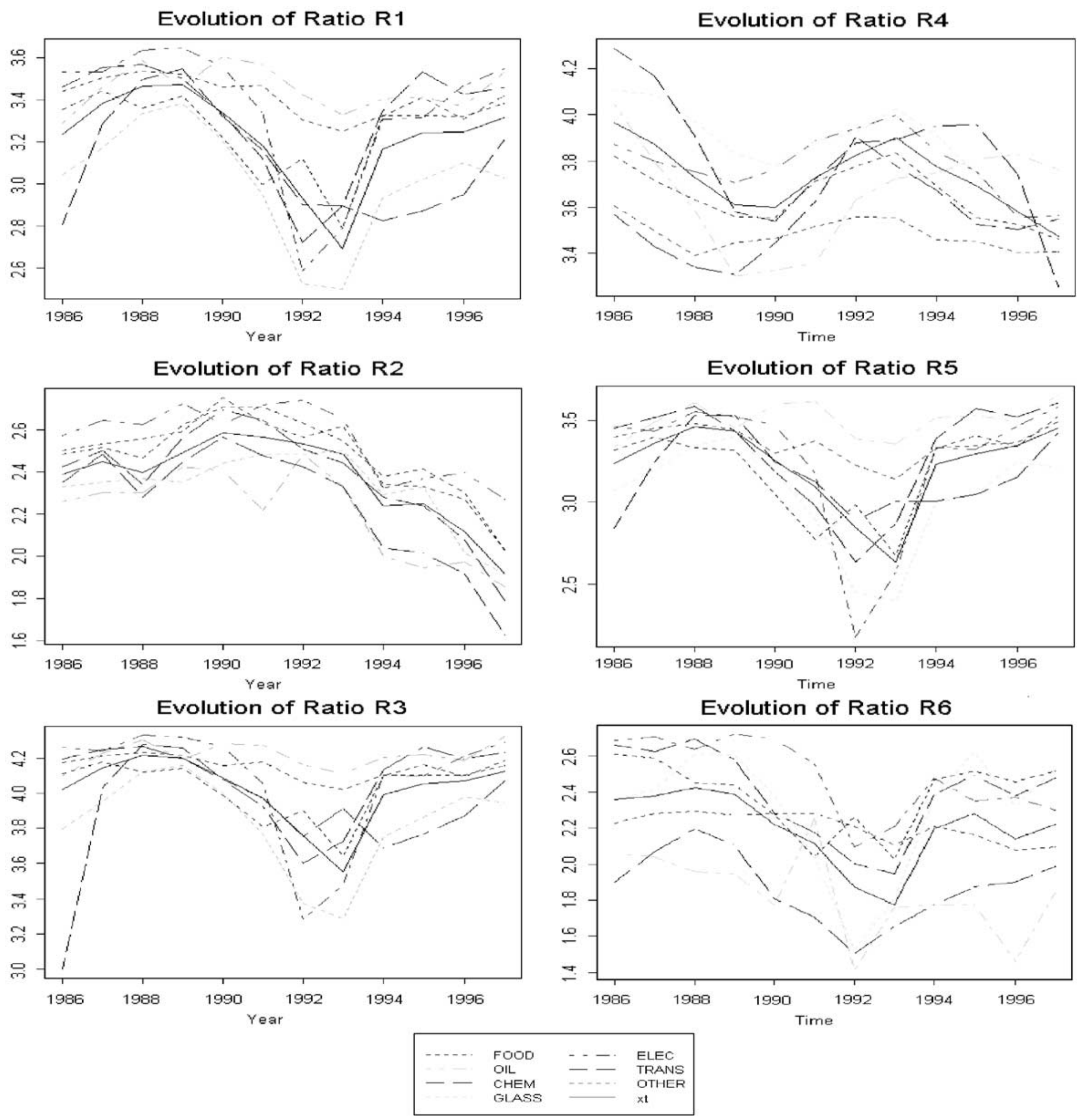

Fig. 1. Evolution of the analysed ratios.

remaining 4000 iterations, with the aim of reducing the autocorrelation present in that sample. The convergence has been determined by using the procedure described in [11] applied to the parameters λ, γ and μ_ω.

Tables 3 and 4 contains the results of the model selection process by way of the partial Bayes factor with $t_0=T-2$ and the posterior Bayes factor, respectively. In all cases, we can note that, with greater or lesser strength, the model chosen is always $\mathbf{M}_1$, with the sole exception of ratio R2. In this latter case, the model chosen using the posterior partial Bayes

Table 3
Partial Bayes factor taking model $\mathbf{M}_0$ as reference

Ratio/model	$\mathbf{M}_1$	$\mathbf{M}_2$
R1	12.77	0.10
R2	4.43	1.10E − 16
R3	7.36	0.11
R4	2.42	0.002
R5	2.00E + 9	1.03E + 8
R6	11.47	0.5

Table 4
Posterior Bayes factor taking model $\mathbf{M}_0$ as reference

Ratio/model	$\mathbf{M}_1$	$\mathbf{M}_2$
R1	37.99	1.58
R2	1.320	6.76
R3	40.10	2.44
R4	5.51	0.04
R5	4.78E + 37	2.18E + 36
R6	16.69	2.29

factor is $\mathbf{M}_2$ and, if the partial Bayes factor is considered, then the model chosen is $\mathbf{M}_1$. Analysing the out-sample forecasting behaviour of both models, and taking into account that the partial Bayes factor for model $\mathbf{M}_2$ is very small, we have in this case taken the decision to also choose model $\mathbf{M}_1$.

6.2. Estimation of the parameters

Tables 5 and 6 contain the estimation obtained for the parameters of model $\mathbf{M}_1$, which is the model selected in all cases. With respect to all the ratio analysed, save for ratio R4 and some series of R2, we find that the active attempts by management effect exerts more influence than the passive industry-wide effects operating on the firms, given that the percentage of movement of the series explained by the first effect is $> 50\%$ in almost all of them. Only in ratio R4 does the passive effect have a greater influence.

The estimated values of the λ coefficients are, in general, close to zero and not significant. By contrast, the estimated values of the γ coefficients are positive and significant in a large number of the series, reflecting the importance that the active effect has over the evolution of the ratios being analysed. Furthermore, we can note that, with the exception of ratio R4, the average adjustment coefficients μ_γ are larger than the μ_λ coefficients, with these reaching the highest value in ratio R2 (49.26%), and with the remaining ratios being very similar (oscillating between 33.6% and 37.95%). Only with respect to ratio R4 can we note the contrary effect, with the estimated values of the λ coefficients, as well as the average adjustment coefficient μ_λ (42.04%), being larger.

The largest and most significant adjustment coefficients γ are given in ratio R2. This is very probably due to the fact that the generalised fall in interest rates has led to an increase in the negotiating capacity of firms with financial entities, in this way increasing their control over financial expenses.

With respect to the Profitability (R1 and R3) and Financial Leverage (R5) ratios, we can observe a very similar behaviour, with greater influence on the part of the active effect. This may be due to the fact that, in their adjustment process, the management of the firm have assumed the objetive of profitability and in achieving it, have been able to manage the selection of the most advantageous accounting rules. Here, we should not forget that the profitability indicators have been affected by income smoothing practices, aimed at presenting expected earning numbers [12].

Ratios R4 and R5 have a different meaning. Thus, R4 offers the broadest definition of stock leverage, which is the ratio of total liabilities to total assets. This can be viewed as a proxy for what is left for shareholders in the case of liquidation. Furthermore, since total liabilities also include items like accounts payable, which may be used for transactions purposes, rather than for financing, it may overstate the amount of leverage [13]. For its part, R5, Financial Leverage, is a synthetic indicator on the relationship between the profitability of the firms and the cost of financing. It shows that if firms are unable to generate enough profitability from their assets to exceed this value, they will face a difficult financial environment [14].

Firms with high leverage operate well in times of economic expansion, improving the dividend expectations of their shareholders. However, these fall rapidly in as a consequence times of recession. The largest coefficients γ explain that the significant change in the ratio is due to the greater weight of management activities, in such a way that the shocks in the environment, such as measures of a financial character or changes to interest rates, are rapidly assumed by management in their objective of improving the cost of capital.

The operating income to net sales ratio (R6) also reflects a greater influence on the part of the active effect in two very specific sectors: the oil sector and, to a lesser extent, the electric, electronic and optical material sector. In the first of these, this effect could be due to the low level of oil prices at the relevant time which led to an increase in the control capacity of the firms in this sector over their profit margins, as well as the oligopolistic character of this market.

The Indebtedness (R4) ratio exhibits a markedly different evolution from the others, with a greater influence being exerted by the passive effect and, in general, higher adjustment coefficients λ. This is due to the fact that the movement of this ratio is influenced not only by decisions adopted within the firm, but also by outside events, such as economic and financial policy measures taken by Governments that might have an effect over the financial strategies implemented by firms.

With respect to ratio R4 in Fig. 1, we cannot appreciate a change in the tendency of the series analysed for this ratio, which is in contrast to what occurs, for example, with the graphic of the series corresponding to R2. More specifically, this implies, at least in the period of time under analysis, that there are no shocks capable of affecting the behaviour of that series in the long-term and, therefore, that it was not necessary for the firms considered to make significant corrections to their position in the industry. All this has its reflection in a non-significant value of the coefficient γ. This behaviour is consistent with the results of earlier works on capital structure. Thus, according to Harris and Ravid [15], the consensus is that "leverage increases with fixed assets,

Table 5
Estimation of the parameters λ and γ

R1	λ_i	S.D. (λ_i)	γ_i	S.D. (γ_i)	V_λ	R^2
FOOD	−0.0111	0.1366	0.1083	0.1608	47.02	0.0735
OIL	−0.0582	0.1741	0.3085	0.1826	26.90	0.2544
CHEM	−0.0209	0.2255	0.3738	0.3491	35.83	0.0151
GLASS	0.0079	0.2186	0.3115	0.3664	50.26	0.1922
ELEC	−0.0253	0.2268	0.4503	0.3626	28.65	0.2549
TRANS	−0.0365	0.1962	0.5231	0.2261	16.18	0.4321
OTHER	−0.0452	0.2168	0.5059	0.3907	30.10	0.1204
R2	λ_i	S.D. (λ_i)	γ_i	S.D. (γ_i)	V_λ	R^2
FOOD	0.1484	0.4983	0.4606	0.3269	64.90	0.3270
OIL	0.0494	0.5989	0.4392	0.2544	49.14	0.2904
CHEM	0.1945	0.6160	0.7921	0.1611	45.18	0.1405
GLASS	−0.3030	0.4969	0.8645	0.3518	34.07	0.5368
ELEC	−0.0960	0.4935	0.3137	0.2196	61.70	0.2717
TRANS	0.2475	0.6824	0.5261	0.1847	51.02	0.1036
OTHER	−0.0335	0.4819	0.4228	0.2096	65.64	0.2497
R3	λ_i	S.D. (λ_i)	γ_i	S.D. (γ_i)	V_λ	R^2
FOOD	−0.0284	0.1222	0.0759	0.1477	50.90	0.0613
OIL	−0.0481	0.1555	0.1803	0.1701	39.06	0.1257
CHEM	−0.0316	0.2122	0.3005	0.4015	40.05	0.0302
GLASS	−0.0156	0.2084	0.2819	0.3980	42.63	0.2190
ELEC	−0.0736	0.2273	0.4234	0.3789	24.48	0.2769
TRANS	−0.1245	0.2037	0.6846	0.2555	10.62	0.5583
OTHER	−0.0812	0.2052	0.4751	0.4273	34.80	0.0952
R4	λ_i	S.D. (λ_i)	γ_i	S.D. (γ_i)	V_λ	R^2
FOOD	0.0531	0.1784	−0.2841	0.2024	33.15	0.4403
OIL	0.5805	0.3088	0.0790	0.2154	69.61	0.5205
CHEM	0.5523	0.3435	0.4256	0.2752	44.14	0.2334
GLASS	0.5490	0.2603	0.0350	0.3102	81.46	0.5147
ELEC	0.2904	0.3371	−0.0025	0.5234	56.42	0.2227
TRANS	0.7000	0.3149	0.8359	0.3363	35.21	0.6958
OTHER	0.3590	0.3170	−0.1141	0.6197	67.24	0.3413
R5	λ_i	S.D. (λ_i)	γ_i	S.D. (γ_i)	V_λ	R^2
FOOD	−0.0768	0.1751	0.1663	0.2170	47.68	0.0357
OIL	−0.0932	0.1952	0.2497	0.2004	36.14	0.1844
CHEM	−0.0289	0.2377	0.3200	0.3979	41.48	0.0167
GLASS	−0.0355	0.2398	0.3333	0.4583	50.00	0.2285
ELEC	−0.0546	0.2647	0.4526	0.3746	26.39	0.3058
TRANS	−0.1058	0.2197	0.6353	0.2802	18.70	0.3367
OTHER	−0.0619	0.2442	0.5420	0.4710	32.53	0.1067
R6	λ_i	S.D. (λ_i)	γ_i	S.D. (γ_i)	V_λ	R^2
FOOD	−0.1056	0.1352	0.1562	0.1236	43.88	0.0573
OIL	−0.2421	0.2693	0.7703	0.2920	12.34	0.5587
CHEM	−0.0566	0.2482	0.2348	0.4394	55.98	0.1411
GLASS	−0.0606	0.2728	0.3463	0.3677	33.05	0.2380
ELEC	−0.1588	0.2505	0.5862	0.3452	31.82	0.2981
TRANS	−0.0657	0.2307	0.3217	0.3597	45.59	0.0914
OTHER	−0.0857	0.2489	0.2662	0.3621	40.69	0.1353

V_λ signifies the percentage of systematic movement of the ratio associated with the passive effect.

Table 6
Estimation of the parameters μ_λ and μ_γ

Ratio	μ_λ	S.D. (μ_λ)	μ_γ	S.D. (μ_γ)
R1	−0.0231	0.1666	0.3749	0.2322
R2	0.0392	0.5355	0.4926	0.3195
R3	−0.0562	0.1521	0.3366	0.2641
R4	0.4204	0.2489	0.1050	0.3551
R5	−0.0676	0.1912	0.3792	0.2766
R6	−0.1097	0.2026	0.3794	0.2622

Table 7
Goodness of fit of the model

Ratio	p-valor IN	cub IN	p-valor OUT	cub OUT
R1	0.9999	0.9730	0.9990	0.9762
R2	1.0000	0.9797	0.9309	0.9578
R3	0.9999	0.9687	0.9991	0.9891
R4	0.9991	0.9434	0.9188	0.8165
R5	0.9999	0.9705	0.9997	0.9967
R6	0.9999	0.9627	0.9673	0.9249

p-value IN given by (4.9) with $t_0 = T,\ t_1 = 4$. p-value OUT given by (4.9) with $t_0 = T - 2,\ t_1 = T - 1$. Cub IN evaluated for a 95% confidence level with $t_0 = T,\ t_1 = 4$. Cub OUT evaluated for a 95% confidence level with $t_0 = T - 2,\ t_1 = T - 1$.

investment opportunities, and firm size". Similar results have been obtained by Rajan and Zingales [13], who add the tangibility of assets. These are characteristics of each sector, required in order to compete in the market of one particular industry.

Finally, we should particularly note that the Transport sector demonstrates very significant γ coefficients in the ratios related to Profitability and Indebtedness (R1, R2, R3, R4 and R5). This could be due to the fact that small and medium sized firms tend to predominate in this activity, with the management of such firms having greater capacity for manoeuvre in increasing or reducing their level of indebtedness according to the economic circumstances with which they are faced at any given time.

6.3. Goodness of fit

The values of the multiple correlation coefficients R^2 are set out in Table 5, whilst Table 7 contains the in and out-sample p-values calculated according to expression (4.9), as well as the coverages of the 95% Bayesian intervals constructed according to that described in Section 5.2.1. Here we can note that, by series, the best fit is produced in those in which the λ and/or γ coefficients are more significant, corroborating the influence that the passive and/or active effects have over their evolution. The p-values associated to the MSE and the coverages of the out sample forecast intervals do not, in general, offer evidence of a bad fit on the part of the model. The exception to this is the case of the ratio R4, when we can note an undercoverage in the out sample forecast intervals. This is due to the bad forecasting behaviour of the model in the Transport sector, where we can observe a sharp fall in that ratio in the last two periods (see Fig. 1). We can conclude, therefore, that the fit of the analysed models is a correct one.

7. Conclusions

In this paper we have proposed a Bayesian hierarchical model which allows us to estimate the model proposed in [4] without having to recur to asymptotic approximations. Similarly it enables us to carry out a model section process and to analyse the goodness of fit of the same, in both in and out sample terms. The proposed methodology has been applied to the analysis of the six financial ratios calculated by the Bank of Spain's CBSO in the Spanish manufacturing sector. In this regard, we have found that the error correction component exerts a greater influence in the majority of such ratios. The Interest Expenses to Liabilities ratio demonstrates a greater sensitivity to this effect. By contrast, factors exogenous to the firm have a greater influence on the Indebtedness ratio. When individual sectors are considered, that of Transport stands out by virtue of having the greatest capacity for manoeuvre in the Profitability and indebtedness ratios.

It would be interesting to broaden the analysis to other ratios and other industrial sectors. Similarly, it is noteworthy that many ratios are related between themselves and, very possibly, demonstrate very similar behaviour, making it worthwhile to extend the proposed methodology to the joint analysis of various ratios. All these aspects remain to be considered in future lines of research.

Acknowledgements

This work has benefited from the financial support provided by Research Project SEC 2001-1798 and 2FD97-2091 of the European Regional Development fund (ERDF). The authors would also like to express their thanks to two anonymous referees and to the Editor for their helpful comments and suggestions on an earlier version of this paper.

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