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Understanding the behavior of financial ratios: the adjustment process

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Abstract

This paper contributes to our understanding of the behavior of financial ratios by means of a hierarchical Bayesian analysis of the partial adjustment model of financial ratios presented in Davis and Peles [Acc. Rev. 68 (1993) 725]. Such an approach allows us to make a robust estimate of the average adjustment coefficient of a set of firms. The proposed methodology is applied to the analysis of a number of financial ratios considered in the above-mentioned paper corresponding to a sample of US manufacturing firms.

JEL classification: G30

Keywords: Financial ratios; Gibbs sampling; Partial adjustment model

1. Introduction

According to Rees (1995) the prominence of financial ratio analysis is a response to the amount of information contained in a set of financial statements and to the problem of comparability between firms of differing sizes. Financial ratios provide useful quantitative financial information to both investors and analysts so that they can evaluate the operation of a firm and analyse its position within a sector over time. Furthermore, ratios make the data better satisfy the assumptions underlying statistical tools such as regression analysis (e.g., homoscedastic

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disturbances, see Foster, 1986) and, for these reasons, it is interesting to characterise their adjustment process. One of the models most commonly used to analyse ratio adjustment is the partial adjustment model. This model was proposed for dividend policy by Lintner (1956) and for financial ratio analysis by Lev (1969); subsequently the model was analysed amongst others by Davis and Peles (1993), Lee and Wu (1988), Peles and Schneller (1989), Wu and Ho (1997), and, more recently, by Nwaeze (2001).

This model postulates that firms have a constant adjustment coefficient η which measures the speed at which the ratio returns to target equilibrium values from out-of-equilibrium conditions. Peles and Schneller (1989) have studied the existence of these equilibrium values assuming that all firms have the same η, the unobserved target is stable over time and there is no sampling bias in measuring the correlation coefficient. Davis and Peles (1993) relax these assumptions and divide η into an industrywide adjustment rate η^{I} and a management rate η^{M}. They analyze a number of ratios and firms and use a minimum χ^2 procedure to estimate η^{I} and η^{M}, concluding that the partial adjustment hypothesis is compatible with the data being analysed. Finally, Wu and Ho (1997) propose an error correction model to estimate η^{I} and η^{M}.

The above works assume, either implicitly or explicitly, that all the firms have the same adjustment coefficient η. However, this hypothesis is not particularly realistic, given that although the firms operating in the same sector carry out their activities in similar circumstances, there is no reason why they should all react with exactly the same speed. Furthermore, some firms could have an adjustment coefficient which is very different from the rest and that could have a strong influence on the estimation of η^{I}. Against this background, we propose a Bayesian hierarchical model that relaxes this hypothesis in such a way that it explicitly permits the adjustment coefficients of the various firms to be different and allows us to obtain a robust estimator of η^{I} by weakening the influence of outliers. To that end, we use prior distributions over the adjustment coefficients, which are mixtures of two components: the first assumes that one coefficient is similar to the other; while the second is a diffuse prior. The mixture weights are the prior probabilities that a firm has an adjustment coefficient different from η^{I}. These types of prior distributions have been used by Efron (1996) and George and McCulloch (1993, 1995), in other contexts. Given that the analysis is not conjugate and there are a large number of parameters to be estimated, we use Monte Carlo Markov Chain methods (MCMC) to estimate them.

Using this methodology we analyze the 11 financial ratios considered by Davis and Peles (1993) for a sample of firms from the *Worldscope Global Database*. We find that for 9 of the 11 ratios, the estimated adjustment coefficients η^{I} are about 70%. This means that the proportion of deviation with respect to the target that is corrected in one year for each ratio is around 70%. The equity-to-debt ratio and the gross margin ratio have adjustment coefficients which are significantly lower, about 50%.

The estimated values are, in general, higher than those reported in Davis and Peles (1993) for the period 1972–1991, suggesting that during the period 1993–2000 the speed of reaction of the firms to unexpected shocks has increased. One possible reason for this increase may be the higher level of economic prosperity during this period, which made it easier for management to control the economic activity of their firms and their financial ratios.

The remainder of this paper is divided into three sections. In Section 2 we describe the hierarchical partial adjustment model considered in this paper and the algorithm used to estimate its parameters. In Section 3 we analyse 11 financial ratios considered in Davis and Peles (1993) using data from the *Worldscope Global Database*. Section 4 closes the paper with a brief review of the main conclusion and future research directions.

2. Hierarchical Bayesian analysis of the partial adjustment model

Consider a sample of N firms of a given industry, with a financial ratio Y for each of these firms, over T periods of time. This information is given by N time series $\{y_{it};\ i = 1, \dots, N;\ t = 1, \dots, T\}$ where y_{it} is the value taken by ratio Y of the firm i in the period of time t.

2.1. The partial adjustment model

The partial adjustment model of financial ratios assumes the existence for each firm i of an equilibrium level, μ_i, for each ratio Y. It is further assumed that at some past time $y_o = \mu_i$ and that in period $t = 1$ the ratio has been subjected to a shock ε_{i1}, and thus $y_{i1} = \mu_i + \varepsilon_{i1}$. The firm will try to eliminate this deviation from the equilibrium level. The adjustment process does not happen immediately and we assume that in 1 period the $100\eta_i$% of the accumulated effects of the previous shocks are eliminated; hence, in period 2, the value of the financial ratio will be:

$$y_{i2} = \mu_i + (1 - \eta_i)\varepsilon_{i1} + \varepsilon_{i2}$$

where ε_{i2} is the shock produced in the period 2. In general, an inductive argument proves that in period t:

$$y_{it} = \mu_i + \varepsilon_{it} + \beta_i \varepsilon_{it-1} + \cdots + \beta_i^{t-1} \varepsilon_{i1}$$

where η_i is the adjustment coefficient of the firm and $\beta_i = 1 - \eta_i$. It follows that:

$$y_{it} - \beta_i y_{it-1} = \mu_i \eta_i + \varepsilon_{it} \Rightarrow y_{it} = \alpha_i + \beta_i y_{it-1} + \varepsilon_{it} \quad \text{where}\ \alpha_i = \mu_i \eta_i \tag{1}$$

The coefficient η_i is called the adjustment coefficient of the ith firm and will measure the reaction of the firm's management to unexpected shocks which affect its ratio. Given that the environment in which the firms operate is similar, it can further be assumed that the adjustment coefficients of the majority of firms will be similar, fluctuating around an average value η^{I} which characterises the behaviour of the industry with respect to the ratio being analysed.

As mentioned earlier, the objectives of this work are two-fold: on the one hand, to estimate η^{I} and, on the other, to locate those firms with an adjustment coefficient that is significantly different from the rest, by virtue of it being abnormally higher or lower than η^{I}. In this way, we can obtain a robust estimation of η^{I}, and thereby weaken the influence of such outliers.

Usually in financial ratio analysis T is small and N is not particularly big. Thus there is more transversal than longitudinal information, giving rise to the need to use models that can process this type of information efficiently without having to recur to asymptotic results. One way to carry out such an estimation is through hierarchical Bayesian models, which allow for the interchange of information between related series. In Section 2.2 we describe a model of this type which assists in resolving these two limitations coming from the small size of T and N.

2.2. The hierarchical Bayesian model

In this section we describe the hierarchical model considered in the paper, as well as the prior distributions of these parameters. The MCMC algorithm used to approximately calculate, the posterior distribution of the parameters of the model[1] has been relegated to Appendix A.

2.2.1. The model

The equations of the model are:

$$y_{it} = \alpha_i + \beta_i y_{it-1} + \varepsilon_{it} \quad \alpha_i, \beta_i \in \boldsymbol{R}; \quad i = 1, \ldots, N; \quad t = 2, \ldots, T \tag{2}$$

with $\{\boldsymbol{\varepsilon}_t; t = 2, \ldots, T\}$ i.i.d. $N_N(0,\boldsymbol{\Sigma})$ where $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, \ldots, \varepsilon_{Nt})'$, Σ is a $N \times N$ symmetric definite positive matrix and $N_N(0,\boldsymbol{\Sigma})$ denotes the Multivariate Normal distribution with mean vector $\mathbf{0}$ and covariance matrix Σ.

2.2.2. The prior distribution

Let $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_N)'$, $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_N)'$, $\boldsymbol{y} = (\boldsymbol{y}_1, \ldots, \boldsymbol{y}_T)'$ where $\boldsymbol{y}_t = (y_{1t}, \ldots, y_{Nt})'$, and $t = 1, \ldots, T$.

We assume that $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$ and $\boldsymbol{\Sigma}$ are independent with:

$$\boldsymbol{\alpha} \sim N_N(\boldsymbol{\mu}_\alpha, \boldsymbol{\Sigma}_\alpha); \quad \sigma_\alpha^2 > 0 \tag{3}$$

$$\boldsymbol{\Sigma}^{-1} \sim \boldsymbol{W}_N(\nu, \boldsymbol{A}^{-1}); \quad \nu > N \text{ and } \boldsymbol{A} = \nu\boldsymbol{\Sigma}_o \tag{4}$$

$$\beta_i|\gamma_i, \delta, \sigma^2 = (1-\gamma_i)N(\delta, \sigma^2) + \gamma_i N(\delta, c^2\sigma^2); \quad i = 1, \ldots, N \text{ independent and } c > 1 \tag{5}$$

where $\boldsymbol{W}_N(\nu,A)$ denotes the Wishart distribution and $\boldsymbol{\Sigma}_o$ is a prior estimation of $\boldsymbol{\Sigma}$; $N_N(\boldsymbol{\mu}_\alpha,\boldsymbol{\Sigma}_\alpha)$ is the normal multivariate distribution with mean vector $\boldsymbol{\mu}_\alpha$ and covariance matrix $\boldsymbol{\Sigma}_\alpha$; $\delta = 1-\eta^{\mathrm{I}}$ and $N(\delta,\sigma^2)$ denotes the normal distribution with mean δ and variance σ^2; $\{\gamma_i; i = 1, \ldots, N\}$ are indicators of the dissimilarity of the adjustment coefficient of the ith firm given by $\gamma_i = 1$ if β_i is significantly different from δ and $\gamma_i = 0$ otherwise $i = 1, N$.

The prior distribution on $\{\beta_i; i = 1, \ldots, N\}$ is a mixture similar to that considered in Efron (1996) and George and McCulloch (1993, 1995) in other contexts. We use the $N(\delta,\sigma^2)$ distribution as the prior distribution of the β_i coefficients if β_i is not significantly different from δ; otherwise, we use an $N(\delta,c^2\sigma^2)$ with constant c sufficiently large for this distribution to be diffuse.

In order to choose c, we will consider x, the cross-point between the $N(\delta,\sigma^2)$ and the $N(\delta,c^2\sigma^2)$ densities, that satisfies $|(x-\delta)/\sigma| = (c\sqrt{2\log c})/(\sqrt{c^2-1})$. We will assume that if $|\beta_i - \delta| \leq |x-\delta|$ then β_i is not significantly different of δ. Thus, for example, if $c = 10$ then $|(x-\delta)/\sigma| = 2.16$ so that if $|(\beta_i - \delta)/\sigma| > 2.16$, β_i is significantly different from δ and, therefore, an outlier of the distribution of the coefficients β whose influence has to be weakened in the estimation of δ.

Additionally, we assume that

$$P[\gamma_i = 0] = p_i; \quad P[\gamma_i = 1] = 1 - p_i; \quad i = 1, N \text{ independent} \tag{6}$$

that is, we assume that β_i has a prior probability of being an outlier equal to $1-p_i$; $i = 1, \ldots, N$. Finally, we assume that

$$\delta \sim N(\mu_\delta, \sigma_\delta^2), \quad \tau^2 = \frac{1}{\sigma^2} \sim G\left(\frac{a_1}{2}, \frac{b_1}{2}\right); \quad \text{independent with } \sigma_\delta^2, a_1, b_1 \geq 0 \tag{7}$$

where $G(a, b)$ denotes the gamma distribution.

We choose $a_1 > 2$ in such a way that the distribution $G(a_1/2, b_1/2)$ is diffuse; the value of b_1 is chosen on the basis of the value of a_1 and a prior estimation of the value of σ^2, σ_o^2, in such a way that

$$\sigma_o^2 = E[\sigma^2] = \frac{b_1}{a_1 - 2} \tag{8}$$

3. Analysis of financial ratios taken from the US manufacturing sector

In this section we analyse the behaviour of 11 financial ratios considered in Lev (1969) and used in the leading papers on adjustment ratios.[2] The definition of the ratios are given in Table 1. The sample used in the study consist of US manufacturing firms of the Worldscope

Table 1
Ratios analysed

Ratio	Definitions	Number of firms (N)
Liquidity measures		
Current	Current assets/current liabilities	484
Quick	(Current assets − inventories)/current liabilities	474
Cash	Cash + short-term investments/current assets	474
Inventory	Inventory/current assets	454
Current asset	Current asset decomposition[a]	350
Performance measures		
Netopsales	Net operating income/sales	446
Netopassets	Net operating income/assets	481
EPS		
EPSexclud	EPS excluding extraordinary items	389
EPSinclud	EPS including extraordinary items	347
Capital structure		
Equity-to-debt	Equity/total debt	488
Gross margin	Gross income/net sales	460

[a] Lev's decomposition ratios are defined as $\sum X_\alpha \log X_\alpha$, where X_α is a financial ratio. For the current asset decomposition, the summation is over all the items of current assets, and X_α equals the ratio of asset α over total current assets.

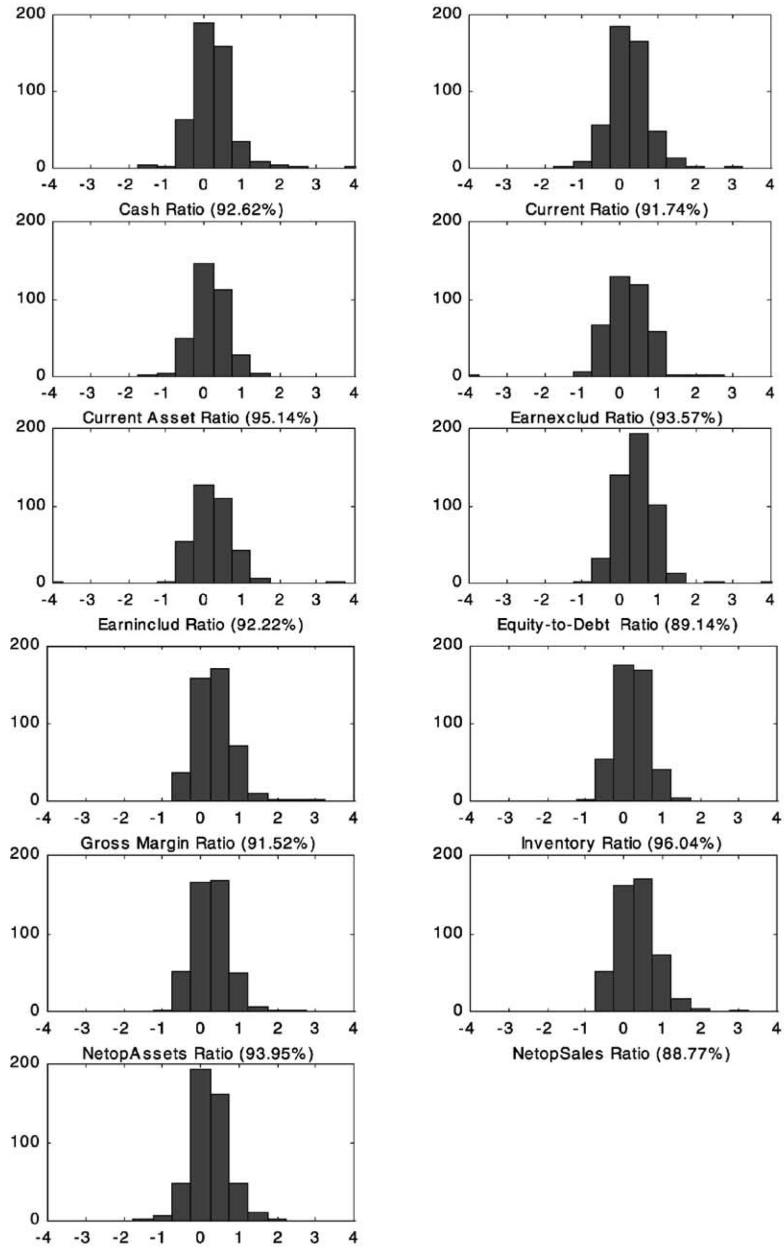

Fig. 1. Histogram of the MLE estimations of the adjustment coefficients $\{\beta_i;\ i = 1, \ldots, N\}$. (The percentage of coefficients with absolute value less than 1 appears between parenthesis.)

Global Database. Sample sizes appears in Table 1. The periodicity of the series is annual and the period analysed covers the years 1993–2000 ($T = 8$).

In Fig. 1 we present, for each ratio, a histogram of the MLE estimators of the β coefficients. Each distribution is unimodal and bell shaped. For most of the ratios the estimations of the β

coefficients are within the interval $(-1, 1)$ and are very similar. The histograms also reveal the existence of some atypical values. Thus, the data supports our hypotheses on the stationarity of the series and on the similarity of their adjustment coefficients.

3.1. Prior distribution and estimation of η^I

We take $\boldsymbol{\mu}_\alpha = \mathbf{0}$, $\boldsymbol{\Sigma}_\alpha = \mathrm{diag}(1000)$, $\nu = N + 1$, $\boldsymbol{\Sigma}_o = I_{N+1}$; $\mu_\delta = 0$ and $\sigma_\delta^2 = 1/4$; $a_1 = 4$ and b_1 given by formula (8) with $\sigma_o^2 = 1/4$; $c = 10$ and $\{p_i = 0.5, i = 1, \ldots, N\}$. The prior distribution constructed in this form is diffuse and, more specifically, allows for the possibility that there are series which exhibit nonstationary behaviour. We ran the Gibbs sampling for 10,000 iterations, taking as a starting point the values of the parameters of the prior distribution and $\boldsymbol{\gamma} = 0$. The first 1,000 iterations were discarded, with the aim of eliminating the influence of the initial values. Convergence was determined through the visual inspection of the series obtained, as well as by using the procedure proposed in Geweke (1992) applied to the parameters $\delta = 1 - \eta^{\mathrm{I}}$ and τ. Other initial values do not substantially change the results. A study of the autocorrelation function of the parameters δ and τ, and of some of the coefficients $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ chosen at random showed that this correlation was not significant from the third lag. Basing ourselves on this study, our final sample we chose one in every three iterations ($S = 3{,}000$), with the aim of obtaining a sample approximately independent of the posterior distribution.

3.2. Statistical results

The results obtained are presented in Table 2, in which we calculate the posterior median of the parameters η^{I} and σ as well as the 95% Bayesian confidence intervals, calculated using the

Table 2
Percentage of dissimilar sectors and estimation of η^{I} and σ

Ratio	Dissim. Series (%)[a]	D&P 72–91	D&P 93–00	95% D&P C.I. of η^{I}	η^{I}	95% Bayesian interval of η^{I}	σ	95% Bayesian interval of σ
Current	1.45	0.375	0.52	(0.349, 0.767)	0.726	(0.635, 0.820)	0.690	(0.613, 0.800)
Quick	1.48	0.350	0.58	(0.325, 0.723)	0.729	(0.630, 0.824)	0.724	(0.634, 0.926)
Cash	4.43	0.375	0.57	(0.384, 0.829)	0.744	(0.539, 0.956)	1.502	(1.184, 2.259)
Inventory	1.32	0.375	0.57	(0.367, 0.809)	0.716	(0.558, 0.877)	1.118	(0.962, 1.391)
Current asset	0.29	0.500	0.68	(0.433, 0.883)	0.784	(0.641, 0.920)	0.891	(0.762, 1.097)
Netopassets	0.67	0.025	0.43	(0.118, 0.656)	0.635	(0.563, 0.714)	0.575	(0.515, 0.647)
Netopsales	2.29	0.075	0.33	(0.061, 0.590)	0.625	(0.329, 0.922)	2.134	(1.736, 3.056)
EPSexclud	1.29	0.375	0.62	(0.437, 0.720)	0.714	(0.625, 0.809)	0.657	(0.583, 0.822)
EPSinclud	2.02	0.475	0.64	(0.478, 0.739)	0.708	(0.601, 0.813)	0.677	(0.583, 0.890)
Equity-to-debt	1.23	0.050	0.28	(0.093, 0.538)	0.517	(0.428, 0.605)	0.698	(0.618, 0.817)
Gross margin	1.30	0.025	0.32	(0.096, 0.513)	0.482	(0.412, 0.551)	0.514	(0.460, 0.581)

[a] The *i*th series is considered as dissimilar from the rest if $P[\gamma_i = 1/\mathbf{y}] > 0.5 + 1.96\sqrt{(0.5 * 0.5)/S}$, that is, if we reject the null hypothesis that $P[\gamma_i = 1/\mathbf{y}] \leq 0.5$ as against the alternative $P[\gamma_i = 1/\mathbf{y}] > 0.5$ with a 5% level of significance.

2.5 and 97.5 quantiles of the posterior distribution. Similarly, this Table shows the percentage of firms whose adjustment coefficients are significantly different from the rest, in the sense that the null hypothesis that $P[\gamma_i = 1/y] \leq 0.5$ is rejected at a 5% level of significance. Similarly, and for comparative purposes, Table 2 presents the estimations of η^{I} calculated using the Davis and Peles (1993) methodology in the periods 1972–1991 (D&P 72–91) and 1993–2000 (D&P 93–00), as well as a confidence interval for η^{I}, with a 95% level of confidence, corresponding to this latter period and constructed using the methodology described in Appendix B.

We can first observe that, in general, the percentage of firms with an adjustment coefficient significantly different from the rest is small in all the ratios analysed. This coefficient ranges between 48.20% for the gross margin ratio and 78.39% for the current asset ratio. Note in particular that all the estimated adjustment coefficients are significantly greater than 0, due to the stationary character of the majority of the series analysed and as already appreciated from Fig. 1. We can further observe that the majority of the estimated adjustment coefficients η^{I} are similar for most of the ratios analysed, with their values fluctuating around 70%. Only the equity-to-debt ratio and the gross margin ratio have adjustment coefficients significantly lower than the rest, 51.74% and 48.20%, respectively, with the exception of the cash and netopsales ratios whose adjustment coefficients are not so well estimated due to the high dispersion σ of the distribution of their coefficients $\{\beta_i; i = 1, \ldots, N\}$.

The fact that in Davis and Peles (1993) the gross margin ratio and the equity-to-debt ratio are also those with the lowest adjustment coefficients raises the question of what characterises these two ratios so that they experience a lower speed of reaction in the face of external changes. From a reading of Table 2 we can note that the gross margin ratio has the lowest speed of convergence towards equilibrium. This ratio measures the results of the firm with respect to the generation of essential resources, that is to say, without including financial or extraordinary results, in such a way that it measures the efficiency of the main activity of the firm. As a consequence it is not easy to act rapidly with respect to this ratio, in that it is affected by factors that are difficult to change in the short-term. Improving this ratio would require either fundamental changes in marketing and distribution systems or a reduction of personnel expenses or an improvement in the purchasing policy. It would only be possible to achieve rapid changes in this ratio in those cases where the firms dominate the market, in such a way that they could increase prices, leaving the other variables unchanged, and thereby increase their sales. For its part, the equity-to-debt ratio illustrates the financial structure of the firm that has a permanent character. According to Davis and Peles (1993), the shocks that change a firm's actual capital structure are counteracted by management, albeit over a long period, which indicates a lower adjustment coefficient to the target within one year.

The estimated values of η^{I} for the period 1993–2000 are higher than those of Davis and Peles (1993) for the period 1972–1991 (see Table 2, column D&P 72–91), both when we use the methodology proposed by these authors and when we use our proposed methodology. However, in the case of the estimators obtained using the Davis and Peles (1993) methodology for the period 1993–2000 (see Table 2, column D&P 93–00), this result is statistically significant only with respect to the ratios cash, net operating income/assets, earning-per-share (EPS) including and excluding extraordinary items, equity-to-debt and gross margin, with this being due to the greater length of the confidence intervals. This is a consequence of the limited number of observations per series and of the implicit hypothesis underlying the estimation technique used by Davis and Peles (1993), namely that the total adjustment coefficient is the same for all the firms analysed. This latter hypothesis is, in our view, hardly realistic given that although the firms operating in the same sector carry out their activities in similar circumstances, there is no reason why these firms should react with the same speed. Thus, in our model we weaken this hypothesis, assuming that whilst the majority of these coefficients fluctuate around a central value (as is made clear in Fig. 1), there is no reason why they should be exactly the same, as demonstrated by our estimations of the standard deviation σ given in Table 2.

If we compare the D&P 93–00 estimations and the Bayesian estimations, we can observe that the former are systematically smaller than the latter with respect to all the ratios analysed. However, from a strictly statistical point of view and taking the model implicit in Davis and Peles (1993) as a starting point, these differences are only significant in the ratios net operating income/sales and EPS excluding extraordinary items (see Table 2). With the aim of determining which of these two estimations is more compatible with the observed data, we have carried out a comparative study of the models estimated with both methodologies. In doing so, we have taken the differentiated series $\{\Delta y_{it} = y_{it} - y_{it-1};\ t = 2, \ldots, T;\ i = 1, \ldots, N\}$ as the point of comparison given that these are the series used by Davis and Peles (1993) to construct their estimator. Table 3 contains the root of the mean square error (RMSE) and the mean absolute deviation criteria (MAD) given by:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\mathrm{MSE}_i} \tag{9}$$

$$\mathrm{MAD} = \frac{1}{N}\sum_{i=1}^{N}\mathrm{MAD}_i \tag{10}$$

Table 3
Comparison of the adjusted models of Davis and Peles and of Gallizo and Salvador

Ratio	RMSE DP	RMSE GS	MAD DP	MAD GS	% MSE_i GS $<$ MSE_i DP	% MAD_i GS $<$ MAD_i DP
Current	1.2899	1.0776	1.1147	0.9018	71.07	67.77
Quick	0.9095	0.8127	0.7797	0.6905	67.51	65.62
Cash	0.1103	0.0975	0.0954	0.083	67.72	66.46
Inventory	0.0687	0.0604	0.0588	0.0516	69.16	64.76
Current asset	0.1028	0.0925	0.0894	0.0796	69.71	65.43
Netopassets	17.09	14.53	15.44	12.89	69.06	67.94
Netopsales	0.9751	0.4837	0.7464	0.4837	67.78	65.70
EPSexclud	1.3896	1.2011	1.2113	1.0456	74.29	69.67
EPSinclud	1.8461	1.5015	1.6057	1.3107	72.33	70.03
Equity-to-debt	2.1019	1.2673	1.8327	0.9755	63.52	60.25
Gross margin	7.0300	5.8928	5.8633	4.9329	68.48	66.52

% MSE_i GS $<$ MSE_i DP: percentage of firms for which MSE_i given in (11) is lower in the hierarchical model proposed in Gallizo and Salvador than in the Davis and Peles (1993) model.
% MAD_i GS $<$ MAD_i DP: percentage of firms for which MAD_i given in (12) is lower in the hierarchical model proposed in Gallizo and Salvador than in the Davis and Peles (1993) model.

where $\forall i = 1, \ldots, N$

$$\mathrm{MSE}_i = \frac{1}{T-2}\sum_{t=3}^{T}(\Delta y_{it} - E[\Delta y_{it}|\{\Delta y_{ij};\ j = 1, \ldots, t-1\}, y_{i1}])^2 \tag{11}$$

$$\mathrm{MAD}_i = \frac{1}{T-2}\sum_{t=3}^{T}|\Delta y_{it} - E[\Delta y_{it}|\{\Delta y_{ij};\ j = 1, \ldots, t-1\}, y_{i1}] \tag{12}$$

and $E\lfloor\Delta y_{it}|\{\Delta y_{ij};\ j = 1, \ldots, t-1\}, y_{i1}\rfloor$ are calculated from the models:

$$\Delta y_{it} = \beta_i \Delta y_{it-1} + \Delta\varepsilon_{it}; \quad t = 3, \ldots, T \tag{13}$$

taking $\{\varepsilon_{i1} = 0;\ i = 1, \ldots, N\}$.

Table 3 also contains the values of these criteria where, as estimations of the adjustment coefficients $\{\beta_i;\ i = 1, \ldots, N\}$, we have taken, on the one hand, $\{\beta_i = 1 - \hat{\eta};\ i = 1, \ldots, N\}$ where $\hat{\eta}$ is the D&P 93–00 estimation and, on the other, the posterior median of these parameters obtained from the sample provided by the Gibbs sampling. Note that in all the ratios analysed the values of the RMSE and MAD criteria are lower when using the hierarchical Bayesian model proposed in this paper. Similarly, the mean quadratic and absolute errors $\{\mathrm{MSE}_i, \mathrm{MAD}_i;\ i = 1, \ldots, N\}$ are also lower for the majority of the firms in the sample, with percentages that fluctuate around 70% for the MSE criterion and around 65% for the MAD criterion. All this makes clear that the assumption of the equality of the firms' adjustment coefficients is clearly rejected by the data and, therefore, that the estimations obtained by the proposed hierarchical model are more realistic.

Furthermore, we can observe that during the period 1993–2000, and again in general terms, there was an increase in the speed of reaction of firms in the face of unexpected shocks. One possible reason for this increase is the higher level of economic prosperity that was enjoyed during this period, which meant that management could more easily control the economic activity of their firms and, more particularly, the value of their financial ratios. Furthermore, our results for the EPS ratios indicate that there is hardly any difference in the adjustment coefficient of the EPS excluding extraordinary items and the EPS including extraordinary items, 71.45% and 70.78%, respectively, which demonstrates that during this period the firms hardly rarely implemented profit smoothing practices. The reason for this might again be explained by the period of economic bonanza alluded to earlier, during which it was not necessary for management to carry out those extraordinary operations that are habitually necessary when firms need to nominally improve their results.[3] Nor should we forget that the period under consideration can be characterised as one of stability in the US economy, with these ratios exhibiting a more stationary behaviour than the rest as regards stability in profits and in shareholders' funds.

3.3. *Sensitivity to the prior and goodness of fit of the model*

Given that the value of data per series ($T = 8$) is small, the results obtained are not informative with respect to the parameters $(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\Sigma})$ which describe the evolution of each one of the firms, with broad bands of uncertainty being associated to these parameters. However, given that the number of series considered is high, the estimations obtained with respect to the average parameters δ and τ are insensitive to the value of the hyperparameters of the prior distribution. This characteristic is made clear in Figs. 2 and 3 which present nonparametric kernel estima-

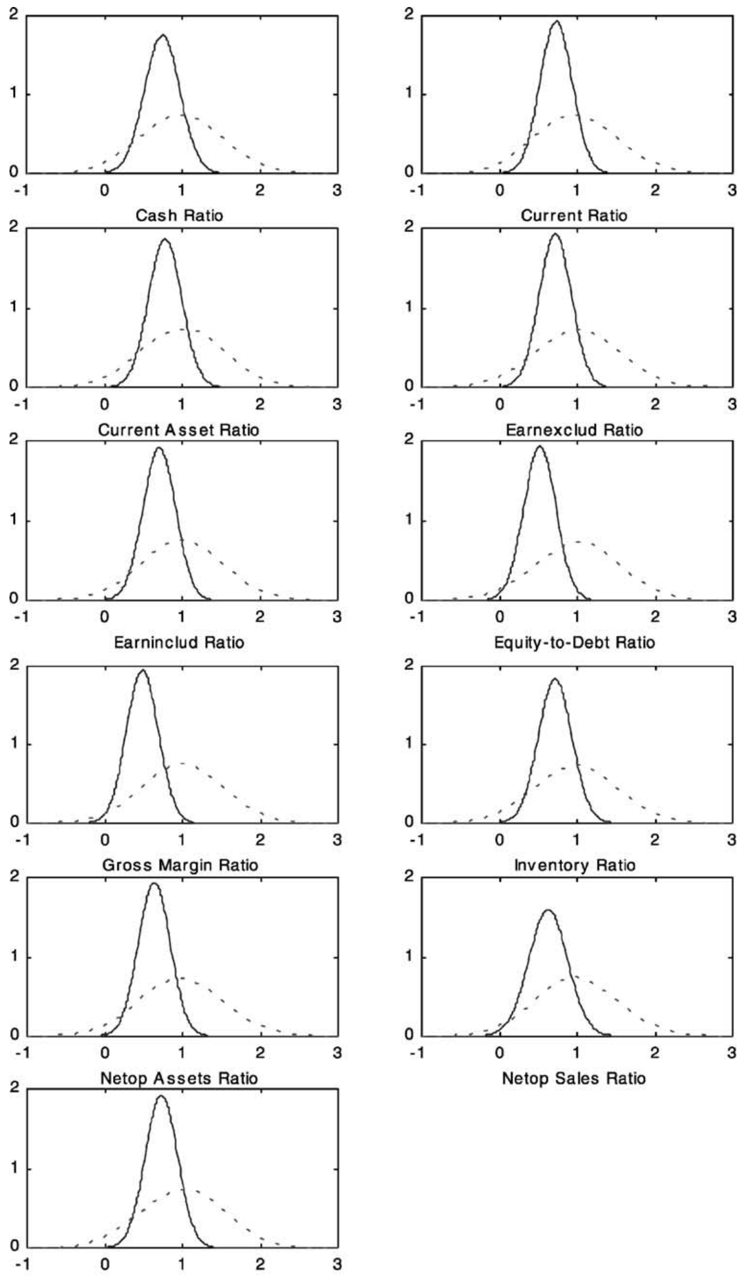

Fig. 2. Prior (dotted line) and posterior (continuous line) distributions of η^{I}.

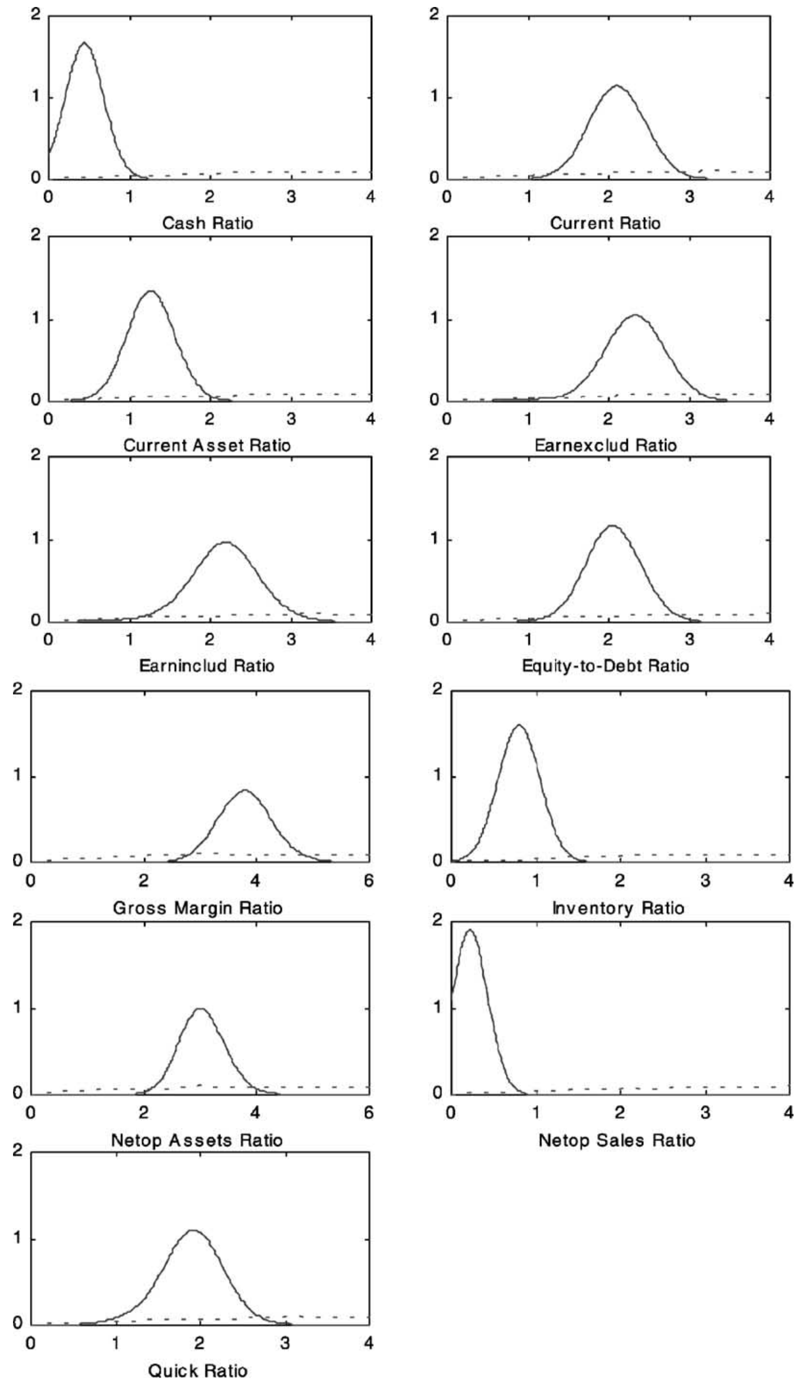

Fig. 3. Prior (dotted line) and posterior (continuous line) distributions of τ.

Table 4
Outsampling predictive performance of the models

Ratio	Out.Cov.95%	Out.Cov.99%
Current	0.9594	0.9931
Quick	0.9571	0.9880
Cash	0.9742	0.9972
Inventory	0.9875	0.9978
Current asset	0.9781	0.9990
Netopassets	0.9529	0.9843
Netopsales	0.9806	0.9958
EPSexclud	0.9597	0.9914
EPSinclud	0.9645	0.9971
Equity-to-debt	0.9495	0.9843
Gross margin	0.9500	0.9855

Note: Out.Cov.α: outsampling coverage of the α% predictive Bayesian interval.

tions of the posterior densities of the parameters δ and τ, where we can note that the posterior distributions of these parameters are much more concentrated around their modes than their prior distributions, reflecting the posterior inferences. This is due to the large volume of information contained by the data on the parameters δ and τ, independent of the prior distribution employed.

Finally, the goodness of fit of the selected models has been analysed evaluating the outsampling coverage of the 95% and 99% Bayesian predictive intervals one step forward. These intervals have been estimated by calculating the quantiles 0.025 and 0.975 of the artificial samples generated through the composition sampling applied to the predictive distributions $\{\boldsymbol{y}_t|\boldsymbol{y}_{t-1}, \boldsymbol{\theta}\ t = t_0 + 1, \ldots, T\}$ and the sample obtained from the distribution $\boldsymbol{\theta}|\boldsymbol{y}_1, \ldots, \boldsymbol{y}_{t_0}$. Table 4 contains these coverages for $t_0 = 6$ (year 1998) and we can observe that they do not exhibit any anomalous behaviour.

4. Conclusions

In this paper, we have presented a Bayesian hierarchical model that allows us to make robust estimations of the average partial adjustment coefficient of a set of financial ratio series corresponding to a group of firms, industrial sectors, or the like, encountered within the same sector, country, etc., without imposing the constancy hypothesis of the firms' total adjustment coefficients that is habitually employed in partial adjustment models. To that end, the model allows us to locate and weaken the influence of those series whose adjustment coefficients are significantly different from the rest. We have then analysed eleven financial ratios previously analysed in Davis and Peles (1993), corresponding to a sample of firms included in the Worldscope Global Database and operating in the US manufacturing sector.

We have found that these estimated adjustment coefficients are similar for the majority of the ratios analysed, fluctuating around 70%, with the exception of the gross margin ratio and the equity-to-debt ratio whose adjustment coefficients, 48.20% and 51.74%, respectively, are significantly lower than the rest. This could be due, on the one hand, to the greater difficulty in adjusting a ratio corresponding to the generation of essential resources without taking into account the financial charge and without computing extraordinary operations (the gross margin ratio). On the other, it is known that it takes more time to change that part of a firm's financial structure that has a permanent character in response to external shocks, which it is only possible to achieve in the long-term (the equity-to-debt ratio).

The estimated values are, in general, higher than those of Davis and Peles (1993) for the period 1972–1991 demonstrating, again in general terms, that during the period 1993–2000 there was an increase in the speed with which firms reacted to unexpected shocks. One possible explanation for this increase was the higher level of economic prosperity that the US economy was enjoying at that time. This had the effect of making it easier for management to control the economic activity of their firms and, therefore, the value of their financial ratios.

Notwithstanding the fact that the series analysed are, in their majority, stationary, there could be other situations in which this hypothesis is not verified. In these cases, an alternative to the model analysed in this paper could be an error correction model similar to that proposed by Wu and Ho (1997). We are currently analysing this possibility and the results will be presented in a separate work.

Notes

1. The mathematical derivation of the exposed results can be found in Salvador and Gallizo (2002).
2. In this regard see, amongst others Ho, Lee, and Wu (1997), Lee and Wu (1988), Lev (1969), Peles and Schneller (1989), and Wu and Ho (1997).
3. Recent studies have demonstrated that smoothing practices are consistent with rational equilibrium behavior of financial managers (Wu et al., 1996, p. 278).
4. We can assume, without loss of generality, that $\alpha_i = 0\ \forall i = 1, \ldots, N$, given that the estimator of Davis and Peles (1993) is invariate for changes of origin and scale.
5. A parametric bootstrap procedure based on the assumption that $D(0,\sigma_i)$ is $N(0,\sigma_i)$ gave very similar results to those described here. As a consequence, and for the sake of brevity, such results have been omitted.

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Appendix A. The posterior distribution

The density of the posterior distribution of ($\boldsymbol{\alpha}$,$\boldsymbol{\beta}$,$\boldsymbol{\Sigma}^{-1}$,$\boldsymbol{\gamma}$,δ,τ^2) can be shown to be given by:

$$\pi(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\Sigma}^{-1}, \boldsymbol{\gamma}, \boldsymbol{\delta}, \boldsymbol{\tau}^2|\boldsymbol{y})$$
$$\propto \prod_{t=2}^{T} \frac{1}{|\boldsymbol{\Sigma}|^{1/2}} \exp\left[-\frac{1}{2}(y_t - \boldsymbol{\alpha} - X_{t-1}\boldsymbol{\beta})'\boldsymbol{\Sigma}^{-1}(y_t - \boldsymbol{\alpha} - X_{t-1}\boldsymbol{\beta})\right]$$
$$\times \exp\lfloor -(\boldsymbol{\alpha} - \boldsymbol{\mu}_{\boldsymbol{\alpha}})'\boldsymbol{\Sigma}_{\boldsymbol{\alpha}}^{-1}(\boldsymbol{\alpha} - \boldsymbol{\mu}_{\boldsymbol{\alpha}})\rfloor$$
$$\times \prod_{i=1}^{N} \left(\left((\tau^2)^{1/2} \exp\left[-\tau^2 \frac{(\beta_i - \delta)^2}{2}\right]\right)^{1-\gamma_i} \left(\left(\frac{\tau^2}{c^2}\right)^{1/2} \exp\left[-\frac{\tau^2}{c^2}\frac{(\beta_i - \delta)^2}{2}\right]\right)^{\gamma_i}\right)$$
$$\times \prod_{i=1}^{N} p_i^{1-\gamma_i}(1 - p_i)^{\gamma_i} \times \exp\left[-\frac{(\delta - \mu_\delta)^2}{2\sigma_\delta^2}\right](\tau^2)^{(a_1/2)-1}$$
$$\times \exp\left[-\frac{b_1}{2}\tau^2\right] I_{(0,\infty)}(\tau^2)|\Sigma^{-1}|^{(\nu-N-1)/2} \exp\left[-\frac{1}{2}\mathrm{tr}(A\boldsymbol{\Sigma}^{-1})\right] I_R(\boldsymbol{\Sigma}^{-1}) \quad \text{(A.1)}$$

where $R = \{\Sigma(N \times N)$ positive definite symmetric matrix$\}$, $\{\boldsymbol{X}_t = \mathrm{diag}(y_{1t}, \ldots, y_{Nt});\ t = 1, \ldots, T\}$ and the symbol $\propto$ means “proportional to”.

The analytical problem is not conjugate and we have to use approximate methods to calculate the posterior moments and the posterior distributions of these parameters. In our case, we have chosen the Gibbs sampling (see, e.g., Robert & Casella, 1999 and Tanner, 1996 or for a good illustration), due to the large number of parameters of the model and the standard form of the full conditional distributions of the model (see Salvador & Gallizo, 2002).

A.1. The Gibbs sampling

The Gibbs sampling forms part of the so-called MCMC methods, whose aim is to obtain an approximate sample of a probability distribution.

The basic idea of these methods consists in building a Markov Chain on the parametric space with only one stationary distribution equal to the posterior distribution of the parameters. If we run the chain until convergence and we take the values of the parameters obtained from the last S steps of the execution, we obtain an approximate sample of size S of its stationarity distribution that we may use to estimate marginal distributions and posterior moments of the parameters of the model (see, e.g., Robert & Casella, 1999 or Tanner, 1996).

In the particular case of the Gibbs sampling, this chain is constructed on the basis of the completely conditioned distributions of the probability distribution we wish to sample. In our case, it has been applied to obtain a sample $\{\boldsymbol{\theta}^{(j)} = (\boldsymbol{\alpha}^{(j)}, \boldsymbol{\beta}^{(j)}, \boldsymbol{\Sigma}^{(j)}, \delta^{(j)}, \sigma^{2(j)}, \boldsymbol{\gamma}^{(j)});\ j = 1, S\}$ of posterior distribution (A.1) (see Salvador & Gallizo, 2002, for more details). Using this sample δ and τ can be estimated by using the Monte Carlo estimators $(1/S)\sum_{j=1}^{S}\delta^{(j)}$ and $(1/S)\sum_{j=1}^{S}\tau^{(j)}$, respectively.

Appendix B. Construction of a confidence interval for the adjustment coefficient based on the methodology of Davis and Peles (1993)

Let $\hat{\eta} \in (-1, 1)$ be the estimator of the total adjustment coefficient η proposed by Davis and Peles (1993) and $\alpha \in (0, 1)$. Further let $\hat{\beta} = 1 - \hat{\eta}$.

The $(1 - \alpha)$ confidence interval for the adjustment coefficient η comes implicitly defined in Figs. 1 and 2 of Davis and Peles (1993) and is given by:

$$\mathrm{IC}_{1-\alpha}(\hat{\eta}) = (\hat{\eta}_{\inf}(1-\alpha), \hat{\eta}_{\sup}(1-\alpha)) \tag{B.1}$$

with $\hat{\eta}_{\inf}(1-\alpha) \leq \hat{\eta} \leq \hat{\eta}_{\sup}(1-\alpha) \in \boldsymbol{R}$ such that:

$$\chi^2(\hat{\eta}_{\inf}(1-\alpha)) = \chi^2(\hat{\eta}_{\sup}(1-\alpha)) = \chi^2_{n-1}(\alpha) \tag{B.2}$$

where χ^2 comes defined by expression (8) of Davis and Peles (1993) and $\chi^2_{n-1}(\alpha)$ denotes the $(1 - \alpha)$ quantile of the Chi-squared distribution with $n - 1$ degrees of freedom ($n = 18$ in the Davis & Peles, 1993 paper).

The above interval reaches its confidence level asymptotically when $T, N \to \infty$. In finite samples there is no reason for this coverage level to be reached, so that it is necessary to determine $q(\alpha) \in (0, 1)$ such that:

$$P_\eta \lfloor \mathrm{IC}_{1-q(\alpha)}(\hat{\eta}) \text{ contains } \eta \rfloor \geq 1 - \alpha \tag{B.3}$$

where the DGP comes given by the set of independent AR(1) processes:

$$Y_{it} = \beta Y_{it-1} + \varepsilon_{it}; \quad i = 1, \ldots, N; \quad t = \ldots, -1, 0, 1, \ldots \tag{B.4}$$

with $\beta = 1 - \eta \in (-1, 1)$, $\{\varepsilon_{it};\ t = \ldots, -1, 0, 1, \ldots\}$ i.i.d. $D(0,\sigma_i)$ and where $D(0,\sigma_i)$ is a distribution with mean 0 and standard deviation σ_i $\forall i = 1, \ldots, N$.[4]

To determine $q(\alpha)$ we use bootstrap methods (see, e.g., Davison & Hinkley, 1997 for a very complete description of these methods) determining $q^*(\alpha) \in (0, 1)$ such that:

$$P_{\hat{\eta}} \lfloor \mathrm{IC}_{1-q^*(\alpha)}(\hat{\eta}^*) \text{ contains } \hat{\eta} \rfloor \geq 1 - \alpha \tag{B.5}$$

and estimate $q(\alpha)$ by way of $q^*(\alpha)$. To that end, we use a semi-parametric bootstrap procedure which assumes that the distribution D is unknown.[5] This procedure is made-up of the following steps:

(a) Construct the standardised residuals $\{\hat{u}_{it} = (\hat{\varepsilon}_{it} - \bar{\varepsilon}_i)/\hat{\sigma}_i;\ t = 2, \ldots, T;\ i = 1, \ldots, N\}$ where $\{\hat{\varepsilon}_{it} = y_{it} - \hat{\beta} y_{it-1};\ t = 2, \ldots, T;\ i = 1, \ldots, N\}$, $\{\bar{\varepsilon}_i = \sum_{t=2}^{T} \hat{\varepsilon}_{it}/(T-1);\ i = 1, \ldots, N\}$ and $\sigma_i^2 = \sum_{t=2}^{T} [(\hat{\varepsilon}_{it} - \bar{\varepsilon}_i)^2/(T-2)]$.

(b) Establish a partition $\{0 = \gamma_0 < \gamma_1 < \ldots < \gamma_M = 1\}$ of the interval [0, 1].

(c) Repeat for $r = 1, \ldots, R$ steps (c1) and (c2).

 (c1) Extract $\{\hat{u}_{it}^{*(r)};\ t = -K, \ldots, 0, 1, \ldots, T;\ i = 1, \ldots, N\}$ a simple random sample from the standardised residuals $\{\hat{u}_{it};\ t = 2, \ldots, T;\ i = 1, \ldots, N\}$ and construct the series:

$$y_{it}^{*(r)} = \hat{\beta} y_{it-1}^{*(r)} + \hat{u}_{it}^{*(r)};\ t = -K, \ldots, 0, 1, \ldots, T;\ i = 1, \ldots, N$$

where $y^{*(r)}_{i,-K} = y_{i1}$; $i = 1, \ldots, N$ and K is chosen to weaken the effect of the initial observation in such a way that the series $\{y^{*(r)}_{it};\ t = 1, \ldots, T\}$ are essentially stationary $\forall i = 1, \ldots, N$.

(c2) Calculate $\{A^{*(r)}_j = \mathrm{IC}_{1-\gamma_j}(\hat{\eta}^{*(r)});\ j = 0, \ldots, M\}$ where $\hat{\eta}^{*(r)}$ is the Davis and Peles (1993) estimator based on the series $\{y^{*(r)}_{it};\ t = 1, \ldots, T\}$.

(d) Calculate the empirical coverages $\{\mathrm{cov}^*_j = (1/(R+1))\sum_{r=1}^{R} I_{A^{*(r)}_j}(\hat{\eta});\ j = 0, \ldots, M\}$ where $I_A(x) = 1$ if $x \in A$ and 0 otherwise.

(e) Determine $j^* \in \{0, \ldots, M\}$ such that $\mathrm{cov}^*_{j^*+1} < 1 - \alpha \leq \mathrm{cov}^*_{j^*}$ and determine $q^*(\alpha)$ by interpolation between γ_{j^*} and γ_{j^*+1}.

In the intervals calculated in Table 2 we have taken $\alpha = 0.05$, $R = 999$, $K = 100$, $M = 10^6$ and $\{\gamma_j = (j/M);\ j = 1, \ldots, M\}$.

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