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Functional Statistical Time Series Analysis of the Dividend Policy of Spanish Companies

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Abstract

A functional statistical analysis of a data panel constituted by 33 companies in the IBEX-35, Spain, during the period 2006 to 2009, is achieved for the investigation of possible changes in the dividend policy. Empirical evidence of positive functional correlation of dividend policy changes with future changes of earnings per share is provided by the data panel studied. The functional estimation of the dividend annual increment per share, in all the companies of the sample, is obtained by implementing a functional version of Kalman filtering algorithm in an Autoregressive Hilbertian (ARH(1)) process framework.

Keywords:
Dividend policy, Financial panel data, Functional time series analysis, Information content of dividends, Kalman filtering.

JEL classification:
C22, C23, C32, C33, G32, G35.

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1. Introduction

Functional statistics provides a suitable framework for the analysis of large dimensional data sets. Financial panel data usually display large dimensionality in time or/and space (companies, enterprises, etc). Even in the case where available sample information is not sufficiently dense in space or in time, the functional nature of the temporal or/and spatial complex correlation structure displayed by financial data makes advisable the functional statistical framework. In this case, interpolation techniques must be applied in order to make possible the analysis in terms of smoothed functional data (see, for example, Ramsay and Silverman, 2005).

In the last one and a half decade, different approaches have been proposed in the statistical functional framework (see Bosq, 2000; Bosq and Blanke, 2007, Ferraty and Vieu, 2006; Ramsay and Silverman, 2005; Ruiz-Medina, 2009, 2011; Ruiz-Medina and Salmerón, 2010; Salmerón and Ruiz-Medina, 2009, among others). Specifically, the statistical analysis based on linear models in functional spaces has been extensively developed (see, for example, Abramovicha and Angelini, 2006; Bosq, 2000; Cardot *et al.*, 2006; Ferraty *et al.,*1999, 2003; Cardot and Sarda, 2005; Fan and Zhang, 2000; James, 2002). The non-parametric functional statistical framework has also emerged as active research area (see Ferraty and Vieu, 2006; Hoover *et al.*, 1998; Masry, 2005; Rachdi and Vieu, 2007; Wu *et al.,*1998, and the references therein). The functional series framework provides powerful tools in the analysis of geophysics and financial data (see Bosq, 2000; Bosq and Blanke, 2007; Ruiz-Medina, 2011; Ruiz-Medina and Salmerón, 2010; Salmerón and Ruiz-Medina, 2009, among others).

In the statistical analysis of financial panel data, the classical theory of fixed and mixed linear effect models, as well as multivariate regression models has been widely applied (see Beck *et al.,* 2008; Giannetti, 2003; Hall *et al.,* 2004; Jong *et al.,* 2008; La Rocca *et al.,* 2010; López-Iturriaga and Rodríguez-Sanz, 2008; Psillaki and Daskalakis, 2009; Utrero-González, 2007, among others). Several simplifications are often assumed in the analysis of correlations shaping the capital structure (see, for example, Rajan and Zingales, 1995). Specifically, the classical statistical models applied in the analysis of spatial correlations in panel data are introduced in the context of spatial linear regression in spatial econometrics (see, for example, Anselin, 1988; Anselin and Bera, 1998), as well as in the context of the covariance matrix estimation methods (see, for instance, Driscoll and Kraay, 1998). Recently, temporal dependence is represented in a semiparametric framework in Youa and Zhoub (2006) considering the time series framework. They propose, for the analysis of panel data, a semiparametric partially linear regression model with an unknown regression coefficient vector, an unknown nonparametric function for nonlinear component, and unobservable serially correlated error term. A vector autoregressive process, which involves a constant intraclass correlation, is fitted to the correlated error term.

The approach presented in this paper allows the analysis of complex correlation structures, since they are represented in a functional framework. In particular, the changes in the dividend policy are estimated considering the ARH(1) process framework. The interaction between companies is incorporated to the analysis, when the annual earning increment per share is jointly studied. Specifically, the interaction between positive or negative annual earnings in different companies is reflected in terms of a colored functional innovation process in the ARH(1) framework. This model provides better results than the one given in terms of white functional in novations, i.e., than in the case where information on the earning changes is not incorporated to the analysis. This fact also allows the analysis of the information content of dividend hypothesis (see, for example, Grullon *et al.,* 2002; Healy and Palepu, 1988; Palacin-Sánchez and Di Pietro, 2011; Watts, 1973).

The autoregressive dynamics is assumed in the temporal evolution of the annual dividend increment per share in all the companies, with spatial correlation represented in terms of the auto-covariance operator of the ARH(1) model. The projection estimator of the functional autocorrelation structure is then computed from a vectorial autoregressive model fitting. The functional prediction in time of the annual dividend increment per share in all the companies is obtained from the forward Kalman filter implementation, in terms of the projection of the data in biorthogonal eigenfunction bases, which diagonalize the functional autocorrelation structure (see Ruiz-Medina *et al.*, 2007; Salmerón and Ruiz-Medina, 2009). This statistical methodology is applied to the annual data obtained from 2006 to 2009 (through the DataStream database), on the per share dividend policy of 33 companies in the IBEX-35 in Spain.

This article is structured as follows: Section 2 describes the ARH(1) model and its diagonalization, as well as its finite-dimensional approximation. The classical vectorial autoregressive model framework is considered to estimate the projected functional autocorrelation structure of the ARH(1) process in Section 3. The Kalman filtering algorithm is then implemented for functional estimation of the evolution of per share dividend annual increment in all companies under study, in Section 4. Section 5 provides the application of the ARH(1)-based estimation methodology proposed for the statistical analysis of the annual data obtained from 2006 to 2009 (through the DataStream database), on the annual dividends and earnings of 33 companies in the IBEX-35 in Spain. Conclusions and final comments are provided in Section 6.

2. The Model

Let H be a real separable Hilbert space of functions defined on a bounded domain $D \subset \mathbb{R}^n$, with the inner product $\langle \cdot, \cdot \rangle_H$, and with associated norm $\|\cdot\|_H$. We consider $\{Z_t, t \in \mathbb{N}\}$ to be a zero-mean stationary Hilbert-valued process in H, that is, for each $t \in \mathbb{N}$, $Z_t \in H$, where for all $t \geq 0$, Z_t are defined on the basic probabilistic space $(\Omega, \mathcal{A}, P)$. We assume that Z satisfies the following equation:

$$Z_t(\mathbf{x}) = \mathcal{A}[Z_{t-1}](\mathbf{x}) + v_t(\mathbf{x}), \quad \mathbf{x} \in D, \quad t \in \mathbb{N}, \tag{1}$$

where v is a strong Hilbertian white noise, that is, a sequence of independent and identically distributed Hilbert-valued random variables in H with

$$E[\|v_t\|_H^2] = \sigma_v^2 < \infty, \tag{2}$$

uncorrelated with the random initial condition Z_0. The autocorrelation operator $\mathcal{A}$ is a bounded operator defined on a dense domain in H. Operator $\mathcal{A}$ can be interpreted as a spatiotemporal correlation operator in the panel data setting. Operator $\mathcal{A}$ and its adjoint $\mathcal{A}^*$ satisfy the following equations:

$$\begin{aligned} \mathcal{A}\psi_i &= \lambda_i \psi_i, \quad i \in \mathbb{N}, \\ \mathcal{A}^*\phi_i &= \lambda_i \phi_i, \quad i \in \mathbb{N}. \end{aligned} \tag{3}$$

That is, $\{\psi_i, i \in \mathbb{N}\}$ and $\{\phi_i, i \in \mathbb{N}\}$ are the right and left eigenvector systems associated with $\mathcal{A}$ and $\mathcal{A}^*$, respectively, and with the eigenvalues $\{\lambda_i, i \in \mathbb{N}\}$ (see, for example, Dautray and Lions, 1992; Dunford and Schwartz, 1971). The eigenvector systems $\{\psi_i, i \in \mathbb{N}\}$ and $\{\phi_i, i \in \mathbb{N}\}$ are biorthogonal

$$\langle \phi_i, \psi_j \rangle_H = \delta_{i,j}, \quad i, j \in \mathbb{N}, \tag{4}$$

where $\delta_{i,j}$ denotes the Kronecker delta function. The projection of the ARH(1) equation (1) into the right eigenvector system $\{\phi_i, i \in \mathbb{N}\}$ leads to the following diagonal equation

$$a_j(t) = \lambda_j a_j(t-1) + v_j(t), \quad j \in \mathbb{N}, \tag{5}$$

in terms of the temporal random coefficients

$$a_j(t) = \int_D Z_t(\mathbf{x}) \phi_j(\mathbf{x}) d\mathbf{x}, \quad t \geq 0, \quad j \in \mathbb{N}, \tag{6}$$

$$v_j(t) = \int_D v_t(\mathbf{x}) \phi_j(\mathbf{x}) d\mathbf{x}, \quad t \geq 0, \quad j \in \mathbb{N}. \tag{7}$$

By truncation, we obtain

$$\mathbf{a}(t) = \mathbf{\Lambda a}(t-1) + \boldsymbol{v}(t), \tag{8}$$

where, at each time $t \in \mathbb{N}$,

$$\mathbf{a}(t) = (a_1(t),\ldots, a_M(t))^*,$$
$$\boldsymbol{v}(t) = (v_1(t),\ldots, v_M(t))^*,$$

and $\mathbf{\Lambda}$ denotes the diagonal $M \times M$ matrix with entries the eigenvalues λ_i, $i = 1,\ldots, M$. Here, for $j = 1,\ldots, M$, and for each time $t \in \mathbb{N}$, $a_j(t)$ and $v_j(t)$ respectively represent the random projections of Z and v, given in equations (6) and (7). For each time t, the functional data $Z_t(\cdot)$ is approximated by the finite set of temporal coefficients $a_j(t)$, $j = 1,\ldots, M$.

3. Projection Parameter Estimation

Consider now the following two models of dividend policy of companies:

$$\mathbf{DPS}_t = \alpha_1 + \beta_1 \cdot \mathbf{DPS}_{t-1} + \varepsilon_{1t}, \tag{9}$$

$$\mathbf{DPS}_t = \alpha_2 + \beta_2 \cdot \mathbf{DPS}_{t-1} + \gamma_2 \cdot \mathbf{EPS}_t + \varepsilon_{2t}, \tag{10}$$

where, for each time $t \in \mathbb{R}_+$, $\mathbf{DPS}_t$ is a vector whose components provide the dividend annual increment per share at time t for each one of the companies considered, fit, ε_{it}, $i = 1, 2$, is a white noise vector independent of the initial values of the process of interest $\mathbf{DPS}$. Here, for each time $t \in \mathbb{R}_+$, $\mathbf{EPS}_t$ represents a vector whose components give the earning annual increment per share at time t for each of the companies studied. All these vectors have the same dimension, n, which coincides with the size of the sample of companies selected.

Model (9) corresponds to an immediate adjustment process to the objective of dividend policy defined by the company in terms of dividend changes. Model (10) also reflects the interrelation between changes in dividend policy and the current earing changes. In this second model, the stability of the dividend and the information content of dividends also constitute important goals.

Models (9) and (10) are now considered in the computation of projection estimators of the parameters of an ARH(1) process. Specifically, denoting by n the number of companies selected in the sample. The adjustment of the ARH(1) process is performed in terms of a finite-dimensional Hilbert space H of dimension n. The eigenvalues $\{\lambda_k,\ k=1,\ldots,n\}$ of operator $\mathcal{A}$ are estimated from the square-root of the empirical eigenvalues of the matrix $\hat{\boldsymbol{\beta}}_i^*\hat{\boldsymbol{\beta}}_i$, where $\hat{\boldsymbol{\beta}}_i$ denotes the estimator of parameter $\boldsymbol{\beta}_i$, for $i=1,\ 2$, obtained from fitting Models (9) and (10) to the data, respectively. The empirical eigenvectors of matrix $\hat{\boldsymbol{\beta}}_i^*\hat{\boldsymbol{\beta}}_i$, $i=1,\ 2$, provide an aproximation of the finite-dimensional approximation of operator $\mathcal{A}$, under Models (9) and (10), respectively, as given in the previous section with $\{\psi_k,\ k=1,\ldots,n\}=\{\phi_k,\ k=1,\ldots,n\}$. In the case of Model (9), the functional innovation process v, in equation (1), is assumed to have auto-covariance operator given by the identity operator multiplied by a positive constant σ_v^2. In the case of Model (10), for each time $t>0$, it is assumed that the functional innovation process, $v_t=\gamma_2\cdot\mathbf{DPS}_t+\varepsilon_{2t}$, has compact and self-adjoint auto-covariance operator. Thus, the interaction between earnings in different companies is incorporated in terms of this operator, also involved in the corresponding spatial auto-correlation model of the ARH(1) process defining the dividend annual increment.

Remark 1 *Note that, from equations (3)-(4)*

$$\mathcal{A}=\boldsymbol{\Psi}\cdot\Lambda\cdot\boldsymbol{\Phi}^*,$$

where $\boldsymbol{\Lambda}$ is the diagonal $n\times n$ matrix with entries $\{\lambda_k,\ k=1,\ldots,n\}$, and $\boldsymbol{\Psi}$ and $\boldsymbol{\Phi}$ are respectively the matrices with columns defined in terms of the left and right eigenvectors $\{\psi_k,\ k=1,\ldots,n\}$ and $\{\phi_k,\ k=1,\ldots,n\}$.

4. Kalman Filtering Algorithm in the ARH(1) Process Context

The estimation of the functional values of $\mathbf{DPS}_t$ at each time period t of interest, in all the companies studied, is achieved by implementing the following version of the Kalman filtering algorithm (see Ruiz-Medina *et al.,* 2007, and Salmerón and Ruiz-Medina, 2009): Given the observations of process Z_t up to time t, the following estimator is computed:

$$\hat{\mathbf{a}}_{t|t}=\hat{\mathbf{a}}_{t|t-1}+\mathbf{K}_t\left(Z_t-\Psi\hat{\mathbf{a}}_{t|t-1}\right),$$

where $\hat{\mathbf{a}}_{t|t}=E\left(\mathbf{a}(t)|Z_t,\ldots,Z_1\right)$ and $\hat{\mathbf{a}}_{t|t-1}=E\left(\mathbf{a}(t)|Z_{t-1},\ldots,Z_1\right)$. Here, $\mathbf{K}_t$ is the gain operator, that is, the filter defining the smoothing effect on the functional data, given by

$$\mathbf{K}_t=\mathbf{P}_{t|t-1}\Psi^*\left(\Psi\mathbf{P}_{t|t-1}\Psi^*\right)^{-1},$$

in terms of the conditional second-order moment

$$\mathbf{P}_{t|t-1} = Var\,(\mathbf{a}(t)|Z_{t-1},\ldots,Z_1) = \mathbf{\Lambda P}_{t-1|t-1}\mathbf{\Lambda} + \mathbf{Q},$$

denoting by $\mathbf{P}_{t|t} = E\,((\mathbf{a}(t)-\hat{\mathbf{a}}_{t|t})\,(\mathbf{a}(t)-\hat{\mathbf{a}}_{t|t})^*)$ and being $\mathbf{Q}$ the covariance operator of v_t. The functional mean-square error is then given by

$$\mathbf{P}_{t|t} = \mathbf{P}_{t|t-1} - \mathbf{K}_t \mathbf{\Psi P}_{t|t-1},$$

and the one-step-ahead predictor is computed as $\hat{\mathbf{a}}_{t|t-1} = \mathbf{\Lambda}\hat{\mathbf{a}}_{t-1|t-1}$.

The initial values considered are

$$\hat{\mathbf{a}}_{0|0} = (\mathbf{0},\ldots,\mathbf{0})^*, \quad \mathbf{P}_{0|0} = \mathbf{\Phi}^* R_{Z_0}\mathbf{\Phi},$$

where R_{Z_0} denote the covariance operators of Z_0.

5. Data Analysis

In this section, the dividend policy of 33 companies in Spain, that have been part of the index IBEX-35 during the time period 2006-2009, is analyzed. The companies are: Abertis, Acciona, ACS, Cintra, FCC, Ferrovial, OHL, Sacyr, Abengoa, Enagas, Endesa, Gamesa, Gas Natural, Iberdrola, REC, Repsol, Técnicas Reunidas, BEC, Banco Popular, Banco Sabadell, Banco Santander, Bankinter, BBVA, Acerinox, Arcelor Mittal, BME, GRIFOLS, Iberia, Inditex, Indra, MAPFRE, Tele 5, Telefónica.

The first eight companies correspond to firms related to infrastructure, the following nine (from Abengoa to Técnicas Reunidas) are related with energy, the subsequent six (from BEM to BBVA) with banking services, the next two with steel industry, and the last eight (from BME to Telefónica) are companies that could not be included in a common sector. In our proposed functional modeling, the above company sample leads to the consideration of a separable Hilbert space with dimension $n = 33$. Since data are only available in all the companies during the time period 2006-2009 (see Tables 1 and 2), functional prediction is achieved in terms of Kalman filtering applied to temporal functional data (smoothed **DPS** and **EPS** surfaces constructed from 33 companies) in terms of their projections in the finitedimensional space H. As described in Sections 3 and 4, this space is generated by $\{\psi_k,\ k=1,\ldots,n\} = \{\phi_k,\ k=1,\ldots,n\}$, the orthogonal eigenvector system of $\hat{\boldsymbol{\beta}}_i^*\hat{\boldsymbol{\beta}}_i,\ i=1,2$.

Table 1. Dividend per Share

Year	Abertis	Acciona	ACS	Cintra	FCC	Ferrovial	OHL	Sacyr	Abengoa	Enagas	Endesa
2006	0,15	0,41	1,87	0,26	0,6	0,45	0	0,35	0,17	0,38	0,23
2007	0,16	0,42	2,5	0,32	1,25	0,9	0,45	0,38	0,21	0,48	0,24
2008	0,17	0,53	3,17	0,35	1,75	1,4	0,81	0,44	0,28	0,6	0,8
2009	0,15	0,57	3,38	0,35	2,05	1,13	0,56	0,49	0,28	0,64	0,28

Year	Gamesa	Gas Natural	Iberdrola	REC	Repsol	T. Reunidas	BEC	B. Popular	B. Sabadell	B. Santander	Bankinter
2006	0,52	0	0,07	0,4	0,61	1,45	0,9	0	0,64	0	0,2
2007	0,63	1,2	0,09	0,47	2,05	1,85	1	0,21	0,77	0	0,26
2008	0,72	1,52	0,09	0,6	1,3	2,11	1,15	0,23	0,89	0,06	0,26
2009	0,77	1,97	0,09	0,65	2,08	1,85	2	0,2	1,01	0,16	0,33

Year	BBVA	Acerinox	Arcelor Mittal	BME	GRIFOLS	Iberia	Inditex	Indra	MAPFRE	Tele 5	Telefónica
2006	0,05	0,3	0,52	0,06	0,29	0,65	0,6	0,4	0	1,01	0,25
2007	0,02	0,52	0,39	0,07	0,3	0,9	0,72	0,4	0,64	1,28	0,25
2008	0,03	0,84	0,78	0,13	0,4	1,09	0,86	0,59	0,79	1,3	0,65
2009	0,17	1,05	0,5	0,13	0,45	1,28	1,05	0,56	1,32	0,86	0,9

Table 2. Eanings per Share

Year	Abertis	Acciona	ACS	Cintra	FCC	Ferrovial	OHL	Sacyr	Abengoa	Enagas	Endesa
2006	0,64	0,75	5,13	0,59	2,04	3,48	0,8	0,72	0,37	0,92	0,46
2007	1,03	0,8	21,84	1,94	5,43	4,86	0,4	0,83	0,29	0,92	0,5
2008	1,21	1,01	15,34	1,2	4,22	5,3	1,1	1,02	0,64	1,2	0,87
2009	1,55	0,87	7,3	0	7,7	4,63	1,14	0,85	0,56	1,21	0,59

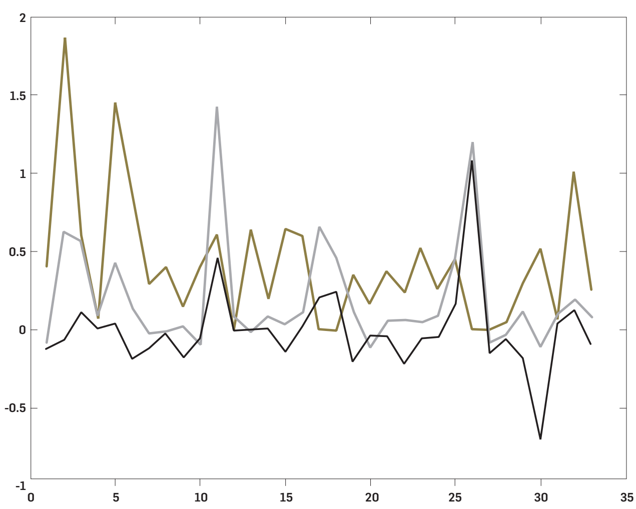
Year	Gamesa	Gas Natural	Iberdrola	REC	Repsol	T. Reunidas	BEC	B. Popular	B. Sabadell	B. Santander	Bankinter
2006	1,1	1,12	0,02	0,83	2,38	3,25	3,22	1,03	1,42	0,14	0,38
2007	1,37	1,81	0,21	0,92	2,21	4,14	6,36	0,78	1,63	0,3	0,45
2008	1,67	2,46	0	1,03	2	5,91	5,24	1,7	1,82	0,45	0,52
2009	1,33	2,02	0,03	1,1	5,35	2,71	0,24	0,78	2,01	0,63	0,58

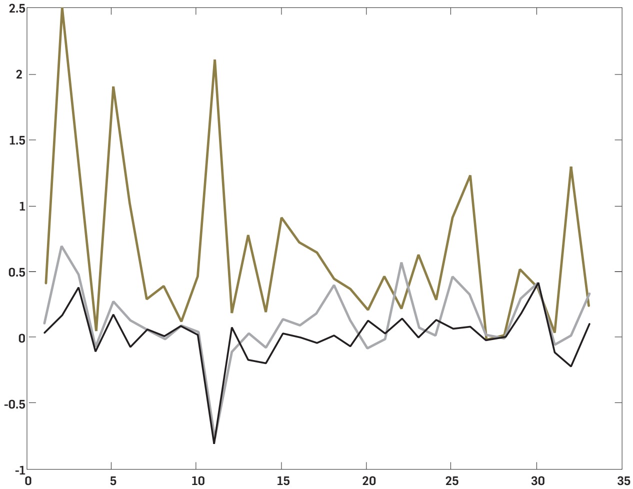
Year	BBVA	Acerinox	Arcelor Mittal	BME	GRIFOLS	Iberia	Inditex	Indra	MAPFRE	Tele 5	Telefónica
2006	0,43	1,29	0,66	0,21	1,3	1,32	2,56	1,37	0,74	1,22	0,91
2007	0,06	1,61	0,75	0,28	1,54	1,59	2,56	1,8	1,44	1,33	0,97
2008	0,35	2,01	0,87	0,32	1,69	1,89	2,61	3,08	2,03	1,43	1,87
2009	0,03	2,02	1,13	0,34	1,52	2,2	1,67	0	2,53	0,66	1,63

Results

Least-squares model fitting is considered to compute $\hat{\boldsymbol{\beta}}_i$, $\hat{\boldsymbol{\alpha}}_i$, for $i=1, 2$ and $\hat{\boldsymbol{\gamma}}_2$, from VAR(1) models (9) and (10). The stationary assumption is tested, as well as the goodness of fit level in terms of the coefficient of determination of order 0.9985 for Model (9), and of order 0.9988 for Model (10). In all the cases tested, the p-values associated with ANOVA are less than 0.05. These results constitute the starting point for the implementation of our functional estimation methodology, since the eigenvector system associated with $\hat{\boldsymbol{\beta}}_i^* \hat{\boldsymbol{\beta}}_i$, $i=1, 2$, generates our empirical finite-dimensional Hilbert space H, for each one of the two cases considered. Thus, the diagonal version (8) of the ARH(1) equation is obtained by projection of our smoothed temporal functional data set into such a system. The Kalman filtering is then implemented as described in Section 4 for the temporal functional increments of **DPS**. The functional estimates are shown in Figure 1 (from top to bottom, estimates corresponding to temporal increments 1, 2 and 3). The green line represents the observations, and blue and red lines the estimates obtained from application of Kalman filtering in terms of the projection into the eigenvector system associated with $\hat{\boldsymbol{\beta}}_i^* \hat{\boldsymbol{\beta}}_i$, $i=1, 2$, after least-squares model (9) and (10) fitting, respectively. Better results are obtained from projection into the empirical eigenvector system fitted from Model (10), as it can be appreciated from functional quadratic errors (F.Q.E.) (see Table 3). (Note that the order of magnitude of F.Q.E. from projection into Model (9) empirical eigenvector system is 10^{-3}, and for Model (10) empirical eigenvector system is of order 10^{-5}).

Figure 1. **DPS Estimates after Applying the Kalman filtering**





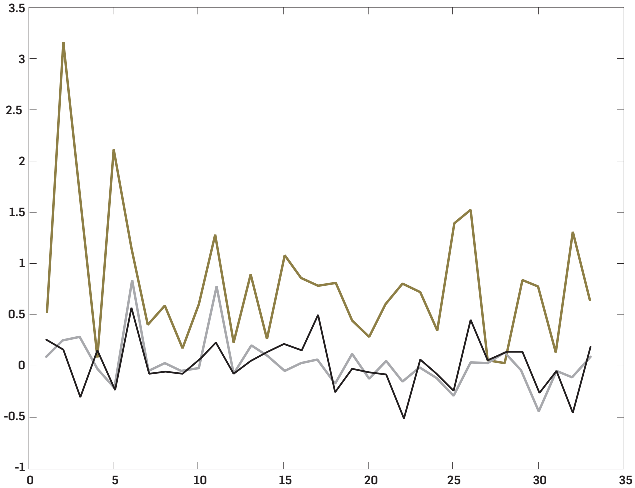
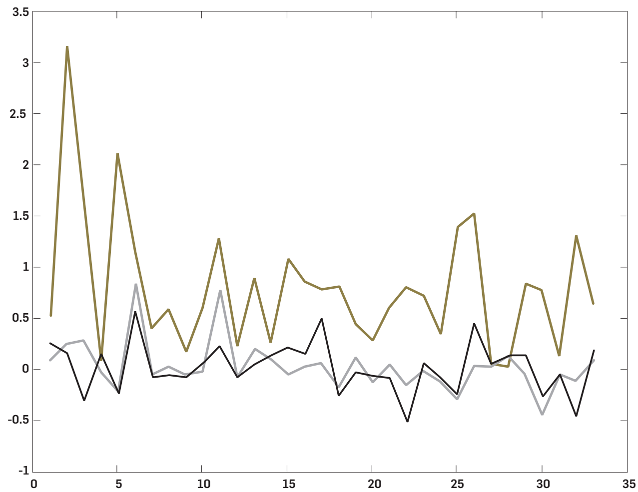


Tabla 3. **Functional Quadratic Errors for Each Model**

DPS differences	Model 1	Model 2
1	3.0291054232189753e-003	1.9806373572665064e-004
2	1.3210284452103026e-003	1.5320847034558545e-004
3	1.6169092585372521e-003	7.8037048156712815e-005

Figure 2 additionally shows a prediction for year 2010 from Model (9) empirical eigenvector system, blue line, and from Model (10) empirical eigenvector system,

Figure 2. **Prediction for 2010 Red Line. Green Line Shows the Last Functional Observation for the Year 2009**



Finally, the information content of dividend hypothesis is supported in terms of a positive functional correlation between the annual increments of dividend and earnings per share observed in all the companies studied. Specifically, the following empirical covariance operators are computed:

$$\hat{R}_0^Y = \frac{1}{3}\sum_{i=1}^{3} Y_i \otimes Y_i^t - \left(\frac{1}{3}\sum_{i=1}^{3} Y_i\right) \otimes \left(\frac{1}{3}\sum_{i=1}^{3} Y_i\right)^t,$$

where the functional process Y can be $\mathbf{DPS}$ or $\mathbf{EPS}$. Here, $\otimes$ denotes the tensorial product of functions in a suitable Hilbert space H. This product allows the definition of elements of $H \otimes H$, which can be identified with the Hilbert space of Hilbert Schmidt operators on H. Additionally, the functional cross-covariance structure between dividend annual and earning annual increment per share is empirically approximated in terms of the following estimated covariance operators:

$$\begin{aligned}
\hat{R}_{\mathrm{DPS,\,EPS}} &= \frac{1}{3}\sum_{i=1}^{3} \mathbf{DPS}_i \otimes \mathbf{EPS}_i^t - \left(\frac{1}{3}\sum_{i=1}^{3} \mathbf{DPS}_i\right) \otimes \left(\frac{1}{3}\sum_{i=1}^{3} \mathbf{EPS}_i\right)^t, \\
\hat{R}_{\mathrm{DPS,\,EPS}_{+1}} &= \frac{1}{2}\sum_{i=1}^{2} \mathbf{DPS}_i \otimes \mathbf{EPS}_{i+t}^t - \left(\frac{1}{3}\sum_{i=1}^{3} \mathbf{DPS}_i\right) \otimes \left(\frac{1}{2}\sum_{i=1}^{2} \mathbf{EPS}_{i+t}^t\right)^t,
\end{aligned} \tag{11}$$

The corresponding functional cross-correlations are then computed from the trace norm of the following empirical operators:

$$\begin{aligned}\hat{R}_1 &= \left(\hat{R}_0^{\mathrm{DPS}}\right)^{-1/2} \hat{R}_{\mathrm{DPS,\,EPS}} \left(\hat{R}_0^{\mathrm{EPS}}\right)^{-1/2} \\ \hat{R}_2 &= \left(\hat{R}_0^{\mathrm{DPS}}\right)^{-1/2} \hat{R}_{\mathrm{DPS,\,EPS}_{+1}} \left(\hat{R}_0^{\mathrm{EPS}}\right)^{-1/2} .\end{aligned} \tag{12}$$

The computed values are 8.45 for the trace of $\hat{R}_1$, and 80.37 for the trace of $\hat{R}_2$, which provides empirical evidence of the fact that the changes in the dividend are followed by changes in the earnings in the same direction, especially in the case of future earnings.

6. Conclusion

In this paper, the statistical analysis of panel data is developed in the context of time functional series models. This framework allows the incorporation of spatiotemporal interaction in the analysis, i.e., correlations along the time and between companies are represented in terms of the functional dependence structure of the ARH(1) process fitted. The functional prediction of the dividend annual increment per share at each time period of interest, for all the companies under study, is obtained by implementing a functional version of Kalman filtering algorithm, derived, by projection, in Ruiz-Medina *et al.* (2007), for the ARH(1) case (extended to the ARH(p) case in Salmerón and Ruiz-Medina, 2009). Ruiz-Medina and Salmerón (2010) proposed a maximum-likelihood functional projection parameter estimation methodology combined with Kalman filtering for ARH(1) processes. In this paper, the projection parameter estimation step is alternatively implemented from vectorial autoregressive model fitting (see Models 9 and 10). The functional estimation results derived in Section 5 from the data illustrate the fact that the ARH(1) process with colored functional innovations provides a better performance of the functional-projection-ARH(1) Kalman filtering algorithm. In particular, earnings per share EPS induces a spatial correlation structure that is also incorporated to the modeling in terms of the innovation auto-covariance operator.

The results derived improves the methodological approach proposed in Bevan and Danbolt (2004) and Jiménez and Palacín (2007), in relation to the influence of the dividend policy in the financial structure of the enterprise. Empirical evidence of information content of dividend hypothesis is also provided from a functional framework, supporting the results derived, for example, in Palacín-Sáncez and Di Pietro (2011) in relation to the theory of information. Note that, here, our interest relies on the illustration of the ability of the approach presented in the analysis of financial panel data displaying complex structural features in their evolution and/or spatial and temporal correlations.

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