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Abstract

Spatial dependency has been broadly studied in several research areas, such as environmental criminology, economic geography, environmental sciences, and urban economics. However, it has been essentially overlooked in other subfields of economics and in the field of finance as a whole. A key element at stake is the definition of contiguity. In the context of financial markets, defining a metric distance is not a simple matter.

In this article, we explore the notion of spatial dependency in a panel of 126 Latin American firms from Brazil, Chile, and Mexico over the period 1997-2006. Firstly, we formulate a spatial version of the capital asset pricing model (S-CAPM), which accounts for alternative measures of distance between firms, such as market capitalization, the market-to-book, enterprise value-to-EBITDA, and the debt ratios. Secondly, we analyze the potential existence of spatial linkages in investment and dividend decisions. We conclude that there may be contemporaneous linkages in firms' decisions of such ratios, which may be indicative of some strategic behavior.

Keywords: spatial panel data, S-CAPM, Tobin's Q

1 Introduction

Spatial statistics, a subfield of statistics, deals with the measurements or observations of a particular phenomenon associated with specific locations or regions (see, for instance, [1]). In particular, one concept developed in spatial statistics is that of spatial correlation, which aims at measuring whether the occurrence of an event at a specific point in space affects another place. Spatial dependency is usually associated with geographic proximity or contiguity. Although spatial phenomena have been extensively studied in various research fields, such as economic geography (e.g., convergence in per capita income growth rates, inter-regional and inter-sectorial flows of labor and capital, and regional resource endowments), environmental sciences (e.g., dispersion of air-borne pollutants, soil erosion, and forest growth), environmental criminology (e.g., social organization and processes of informal social control within neighborhoods), geographical

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epidemiology (e.g., mapping disease areas), and urban economics (e.g., human interaction patterns and spatial behaviors), the study of spatial linkages in financial markets has been essentially overlooked.

The measurement of spatial correlation requires the definition of a spatial weights matrix, which is customarily constructed in terms of the (Euclidean) geographical distance between neighbors. In finance, however, it is not obvious how distance should be gauged. In particular, geographical proximity may facilitate financial integration, but it is not certainly a necessary condition for such an integration to hold, given that most transactions are performed electronically nowadays. Therefore, the challenge is how to define contiguity in the context of financial markets. There is not certainly a definite answer to this issue. Hence, we resort to alternative definitions of distance based on firm financial indicators.

The focus of this article is the quantification of the risk premium on the market portfolio in the context of what we define as a spatial capital asset pricing model (S-CAPM). Instead of just including firms characteristics as additional risk factors, as has been the standard procedure in the finance literature since Fama and French (1992)'s seminal article (see [2] for references and a thorough discussion of this and other issues surroundings beta), we allow for the possibility that such extra risk factors of a given firm affect the evolution of the expected returns of other firms as well. In addition, and as an extension, we analyze the potential existence of spatial linkages in investment and dividend decisions.

Our study makes use of a sample of over 100 firms belonging to Brazil, Chile, and Mexico during the period 1997-2006. In our analysis, we resort to the statistical tools developed in the field of spatial econometrics, which are suitable to the analysis of cross section and panel data. Good sources on these techniques are the survey articles by [3] and [4] and the textbook by [5]. To our knowledge, our statistical approach to the CAPM is new in the finance literature. Indeed, spatial statistics has been rarely applied in this field. An exception is the unpublished work by [6].

The article is organized as follows. Section 2 describes the methodological tools utilized in our analysis, whereas Section 3 describes the data and discusses our empirical findings. Section 4 summarizes our main findings.

2 Methodology

2.1 Spatial cross-section econometrics

Let us consider N geographical units that are characterized by the existence of spatial autocorrelation, that is $\mathrm{cov}(y_i, y_j) \neq 0$, where i and j represent observations with their corresponding locations and y_i and y_j are the values of the random variable of interest at such particular locations (see, for instance, [3]).

Given a sample of N observations, the elements of the N × N matrix containing the above-mentioned covariance terms will not be identifiable. One way to address this issue is by assuming a particular spatial stochastic process. We will concentrate on this approach in this article. Alternative routes found in the literature are either to parameterize the covariance structure or to leave it unspecified and deal with it non-parametrically.

We concentrate on two types of spatial regression models: a spatial lag model and a spatial autoregressive (SAR) error model. A spatial lag model is of the form

$$\mathbf{y} = \rho \mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{1}$$

where ρ is a spatial autoregressive coefficient, the element i of the vector $\mathbf{Wy}$ is given by $[\mathbf{Wy}]_i = \sum_{j=1,..,N} \omega_{ij} y_j$, where $\mathbf{W}$ is a weights matrix whose elements on the main diagonal are zero.[2] Therefore, $[\mathbf{Wy}]_i$ represents a weighted average of the dependent variable at neighboring locations. $\mathbf{X}$ is a matrix of exogenous regressors, $\boldsymbol{\beta}$ is a vector of parameters, and $\boldsymbol{\varepsilon}$ is a vector of spherical errors with variance-covariance matrix given by $\sigma^2 \mathbf{I}_N$.

Given that $\mathbf{Wy}$ is correlated with $\boldsymbol{\varepsilon}$, ordinary least-squares applied to (1) will yield inconsistent estimates of ρ and $\boldsymbol{\beta}$. One way to circumvent this problem is by resorting to spatial two-stage least squares. Alternatively, under the assumption of normally distributed errors, one can obtain a concentrated log-likelihood of the sample as a function of ρ (see [3] or [5], chapter 6). Due to its computational simplicity, we utilize spatial two-stage least squares by using $\mathbf{WX}$ as a set of instruments for $\mathbf{Wy}$:

$$\hat{\boldsymbol{\gamma}}_{IV} = (\mathbf{Z}'\mathbf{P_Q}\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{P_Q}\mathbf{y}$$

[2] As mentioned in the Introduction, the weights matrix is constructed on the basis of the distances between neighbors. The distance between one particular location and itself is zero.

$$\mathrm{Var}(\hat{\boldsymbol{\gamma}}_{IV}) = \hat{\sigma}^2(\mathbf{Z}'\mathbf{P_Q}\mathbf{Z})^{-1} \qquad \hat{\sigma}^2 = \frac{(\mathbf{y}-\mathbf{Z}\hat{\boldsymbol{\gamma}}_{IV})'(\mathbf{y}-\mathbf{Z}\hat{\boldsymbol{\gamma}}_{IV})}{N} \tag{2}$$

where $\gamma=[\rho\ \beta]'$, $\mathbf{Z}=[\mathbf{Wy}\ \mathbf{X}]$, $\mathbf{Q}=[\mathbf{WX}\ \mathbf{X}]$, and $\mathbf{P}_Q = \mathbf{Q}(\mathbf{Q}'\mathbf{Q})^{-1}\mathbf{Q}'$.

The SAR error model is given by

$$\mathbf{y}=\mathbf{X}\boldsymbol{\beta} + \varepsilon \qquad \varepsilon=\lambda\mathbf{W}\varepsilon + \mathbf{u} \tag{3}$$

where $\mathbf{u}$ is assumed to be a vector of spherical errors.

The model can be re-written as

$$\mathbf{y}=\mathbf{X}\boldsymbol{\beta} + \varepsilon \qquad \varepsilon=(\mathbf{I}_N-\lambda\mathbf{W})^{-1}\mathbf{u} \tag{3$'$}$$

Hence, if $\mathbf{u}\sim N(0, \sigma^2 I_N)$, then $\varepsilon\sim N(\mathbf{0}, \boldsymbol{\Omega})$ where $\boldsymbol{\Omega}=\sigma^2(\mathbf{I}_N-\lambda\mathbf{W})^{-1}[(\mathbf{I}_N-\lambda\mathbf{W})^{-1}]'$, i.e., $\boldsymbol{\Omega}=\sigma^2[(\mathbf{I}_N-\lambda\mathbf{W})'(\mathbf{I}_N-\lambda\mathbf{W})]^{-1}$, and one can obtain a concentrated log-likelihood function for N independent observations in terms of λ:

$$\ln L \propto -\frac{N}{2}\ln(\sigma^2) + \ln|\mathbf{I}_N - \lambda\mathbf{W}| - \frac{1}{2\sigma^2}\boldsymbol{\upsilon}'\boldsymbol{\upsilon} \tag{4}$$

where $\upsilon\equiv(\mathbf{I}_N-\lambda\mathbf{W})(\mathbf{y}-\mathbf{X}\boldsymbol{\beta})$, $\hat{\boldsymbol{\beta}}_{ML} = (\tilde{\mathbf{X}}'\tilde{\mathbf{X}})^{-1}\tilde{\mathbf{X}}'\tilde{\mathbf{Y}}$, $\tilde{\mathbf{X}} \equiv \mathbf{X} - \lambda\mathbf{WX}$, $\tilde{\mathbf{Y}} \equiv \mathbf{Y} - \lambda\mathbf{WY}$, $\hat{\sigma}^2_{ML} = \frac{\hat{\boldsymbol{\upsilon}}'\hat{\boldsymbol{\upsilon}}}{N}$.

Given that for a given value of λ, $\hat{\boldsymbol{\beta}}_{ML}$ and $\hat{\sigma}^2_{ML}$ can be readily computed, the maximization of (4) can be accomplished by searching over a grid of values for λ. Standard errors of the parameter estimates can be obtained from the first derivatives of the log-likelihood function, i.e., $\mathrm{Var}(\hat{\boldsymbol{\theta}}) = \left(\sum_{i=1}^{N}\frac{\partial l_i}{\partial\boldsymbol{\theta}}\frac{\partial l_i}{\partial\boldsymbol{\theta}'}\right)^{-1}$, where l_i is the log-likelihood function for observation i and $\theta'=(\lambda\ \beta\ \sigma^2)'$.

Prior to fitting a spatial regression model to the data, one can test for the existence of spatial dependence by applying Moran’s test to the residuals from an ordinary least-square regression. In general, Moran’s statistic is given by

$$M = \frac{N}{S}\frac{\mathbf{z}'\mathbf{W}\mathbf{z}}{\mathbf{z}'\mathbf{z}} = \frac{N}{S}\frac{\sum_i\sum_j \varpi_{ij} z_i z_j}{\sum_i z_i^2} \tag{5}$$

where ϖ_{ij} is the (i, j)-element of the weights matrix, N is the number of locations, S is the sum of the elements of the weights matrix, and z_i is the demeaned value of the variable of interest at location i. The distribution of M, under the null hypothesis of no spatial autocorrelation, can be derived by assuming that z_i and z_j are identically distributed and that they represent independent draws from a normal distribution.

2.2 Spatial panel econometrics

The lag-spatial and SAR error models can be generalized to the case when the N locations are observed over time (see [4]). In this section, we refer to two Lagrange-multiplier (LM) statistics that enable us to test whether the SAR error regression and its spatial lag alternative are more suitable to the data than a pooled regression model.

Let us consider a balanced panel of N locations or units with T observations each. A pooled regression model can be represented as

$$\mathbf{y}=\mathbf{X}\boldsymbol{\beta}+\boldsymbol{\varepsilon}$$

where $\mathbf{y}$ is an NT× 1 vector, $\mathbf{X}$ is an NT×K matrix and $\boldsymbol{\varepsilon}$ is an NT×1 vector of error terms.

The LM statistic for testing H_0: $\mathbf{y}=\mathbf{X}\boldsymbol{\beta}+\boldsymbol{\varepsilon}$, with $\boldsymbol{\varepsilon}$ being a vector of spherical errors against H_1: $\mathbf{y}=\mathbf{X}\boldsymbol{\beta} + \varepsilon$, $\varepsilon=\lambda\mathbf{W}_N\,\boldsymbol{\varepsilon} + \mathbf{u}$, i.e., H_0: $\lambda=0$ against H_1: $\lambda\neq 0$, is given by

$$\mathrm{LM_E} = \frac{[\hat{\boldsymbol{\varepsilon}}'(\mathbf{I}_T \otimes \mathbf{W}_N)\hat{\boldsymbol{\varepsilon}}/(\hat{\boldsymbol{\varepsilon}}'\hat{\boldsymbol{\varepsilon}}'/\mathrm{NT})]^2}{\mathrm{T\,tr}(\mathbf{W}_N^2 + \mathbf{W}_N{}'\mathbf{W}_N)} \xrightarrow{d} \chi^2(1) \qquad (6)$$

where $\otimes$ denotes the Kronecker product, $\mathbf{W}_N$ is the weights matrix, and $\hat{\boldsymbol{\varepsilon}}$ is the residual from the pooled regression model, that is, $\hat{\boldsymbol{\varepsilon}} = \mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}}$.

We should note that, unlike the usual set-up of panel data analysis, observations are firstly stacked by units and then by time period. That is to say, we group the observations of units 1 through N at time t=1, next the N observations corresponding to t=2, and so on up to time T. By convention, the weights matrix $\mathbf{W}_N$ is held constant through time.

Similarly, the LM statistic for testing H_0: $\mathbf{y}=\mathbf{X}\boldsymbol{\beta}+\varepsilon$ against H_1: $\mathbf{y}=\rho\mathbf{W}_N\,\mathbf{y}+\mathbf{X}\boldsymbol{\beta}+\varepsilon$, i.e., H_0: $\rho=0$ against H_1: $\rho\neq 0$, is given by

$$\mathrm{LM_L} = \frac{[\hat{\boldsymbol{\varepsilon}}'(\mathbf{I}_T \otimes \mathbf{W}_N)\hat{\boldsymbol{\varepsilon}}/(\hat{\boldsymbol{\varepsilon}}'\hat{\boldsymbol{\varepsilon}}'/\mathrm{NT})]^2}{[(\mathbf{W}_N\hat{\mathbf{y}})'\mathbf{M}(\mathbf{W}_N\hat{\mathbf{y}})/\hat{\sigma}^2] + \mathrm{T\,tr}(\mathbf{W}_N^2 + \mathbf{W}_N{}'\mathbf{W}_N)} \xrightarrow{d} \chi^2(1) \qquad (7)$$

with $\mathbf{W}_N\hat{\mathbf{y}} = (\mathbf{I}_T \otimes \mathbf{W}_N)\mathbf{X}\hat{\boldsymbol{\beta}}$ and $\mathbf{M} = \mathbf{I}_{NT} - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$.

2.3 Metric distance

In order to compute a weights matrix, we state that its (i, j)-element is given by the Euclidean distance, d_{ij}, between a specific financial indicator associated with firms i and j:

$$d_{ij} = \sqrt{2(1-\rho_{ij})} \tag{8}$$

where ρ_{ij} is Spearman's correlation coefficient. Equation (8) defines a Euclidean distance adequately because it satisfies the following three properties: i) $d_{ij}=0 \Leftrightarrow i=j$, ii) $d_{ij}=d_{ji}$, and iii) $d_{ij} \leq d_{ik}+d_{kj}$ (see [7], chapter 13). We prefer Spearman's over Pearson's correlation coefficient because, unlike the latter, the former is a concordance measure of association between two random variables. That is, it has the property of being invariant to increasing transformations of the data.

3 Empirical testing of spatial linkages

3.1 The data

Our data set is comprised of 50 Chilean, 42 Brazilian, and 34 Mexican firms, which have been selected from the Economatica database. Income statements and balance sheets are available at a quarterly frequency for Chilean firms, but only at an annual frequency for Brazilian and Mexican firms. Therefore, we utilize annual data to construct the financial ratios of interest. Figures are inflation adjusted and expressed in their original currency. The sample period under consideration is 1997-2006. By focusing on that period, we can rely on a greater number of firms, given that some sampled firms became listed in 1997. It is worth noting that Economatica does not keep track of privately-owned firms.

In Table 1, we report the median values of six financial ratios for each year in the sample: dividend yield, Tobin's Q, market capitalization relative to firm size, market/book value, debt ratio, and EV/EBITDA.[3] Market capitalization is re-scaled by firm size in order to make figures comparable among firms across countries, given that they are expressed in domestic currency.

We observe that there was an increase of market capitalization, relative to firm size, over time, which also drove both Tobin's Q and the market-to-book ratio upwards. Meanwhile, the median debt and dividend yield ratios remained relatively stable over the

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[3] We use the median rather than the mean because it is more robust to the presence of outliers.

same time period. The EV (Enterprise Value) to EBITDA (Earnings before interest, taxes, depreciation, and amortization) ratio measures how long it would take to generate the firm value given its current operational cash flows.[4] This ratio presented a downward trend at the beginning of the sample to oscillate around 8.0 subsequently.

All the computer code involved in the estimation results reported in the subsequent sections was written in S-Plus 7.0.

3.2 Spatial Capital Asset Pricing Model (S-CAPM)

In this section, we first focus on estimating the risk premium on the market portfolio by formulating a spatial CAPM for the whole sample of 126 firms. To this end, we select Morgan Stanley's Emerging Markets (EM) Latin America standard core index in US dollars (USD) as a good approximation of the market portfolio. Given that the market portfolio is expressed in USD, we accordingly convert the stock returns into USD. The risk-free rate in USD is chosen to be the 10-year US Treasury Bill. Data on the exchange rates of each country and the T-Bill are also obtained from Economatica. Next, we estimate separate CAPM for each country by using the corresponding MS index denominated in local currency. A proxy for the risk-free rate of each country is obtained from the International Financial Statistics (IFS) of the International Monetary Fund (IMF) as of June 2007. Specifically, we utilize each country's discount rate.[5]

In both applications, we resort to the two spatial regression models described in Section 2.1, and compute alternative weights matrices based on the metric distance defined earlier. Specifically, we consider four financial indicators to quantify the distance between 'neighboring' firms: market capitalization (relative to firm size), the market-to-book, EV/EBITDA and debt ratios.

In our first application, we carry out the estimation of the risk premium on the EM Latin America index in two stages. At the first stage, we compute the beta for each sampled firm by using the standard CAPM. In order to have more degrees of freedom, we use quarterly data of stock prices to compute the returns in local currency, which in turn are converted into USD. In order to compute each beta, we use Yohai [8]'s MM estimate, which is robust to the presence of outliers and satisfies both consistency and asymptotic

[4] The smaller EV/EBITDA ratio, the less expensive the firm becomes in relative terms.
[5] The discount rate is the rate at which central banks lend or discount eligible paper for deposit money banks. It is also known as the bank rate. (Source: http://stats.oecd.org/glossary).

normality.[6] At the second stage, we run a regression of the median returns of the sampled firms on the betas obtained at the first stage in order to obtain an estimate of the risk premium on the market portfolio. To this end, we fit to the data the spatial lag and SAR error model specifications described earlier.

In this context, a spatial lag CAPM to determine the risk premium on the market portfolio is given by $\mathbf{r}-\boldsymbol{\iota}r_f = \rho\mathbf{W}(\mathbf{r}-\boldsymbol{\iota}r_f) + (r_m - r_f)\tilde{\boldsymbol{\beta}} + \boldsymbol{\varepsilon}$, where $\boldsymbol{\varepsilon}$ is a vector of spherical errors, $(\mathbf{r}-\boldsymbol{\iota}r_f)'=(r_1-r_f \ldots r_N-r_f)'$, $[\mathbf{W}(\mathbf{r}-\boldsymbol{\iota}r_f)]_i = \rho \sum_{j=1,..,N} \omega_{ij}(r_j - r_f)$ and $\tilde{\boldsymbol{\beta}}' = (\tilde{\beta}_1 \ldots \tilde{\beta}_N)'$. The vector $\tilde{\boldsymbol{\beta}}$ is made up of the betas obtained at the first stage and, therefore, (r_m-r_f) becomes a parameter to be estimated at the second stage. This specification implies that the risk premium of one firm is a linear function of a weighted average of the risk premia on neighboring firms.

Alternatively, a spatial error model would take the form of $\mathbf{r}-\boldsymbol{\iota}r_f = (r_m - r_f)\tilde{\boldsymbol{\beta}} + \boldsymbol{\varepsilon}$, where $\boldsymbol{\varepsilon}=\lambda\mathbf{W}\boldsymbol{\varepsilon} + \mathbf{u}$. Under this model specification, the micro unanticipated component of a firm risk premium is a linear function of a weighted average of the micro unanticipated components of neighboring firms. In other words, a SAR error model assumes that the nonsystematic risk of a particular firm is affected by that of neighboring firms.

Four alternative weights matrix $\mathbf{W}_N$ are constructed by resorting to the annual data contained in the balance sheets and income statements of the 126 sampled firms. Such matrices enable us to have a sense of the distance between firms on the basis of the financial ratios referred to at the beginning of this section. The weights matrices so constructed are next utilized in the regression model of the median returns on the firms betas.

As a benchmark, we estimate the risk premium on the market portfolio by ordinary least squares, and test for the presence of spatial correlation in the regression residuals by

[6] For a linear model $y_i=\boldsymbol{\beta}'\mathbf{x}_i+\varepsilon_i$, with k regressors, a robust M-estimate of β is the solution of the minimization of $\sum_{i=1}^{n}\rho\left(\frac{y_i-\boldsymbol{\beta}'\mathbf{x}_i}{\hat{s}}\right)$, where ρ(.) is a symmetric, bounded function and $\hat{s}$ is a robust estimate of the scale parameter of the residuals, which solves the equation $\frac{1}{n-k}\sum_{i=1}^{n}\rho\left(\frac{y_i-\boldsymbol{\beta}'\mathbf{x}_i}{\hat{s}(\beta)}\right)=0.5$. The number 0.5 represents the breakdown point, which represents the maximum fraction of outliers the sample may contain without having a substantial impact on the parameter estimate of s. The concept of MM-estimate is a generalization of the M-estimate and it was introduced by [8]. A good source on robust estimation is [9].

utilizing the aforementioned weights matrices. Our estimation results are reported in Tables 2 and 3. First of all, from Table 2, we see that the estimate of the market risk premium is 1.7 percent per quarter, that is, about 6.97 per year. However, this is barely statistically significant at the 11-percent level. The presence of spatial correlation is tested by applying Moran’s statistic to the least-square residuals. As we see, the absence of spatial correlation is rejected for the weights matrices computed on the basis of market capitalization (relative to firm size) and the market-to-book ratio, whereas it is not for the weights matrices based on the EV/EBITDA and debt ratios.

Now, if we focus on the SAR error and spatial lag models fitted to the data, we notice that the risk-premium estimates obtained by using the weights matrices based on the EV/EBITDA and debt ratios do not differ much from that yielded by least squares. This is not surprising because we concluded that spatial correlation is weak under the metric distance built on those two financial ratios.

From Table 2, we also observe that the risk-premium estimates are larger for the weight matrices based on market capitalization (relative to firm size) and the market-to-book ratio, and that they are statistically significant at the 5 percent level in most cases. For the six models reported in the table, we tested for departures from normality in the error term by Shapiro-Wilk test and by a visual inspection of a QQ-plot (Figure 1, panels (a) through (d)). Shapiro-Wilk test does not lead to rejection of normality in any of the six models, but the QQ-plots suggest that the residuals from the SAR error and the spatial lag models computed on the basis of the distances between firm market capitalizations are better behaved in the tails of the distribution than the other alternative model specifications.

If we turn to the spatial-effect estimates, we see that they are relatively small but statistically significant (Table 3, panels (a) through (d)). For instance, for the spatial lag model based on market capitalization, a quarterly increase of 100 basis points in the weighted average of the dependent variable (i.e., the risk premium on a firm stock) at neighboring locations leads to a quarterly increase of 0.56 basis points in the risk premium of a given firm. As remarked earlier, the interpretation of the SAR error model is fairly different because the interaction among firms in this case is through firm-specific or micro shocks. For the market-capitalization weights matrix, a quarterly increase of 100 basis points in the weighted average of micro shocks at neighboring firms translates into a quarterly increase of 0.52 basis points in the nonsystematic-risk component of a given firm. In general, the estimates of ρ and λ tend to be fairly similar across the different weights matrices under consideration.

In order to check the robustness of our results, we also estimated spatial models separately for each country. In this case, we opted for returns denominated in local currency in order to avoid any distortions arising from the behavior of exchange rates. The only caveat is that the sample sizes of firms per country we rely on are rather small. Our results are shown in Tables 4 and 5. For the sake of brevity, we only report the results obtained for a single weights matrix per country. Our evidence is mixed. First of all, there is no evidence of spatial effects in the Chilean returns equation, but the estimate of the risk premium on the local index is statistically significant at the 5-percent significance level. By contrast, spatial dependency appears to be present in the Brazilian sample under either model, whereas the statistical significance of the risk-premium estimates is weaker (particularly so in the spatial lag model).

The estimation results for Mexico seem more surprising. Indeed, under the spatial lag model, the firm betas do not seem to have any explanatory power, and the spatial interaction among firms arising from their corresponding risk premium is the only relevant factor, at least for a significance level of 10 percent. The SAR error model in turn fits the data rather poorly as neither the spatial interaction of micro shocks or beta is statistically significant at the conventional significance levels.

In sum, for the whole sample of countries, we conclude that there exist spatial effects, and that such effects can be captured by an additional risk factor (i.e., spatial lag model) or by the error term in the form of nonsystematic risk of neighboring firms (i.e., SAR error model). Beta may continue to have explanatory power even after taking account of spatial dependence. When looking at individual countries, the evidence is mixed. On one hand, we conclude, in Fama and French’s vein, that beta is “dead”, and that only spatial dependency either through the firm risk premium or nonsystematic risk appears to matter. Whereas, on the other hand, we find that beta may be the only relevant risk factor.

3.3 Investment and dividend decisions

In this subsection, we focus on the potential role of spatial linkages in firm growth opportunities and dividend decisions. The relation between cash flows and investment at the firm level has been the focus of several studies (e.g., [10], [11], and [12]), and it has been linked to some existing theories of capital structure (e.g., free-cash flows and pecking order). Indeed, Ref. [14] points out that under the free-flow cash hypothesis, given that monitoring is costly, and managers can benefit from overinvestment, investment spending will be strongly influenced by cash flow availability. This will be particularly so for firms not paying dividends. As a consequence, firms will be associated with low levels of marginal Tobin's Q, and the equilibrium level of marginal Q will be less than one. In particular, those firms, which do not pay dividends, will be the ones will exhibit the lowest levels of marginal Q. Under the pecking order hypothesis, there exists an adverse selection problem stemming from the fact that managers have more information than the market about the quality of their existing assets and investment projects, which they are unable to convey to the market in a credible fashion. As a consequence, profitable investment opportunities may be forgone, and cash-flow constrained firms will have an equilibrium value of marginal Q that will be greater than one. In particular, those firms which face many profitable investment opportunities or large information asymmetries will rely more heavily on cash flows and pay low or no dividends.

We first test separately whether there may exist spatial linkages in firm growth opportunities and dividend policy, as measured by Tobin's Q and the dividend yield, respectively. To that end, we apply a spatial correlation test for panel data to the whole sample and to each country in isolation. We next investigate the potential linkage between growth opportunities and dividend policy, and conjecture which of the aforementioned hypothesis might be more congruent with our findings.

Panel (a) of Table 6 reports our results of applying the Lagrange multiplier tests of spatial correlation to the panel data of Tobin's Q and dividend yield to the panel of 126 countries. As we see, we reject the absence of spatial effects under either specification. The interpretation of the test differs according to the model specification, as discussed earlier. Under the SAR error model, unobservable factors that impact the choice of Tobin's Q and the dividend yield in turn are correlated across firms. Under the spatial lag specification, the weighted average of each corresponding ratio in neighboring firms directly affects another firm's choices. Our findings are robust to the selection of different weights matrices.

The evidence for the three sampled countries is mixed. For instance, for Brazil, we do not find support for the existence of spatial effects in Tobin's Q choice, while the opposite holds for the dividend yield. By contrast, for Chile, the evidence supports the existence of spatial effects in the choice of Q but not in dividend policy. Our conclusions for Mexico depend on the weights matrix under consideration. For instance, by using as metric distance the market capitalization and market-to- book ratios, we do not find evidence of spatial effects under either the SAR error or spatial lag model. However, under the other two metric distances—EV/EBIT and debt ratios—spatial effects are found for both Tobin's Q and dividend policy under both model specifications.

According to the two capital structure hypothesis outlined earlier, growth opportunities and dividend policy may not be independent. Therefore, we next test for the presence of spatial dependency in Tobin's Q by using the dividend yield as a metric distance to construct a weights matrix. In order to determine both the sign and magnitude of the spatial correlation coefficient, we resort to Moran's statistic and compute its value for each year in the sample (Table 7).

First of all, for the whole sample of firms, we find that Moran's spatial correlation is statistically significant over 1997-2000. Its magnitude is negative but relatively small (i.e., –0.05 on average over that period). The sign of the correlation coefficient deserves some interpretation. As we know, the distance between firms is measured in terms of Spearman's correlation coefficient between their dividend yields. This implies that two firms whose dividend yields are positive and highly correlated will be close to one another, and, hence, their corresponding weight will be small. The weights in Moran's statistic will be largest for paired firms which exhibit highly heterogeneous dividend policies. On the other hand, Moran's statistic will be negative when the numerator of expression (5) is negative. For paired firms, the negative sign will arise when one firm's Q is below the sample average while the other's is above it. Overall, this implies that heterogeneity in Tobin's Q will be amplified by heterogeneity in dividend policy.

Unfortunately, the sign of Moran's spatial correlation itself does not suffice to hint which theory receives more support as to the relation between growth opportunities and dividend policy. However, the median Tobin's Q for the whole sample during 1997-2000 exceeds 1. This suggests that spatial dependency may have taken place during an overinvestment period.

When focusing on individual countries, Chile is the only one whose firms exhibit spatial dependence in Tobin's Q. And, such spatial effects are observed along the whole sample period, except for 1998 and 1999. The magnitude of Moran's spatial correlation is again small and negative. The main difference with respect to the whole sample is that the median Tobin's Q was equal or greater than 1 for most of the sample period. This indicates that the median firm may have experienced liquidity constraints and, therefore, the pecking order hypothesis would be more suitable to the evidence in this case.

In sum, we conclude that firms appear to behave strategically as regards to their investment decisions and dividend policy, in that other firms' choices matter. In addition, we find some evidence of an interaction between growth opportunities and dividend policy, which is congruent with the literature of capital structure.

4. Conclusions

In this article, we tested for spatial dependency in a panel of 126 Latin American firms from Brazil, Chile, and Mexico over the period 1997-2006. We first formulated a spatial version of the capital asset pricing model (S-CAPM). Instead of just including firm characteristics as additional risk factors, we allow for the possibility that such extra risk factors of a given firm affect the evolution of the expected returns of other firms as well. For the whole sample of countries, we conclude that there exist spatial effects and beta may continue to have explanatory power even after taking account of spatial dependence. When looking at individual countries, the evidence is mixed. On one hand, we conclude, in Fama and French's vein, that beta is "dead", and that only spatial dependency either through the firm risk premium or nonsystematic risk appears to matter. Whereas, on the other hand, we find that beta may be the only relevant risk factor.

As an extension, we analyzed the potential existence of spatial linkages in investment and dividend decisions. We conclude that there may be contemporaneous linkages in firms' decisions of such ratios, which may be indicative of some strategic behavior. In addition, we find some evidence of an interaction between growth opportunities and dividend policy, which is congruent with the literature of capital structure.

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Table 1 Median values of financial ratios for a sample of Latin American firms

Period	Dividend yield	Tobin's q	Market capitalization/ firm size	Market/book	Debt ratio	EV/EBITDA
1997	0.058	0.913	0.683	0.839	0.226	11.10
1998	0.090	0.779	0.378	0.499	0.249	7.23
1999	0.040	0.867	0.499	0.738	0.230	8.28
2000	0.054	0.858	0.442	0.663	0.240	7.84
2001	0.048	0.879	0.408	0.696	0.251	7.37
2002	0.035	0.947	0.432	0.861	0.228	7.36
2003	0.035	1.095	0.607	1.188	0.254	9.05
2004	0.033	1.246	0.818	1.545	0.231	7.86
2005	0.042	1.231	0.787	1.463	0.214	7.60
2006	0.028	1.367	0.917	1.774	0.214	8.82

Notes: (1) The dividend yield is defined as the dividend over market price per share. (2) Tobin's Q is measured as the market value over the book value of assets. The market value of assets is measured as market capitalization plus total liabilities. (3) Market capitalization is re-scaled by firm size in order to make figures comparable given that they are expressed in domestic currency. (4) The debt ratio is defined as total debt over total assets. (5) EV/EBITDA is the enterprise value to EBITDA. Data source: Economatica.

Table 2 Risk premium on MS Emerging Markets Latin America standard core index (USD)

Model	Risk premium	p-value	SW statistic-residuals (p-value)	R^2
Least squares	0.017	0.107	0.391	0.021
Moran's statistic for spatial correlation applied to LS residuals (p-values in [.]) Weights matrix				
Market cap/size	Market/book	EV/EBITDA	Debt ratio	
–7.34 [0.00]	–7.58 [0.00]	0.896 [0.37]	–1.271 [0.20]	

Model	Risk premium	p-value	SW statistic-residuals (p-value)	R^2
(a) Weights matrix based on market capitalization relative to firm size				
SAR error model	0.023	0.032	0.559	0.037
Spatial lag model	0.021	0.052	0.641	0.046
(b) Weights matrix based on the market-to-book ratio				
SAR error model	0.025	0.022	0.339	0.045
Spatial lag model	0.022	0.045	0.417	0.062
(c) Weights matrix based on the EV/EBITDA ratio				
SAR error model	0.019	0.001	0.323	0.026
Spatial lag model	0.018	0.077	0.338	0.024
(d) Weights matrix based on the debt ratio				
SAR error model	0.018	0.082	0.342	0.024
Spatial lag model	0.017	0.099	0.359	0.022

Notes: (1) Shapiro-Wilk (SW) statistic enables us to test for departures from normality. Jarque-Bera's test applied to the residuals from each model yields similar answers. (2) R^2 is computed by the standard formula utilized under least squares, $\sum \hat{y}^2 / \sum y^2$, where $\hat{y}$ and y are the demeaned fitted and actual values of the dependent variable, respectively. In the context of spatial regressions, however, such R^2 is not guaranteed to lie between 0 and 1.

Table 3 Spatial effects: estimates of ρ and λ

Model	ρ	p-value	λ	p-value
(a) Weights matrix based on market capitalization relative to firm size				
SAR error model	--	--	0.0052	0.000
Spatial lag model	0.0056	0.000	--	--
(b) Weights matrix based on the market-to-book ratio				
SAR error model	--	--	0.0054	0.000
Spatial lag model	0.0061	0.000	--	--
(c) Weights matrix based on the EV/EBITDA ratio				
SAR error model	--	--	0.0051	0.000
Spatial lag model	0.0050	0.000	--	--
(d) Weights matrix based on the debt ratio				
SAR error model	--	--	0.0051	0.000
Spatial lag model	0.0051	0.000		

Table 4 One-single country CAPM

Model	Risk premium	p-value	SW statistic-residuals (p-value)	R^2
(a) Brazil				
Weights matrix based on market capitalization relative to firm size				
SAR error model	0.034	0.090	0.02	0.093
Spatial lag model	0.032	0.110	0.02	0.150
(b) Chile				
Weights matrix based on the market-to-book ratio				
SAR error model	0.015	0.000	0.02	0.038
Spatial lag model	0.023	0.017	0.05	0.092
(c) Mexico				
Weights matrix based on the EV/EBITDA ratio				
SAR error model	0.029	0.148	0.05	0.052
Spatial lag model	0.020	0.360	0.04	0.023

Notes: (1) Shapiro-Wilk (SW) statistic enables us to test for departures from normality. Jarque-Bera's test applied to the residuals from each model yields similar answers. (2) R^2 is computed by the standard formula utilized under least squares, $\sum \hat{y}^2 / \sum y^2$, where $\hat{y}$ and y are the demeaned fitted and actual values of the dependent variable, respectively. In the context of spatial regressions, however, such R^2 is not guaranteed to lie between 0 and 1.

Table 5 Spatial effects: estimates of ρ and λ

Model	ρ	p-value	λ	p-value
(a) Brazil				
SAR error model	--	--	0.022	0.000
Spatial lag model	0.025	0.000	--	--
(b) Chile				
SAR error model	--	--	–0.057	0.150
Spatial lag model	–0.012	0.440	--	--
(c) Mexico				
SAR error model	--	--	0.013	0.310
Spatial lag model	0.016	0.073	--	--

Note: The weights matrices are computed based on market capitalization (normalized by size), the market-to-book ratio, and the debt ratio in the case of Brazil, Chile, and Mexico, respectively.

Table 6 Test of spatial correlation: panel data of Tobin's Q and dividend yield

(a) Whole sample

SAR error				
	Tobin's Q		Dividend yield	
Weights matrix	statistic	p-value	statistic	p-value
Market cap.	15.6	0.000	28.7	0.000
Market to book	25.5	0.000	12.1	0.000
EV/EBIT	28.6	0.000	41.1	0.000
Debt ratio	26.3	0.000	53.7	0.000
Spatial lag				
	Tobin's Q		Dividend yield	
Weights matrix	statistic	p-value	statistic	p-value
Market cap.	10.3	0.001	21.5	0.000
Market to book	12.5	0.000	7.27	0.007
EV/EBIT	26	0.000	38.6	0.000
Debt ratio	24	0.000	51	0.000

Table 6 continued

(b) Individual countries

SAR error

	Brazil				Chile				Mexico			
	Tobin's Q		Dividend yield		Tobin's Q		Dividend yield		Tobin's Q		Dividend yield	
Weights matrix	statistic	p-value	statistic	p-value	statistic	p-value	statistic	p-value	statistic	p-value	statistic	p-value
Market cap.	0.58	0.450	29	0.000	458	0.000	0.11	0.740	1.2	0.270	2	0.160
Market/book	0.73	0.390	69	0.000	320	0.000	0.02	0.900	17	0.000	2.5	0.110
EV/EBIT	1.10	0.290	66	0.000	645	0.000	0.01	0.920	19	0.000	6.1	0.014
Debt ratio	0.94	0.330	59	0.000	703	0.000	0.04	0.840	15	0.000	9.1	0.003

Spatial lag

	Brazil				Chile				Mexico			
	Tobin's Q		Dividend yield		Tobin's Q		Dividend yield		Tobin's Q		Dividend yield	
Weights matrix	statistic	p-value	statistic	p-value	statistic	p-value	statistic	p-value	statistic	p-value	statistic	p-value
Market cap.	0.47	0.490	17.0	0.000	131	0.000	0.10	0.750	0.37	0.540	1.8	0.180
Market/book	0.65	0.420	53.0	0.000	46	0.000	0.01	0.910	3.5	0.062	2.2	0.140
EV/EBIT	1.10	0.290	63.0	0.000	316	0.000	0.01	0.930	14	0.000	6	0.014
Debt ratio	0.92	0.340	56.0	0.000	358	0.000	0.04	0.850	11	0.001	8.9	0.003

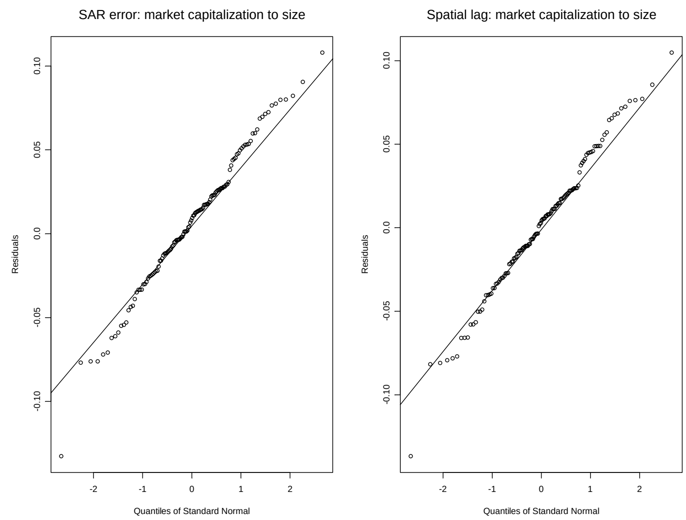
Table 7 Moran's spatial correlation of Tobin's Q

	Whole sample			Brazil			Chile			Mexico		
Year	statistic	p-value	Q	statistic	p-value	Q	statistic	p-value	Q	statistic	p-value	Q
1997	–0.084	0.000	0.913	–0.016	0.337	0.690	–0.047	0.000	0.926	–0.023	0.523	1.320
1998	–0.061	0.000	0.779	–0.018	0.434	0.618	–0.027	0.366	0.850	–0.025	0.632	1.024
1999	–0.029	0.000	0.867	–0.020	0.632	0.791	–0.026	0.412	0.939	–0.022	0.443	0.960
2000	–0.023	0.000	0.858	–0.020	0.605	0.788	–0.033	0.077	0.888	–0.019	0.294	0.908
2001	–0.012	0.146	0.879	–0.022	0.750	0.773	–0.045	0.001	1.000	–0.017	0.224	0.901
2002	–0.012	0.130	0.947	–0.022	0.788	0.909	–0.065	0.000	1.000	–0.015	0.170	0.950
2003	–0.012	0.130	1.095	–0.023	0.848	1.018	–0.072	0.000	1.195	–0.025	0.596	0.960
2004	–0.011	0.352	1.246	–0.022	0.809	1.126	–0.047	0.000	1.283	–0.024	0.544	1.149
2005	–0.008	0.908	1.231	–0.022	0.790	1.153	–0.034	0.051	1.320	–0.021	0.396	1.222
2006	–0.007	0.603	1.367	–0.019	0.555	1.316	–0.035	0.034	1.428	–0.024	0.548	1.274

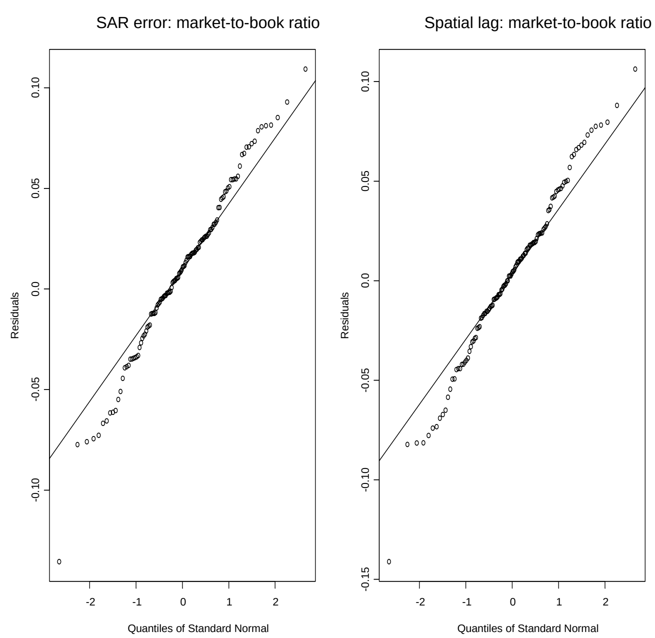
Note: Moran's spatial correlation is computed according to equation (5).

Figure 1 QQ plots of SAR error and spatial lag models for different weights matrices

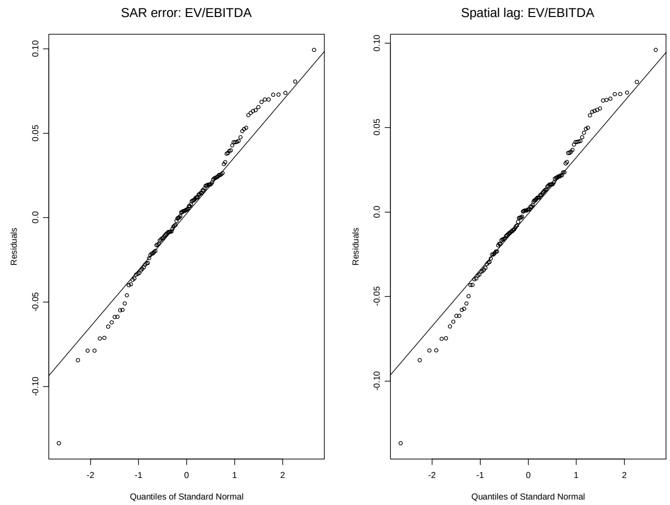
(a)



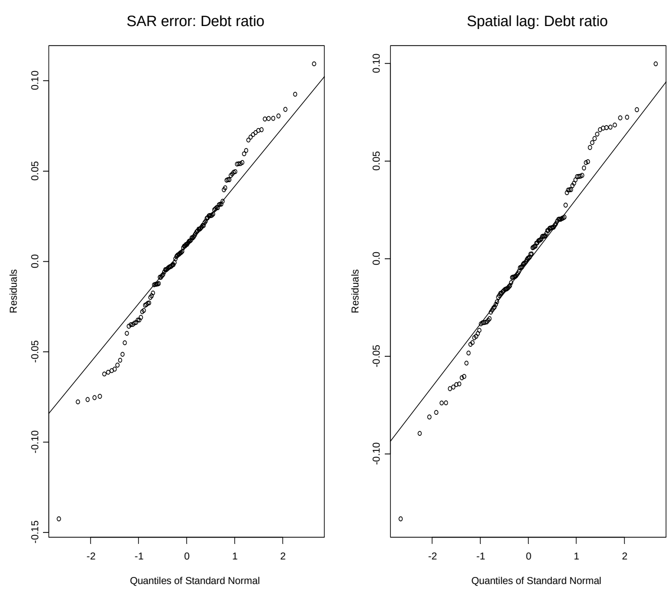
(b)



(c)


SAR error: EV/EBITDA
Spatial lag: EV/EBITDA
Residuals
Quantiles of Standard Normal
0.10
0.05
0.0
-0.05
-0.10
-2
-1
0
1
2

(d)


SAR error: Debt ratio
Spatial lag: Debt ratio
Residuals
Quantiles of Standard Normal
0.10
0.05
0.0
-0.05
-0.10
-0.15
-2
-1
0
1
2

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