Peer effects of stock returns and financial characteristics: Spatial approach for an emerging market

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Abstract

We analyze the peer effects related to the stock returns and the financial characteristics of 166 Brazilian companies listed in the Brazilian market (Bovespa). Using quarterly data from 2007 to 2014, we estimate spatial panel data models to capture the correlation among stock returns of peer companies by employing two spatial weight matrices: a branch of activity and a technological intensity sector. Studies have shown there is not a unique set of factors that can alter the stock returns since it is important to understand their interaction with other companies, their sectoral position, and the macroeconomic environment. Using this concept, our results indicate there is a positive and statistically significant spatial dependence between stock return from peers companies as well as a negative and statistically significant feedback effect of fundamental characteristics such as book-to-market and dividend-price ratio. This information is important for investors since the higher the book value or the dividend payment, the lower the stock return of the peers.

Keywords: Stock return. Spatial Econometrics. Financial characteristics. Peer effects.

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1. Introduction

Although many studies have identified important variables to understand and predict stock returns, the co-movement amongst stock returns has recently received some interest in financial literature. Barberis et al. (2005) suggest the presence of a behavioral factor in order to understand the correlations among domestic stock returns. Phan et al. (2015) point out that there is a correlation between the stock return of a company and their industrial characteristics (as size and price-earnings ratio) as well as the trading volume and book-to-market ratio from its peers. Leary and Roberts (2014) use this co-movement strategy to analyze the peer effects[3] on the financial policy since many studies assumed that the choice of a company's capital structure does not depend on the characteristics and actions of their peers, ignoring the effects of the behavior of similar companies in financial decisions[4]. New perspectives about the relationship among corporate finance and stock returns analysis have been developed lately.

Some research uses traditional econometrics to identify the effects from peers on the stock return or any additional financial concept, either by using companies' characteristics or strategies of their sector. A different form to obtain these effects is by using spatial econometrics. Jean Paelinck and Klaassen (1979) created this term in their book analyzing the growth in regional economic studies focused on estimation problems and implementation of multiregional econometric models (Anselin, 1988; Almeida, 2012). This branch of econometrics is present in a variety of areas from macroeconomics aggregate growth to social organizations and mapping diseases as well as urban economy[5]. Nevertheless, this technique is relatively recent to financial data.

Arnold et al. (2013), Weng and Gong (2016), Fernandez (2011) and many other studies employ spatial econometrics in corporate finance and stock returns analysis. Arnold et al. (2013), studying the effects of three types of spatial dependence on stock returns, estimate the stock return impact of a particular firm on the stock return of its peers. They choose three spatial weight matrices to analyze the effects of industrial and national spatial dependence considering the daily asset prices of companies listed on Euro Stoxx 50 from 2003 to 2009. They suggest that the spatial approach is more adequate to estimate risk with a VaR model since it was able to capture the cross-sectional dependence, especially compared to a factor model. Schmitt et al. (2013) also implement spatial econometrics to test stock return covariance matrix as a portfolio optimization method.

The key point of spatial econometric is the choice of the metric applied in the construction of the spatial weight matrix. Gong and Weng (2016) confirm this affirmation by proposing a spatial autoregressive model to predict stock returns. For them, stock returns are not only affected by firms features like size, book-to-market ratio, market value or trading volume but are also altered by relative values of the sectoral characteristics. Other studies employ spatial econometric as a tool to understand the relationship amid global stock markets (Asgharian et al. 2013; Fernandez, 2011; Arnold et al., 2013; Weng and Gong, 2016).

In this work, we investigate the existence of a spatial dependence on the stock returns among peer companies using panel data spatial econometrics. More specifically, we analyze the firm's stock return behavior considering two types of spatial dependence, sectoral activity information and technological intensity for Brazilian companies listed on Sao Paulo Stock Exchange. This study contributes to the finance literature of emerging markets by considering

[3] To illustrate the peer effects, consider a shock to firm A's profitability that will not only affect firm A's financing choice, but also that of every member of firm A's baseline group. This modification will result in a feedback response onto firm A's decisions and so on (Leary and Roberts, 2014, p. 142).

[4] According Foucault and Fresard (2014), the competitors are not the only possible peer companies, but can also be companies exposed to common demand shocks, such as suppliers, customers or complementary products.

[5] See Arbia and Baltagi (2009) and Gomes et al (2015) to a collection of spatial econometrics applications.

the dependence structure among stock market, technological intensity and industrial activity characteristics. To the best of our knowledge, this work is the first to investigate the correlation among these factors by using spatial panel data model for Brazilian firms. Although there are many studies of spatial econometrics in applied economics, in context of finance market they are yet incipient, because of the tough task of constructing the spatial weight matrices in the financial market scope.

We also investigate whether financially constrained firms are subject to co-movement on their stock return. The firm's investment depends on the degree of financial constraint, which in turn will affect their market value and stock returns. Understanding the relation between financial constraint and asset prices is also important for macroeconomic policies, like credit conditions or monetary policy, particularly for an emergent market economy as Brazil.

Our findings show that firms’ stock returns are significantly affected by their peers. In general, we identify that firms' financial policies are related to their peers, which indicates that common factors can explain asset price variations. In particular, the empirical results are important for the investors’ decisions on the portfolio selection problem. We also find that the financially constrained firms are negatively related to the stock returns of their peers. These frictions mean that investment decisions are not made independently of the behavior or characteristics of their peers, but there is a structural dependence that has not yet been explored in financial literature.

We use data from 166 Brazilian companies listed on the Sao Paulo Stock Exchange (BOVESPA) from the first quarter of 2007 to the third quarter of 2014. We estimate two spatial models known as Spatial Autoregressive Model (SAR) and Spatial Durbin Model (SDM) with static spatial weight matrices, which consist of sectoral information and technological intensity as the economic distance criteria.

We organize the remainder of the paper as follows. Section 2 describes the relationship between stock returns and spatial relations. Section 3 summarizes the spatial econometrics, the empirical model, and the dataset. Section 4 details the empirical results while the final section summarizes the main findings of the study.

2. Stock return and spatial dependence

Some authors have sought to understand the intricate features of co-movement from stock returns, financial policies or economic dependence. Although testing for the financial constraints effects, Lamont et al. (2001) suggest firms with some financial problems might share a common restriction factor on their stock returns. To do this, the authors used an index of financial constraint, the KZ index from the Kaplan and Zingales (1997)’s work. Their analysis show that if a firm has financial problems, it must compensate their investors for keeping assets and they conclude that constraint firms have a negative commoving on the stock returns[6]. On the other hand, Chan et al. (2010) show the stock returns from constrained companies move with the stock returns of firms belonging to their group, which indicates it must exist some common restriction factor on stock returns.

The financial constraints problems and its impact on stock returns are two subjects studied by researchers using diverse and sophisticated econometrics models. Some research shows that the changes in stock returns depend on specific characteristics sector's or derive from any other economic distance in international stock markets analysis. (Phan et al., 2015; Suchecka and Laszkiewicz, 2011; Asgharian et al., 2013).

[6] The irrational behavior of the investors can be a factor to influence the lower returns rather than having any relationship with the company’s restriction factor.

Leary and Roberts (2014) provide another example of the importance of the dependence among firms in financial subjects. They show evidence of a company's dependence to other companies (either competitor or allies) when considering capital structure's choice. These authors use characteristics of firms in a particular sector, known as baseline group, to understand the correlation between two companies of the same group. In addition, Leary and Roberts (2014) also reveal the presence of endogeneity problems and their impact on identifying the appropriate characteristics of the reference group on the individual decisions. According to the authors, selection bias and/or omitted common factor can cause this endogeneity problem. The selection bias surfaces when firms belong to the same institutional environment and have similar features that can correlate their financial policy to characteristics and the actions of the baseline group. On the other hand, the omitted common factor arises when changes in the company's characteristics from the baseline group can produce a feedback effect on capital structure decisions of a firm.

Fernandez (2011) is one of the first examples of the use of spatial econometric models to understand how firm A' stock returns are affected by the risk of its peers. To do so, she augment the CAPM concept by incorporating a spatial risk factor for the peer firms through spatial weight matrices using the Spearman correlation's coefficient of financial indicators. The author works with a sample of 126 companies from 1997 to 2006 of three emerging countries and estimates a spatial VaR (Value-at-Risk) model to corroborate the benefits from this Spatial CAPM to stock return's forecasts. She concludes that there is a spatial dependence on Brazilian sample, although the risk premium is not statistically different from zero, possibly due to the small sample size (42 listed companies in the Brazilian stock market).

Gong and Weng (2016) with a microeconomic approach consider the Shanghai Stock Market. They believe stock returns depend on individual and relative factors. For the first ones, they consider size, book-to-market ratio, and momentum while the relative positions involve the trading volume ranking, market capitalization, sectoral measures, and investors' trade behavior. They compare the performance of portfolio prediction of a VaR model using a spatiotemporal model with the results provided in Arnold et al. (2013) and Wied (2013). Their spatial weight matrices use the copula theory to verify the contagion between two stock returns. Using a database of 144 Chinese enterprises with daily stock returns from 2004 to 2014, Gong and Weng (2016) find that the higher Chinese market volatility the worst is the crisis period. They also show the existence of financial contagion between two Chinese regions when they are spatial dependents each other, intensively viewed in times of crisis.

Asgharian et al. (2013), using spatial econometric models, seek macroeconomic elements that modify the dependence degree among different global stock markets. They identify the extension of the linkage amid stock markets and the co-movement effect on another market. The authors also indicate that spatial econometric helps to comprehend the contagion effects and spillovers from the market risks on a macroeconomic level. Testing eight economic spatial weight matrices on two spatial Durbin models with one and two spatial lags, they conclude market's returns are affected by fundamental variables like GDP growth and the spatial lag market's returns.

Lastly, the portfolio literature does not explore the evidence of stock returns commoving. Kogan and Papanikolaou (2013) assert that this occurs among companies with similar characteristics, as well as firms belonging to different sectors. In addition, enterprises with more growth opportunities remunerate lower risk premium and its stock returns co-vary with the stock return for similar enterprises. To Fama and French (1993 apud Kogan and Papanikolaou, 2013), the jointly varying stock returns patterns amongst companies with similar characteristics must be interpreted as observed differences on exposed systematic risk when considering a cross-sectional level of average stock returns.

3. Data and Methods

Portfolio diversification can decrease its risk when contain assets from the stock market, government securities and other financial applications. Hence, the co-movement of stock returns and the feedback from specific enterprises' shocks can help the investors on their investment decision. Nonetheless, it is a difficult assignment to find the right correlated variables among companies to apply spatial econometric tools on financial data. To Asgharian et al. (2013), the existence of a similar financial characteristic between two companies is not proof of the spatial dependence of their stock returns simply because their stock returns have a similar pattern. Therefore, this section explains the variables selection, the spatial technique and the interpretation for the estimations.

3.1.Database and samples

The database consists of quarterly information of 166 enterprises listed on Sao Paulo Stock Exchange from the first quarterly of 2007 to the third quarterly of 2014. We excluded companies that did not have sufficient stock return information as well as the ones without the financial information for the construction of the financial constraint index. Therefore, the final sample has 5,146 observations[7].

Our dependent variable is the logarithm of stock return following Campbell et al. (1997). We also calculate the *KZ* index as a measure of the financial constraints of an enterprise (Kaplan and Zingales, 1997; Lamont et al., 2001). This index describes the distance of internal and external financing of the company. "Financially constrained firms, also known as equity-dependent firms, tend to face higher costs for financing their needs externally" (Chen and Wang, 2012, p. 312). An enterprise with higher *KZ* index value is financially constrained as the difference of internal and external capital costs are higher than others are. We use expression (1) below to calculate it.

$$KZ = -1,001908\left(\frac{FC}{K_{t-1}}\right)_{it} + 0,2826389Q + 3,139193\left(\frac{Debt}{CT_{t-1}}\right)_{it} - 39,3678\left(\frac{divid}{K_{t-1}}\right)_{it} \\ -1,314759\left(\frac{Cash}{K_{t-1}}\right)_{it} \tag{1}$$

in which t is the quarterly period, $t = 1, \dots, T$; i refers to a company and $i = 1, \dots, n$; K_{it} is the capital stock, measure as the company's property; FC_{it} is the cash flow; Q_{it} is the Tobin's *q*; $Debt_{it}$ is the total liabilities variable; TC_{it} is the total capital, which is the sum of short run debt, the long run debt and the owners' equity; $Divid_{it}$ is the dividend payments, and $Cash_{it}$ is the cash and cash-equivalent for the company[8].

Return on equity, *ROE*, is the indicator of the premium received by the shareholders for their investment. We calculate it as the ratio of net earnings and the owners' equity to measure the firm's capacity to incorporate value to itself using the internal funding. To test the effect of the company's dividend policy on stock return, we construct the dividend-price

[7] We select companies with the most tradable equity class on the period and we deflate the data according the Consumption Price Index (IPCA), an index that measures the prices of the Brazilian economy. In addition, the database do not contemplate financial sector, public administration, and trade and services companies.

[8] The information are on the company's balance sheet. We transform the KZ index in a categorical variable that equals one for the observations with the 25% highest KZ index (financial constrained), zero for the ones with the 25% lowest KZ index (financial unconstrained) and two for the ones with a median KZ index.

ratio as the ratio of total dividend payment and total assets. We test if, considering the Brazilian case, the dividend-policy irrelevance proposition of Miller and Modigliani is valid. Golez (2014), for derivative market, suggests this variable is a proxy for expected stock return when the expected dividend growth varies on time[9].

To capture the investment opportunity, our last variable is the book-to-market ratio as the ratio of the company's book value and its market value. Leary and Roberts (2014) and Cullen et al (2014) also use this variable to test for stock return or to understand the effects of peer companies' financial policies. To Leary and Roberts (2014, p.147), "the peer firm average likely captures some variation in characteristics relevant for firm *i*'s capital structure that is not capture by firm *i*'s own market-to-book ratio". Therefore, we consider the inverse of this variable as an investment opportunity measure.

Since the methodological procedures for spatial panel data using Stata must use a balanced database, we consider two subsamples: (i) with a multivariate normal regression, we use an imputation method to create a sample that accommodates arbitrary missing-value patterns[10], and (ii) we reduce the sample to companies with all the valid information. For the first subsample, the information on table A.1 reveals the method can be used without dramatic modification on the average values. For the second subsample, we have 130 companies with complete information for this period and we create a new spatial weight matrix with this dimension. Table A.1 also describes the statistical summary of this sample. One can see some modifications on the sample with a reduced number of companies. The first implication would be higher values estimated on the spatial models, although the average stock returns are similar to the original sample.

3.2.Econometric approach

Spatial econometric is a popular topic in regional economy, but its use on financial applications is innovative. Its main idea is to understand how the spatial dependence affects the dependent variable of a point in space relatively its value at another point in space (Almeida, 2012). This argument is important as the existence of spatial dependence or heterogeneity violates the Gauss-Markov assumptions making the estimation biased, inconsistent, and inefficient (Anselin, 1988; Almeida, 2012).

The researcher can use geographical distance or any concept as a measure of distance to the spatial weight matrix. Beck et al. (2006) apply spatial econometrics to social science using an economic distance. Asgharian et al. (2013) test eight metrics of spatial weight matrices also using economic distance to identify the contagion correlation in international stock markets. Likewise, Arnold et al. (2013) and Suchecka and Laszkiewicz (2011) use non-spatial criteria as a measure of correlation among stock returns[11].

Thus, the main concept of this technique is the construction of an adequate distance matrix to understand the observed problem and to model the spatial dependence of the units. If the researcher do not consider the spatial effects, an omission problem can affect the estimations, leading to erroneous interpretations. Depending on the spatial correlation source, Anselin (1988), LeSage and Pace (2009), and Elhorst (2014) establish a variety of spatial regression structures and we select the Spatial Autoregressive Model (SAR) and the Spatial Durbin Model (SDM)[12].

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[9] We select book-to-market and dividend-policy indicators as financial characteristics since Avramov (2002) use them on a time series analysis.

[10] This method uses an iterative Markov chain Monte Carlo (MCMC) method to impute missing values.

[11] Some researchers on spatial econometrics without geographic measures are Chagas (2014), Conley and Dupor (2003) and Beck et al. (2006).

[12] For more detailed explanations about the other models, see LeSage and Pace (2009) and Elhorst (2014).

Formally, the spatial autoregressive models (SAR) contain, as an independent variable, a spatial lag of the dependent variable which role is to incorporate a multidirectional relationship between the spatial units. That means a spatial observation shock can feed back other spatial observations through the spatial system (Anselin, 1988; LeSage and Pace, 2009). Consequentially, this implies an endogeneity problem (from Wy), which makes the maximum likelihood estimation model a method for unbiased and consistent parameters estimation. One can write a SAR model as $y = \rho Wy + X\beta + \varepsilon$, with Wy as the spatial lag of the dependent variable.

The spatial Durbin model (SDM) suggest the existence of a phenomenon that must use a spatial lag dependent variable (Wy) and a spatial lag exploratory variable (WX). Elhorst (2014) specify the panel data version of this model considering equation (2) in its matrix form[13].

$$\mathbf{y} = \rho\left(\mathbf{I_T} \otimes \mathbf{W}\right)\mathbf{y} + \mathbf{X}\beta + \left(\mathbf{I_T} \otimes \mathbf{W}\right)\mathbf{X}\theta + \boldsymbol{\iota}_\mathbf{n}\alpha + \varepsilon \tag{2}$$

where W is a $N \times N$ spatial weight matrix, and ρ is a vector of the spatial dependence. y is a vector with NT observations for the dependent variable; X is a $NT \times K$ matrix with K exploratory variables; β and θ are $K \times 1$ vector of parameters; ι_n is a $NT \times N$ matrix containing N individual constants; ε is a $NT \times 1$ vector of idiosyncratic error terms; I_T is the identity matrix, and $\otimes$ is the Kronecker product.

Note from (2) that the Spatial Durbin Model has endogeneity problems and, therefore, any estimation with ordinary least square is inconsistent. Thus, Anselin (1988), LeSage and Pace (2009) and Elhorst (2014) recommend the maximum likelihood estimator or the generalized method of moment as the estimation procedures that are unbiased and consistent. We use the maximum likelihood estimator for each spatial weight matrix and its spatial dependence. We consider a vector of NT observations consisting of quarterly stock returns and a $NT \times K$ matrix with K independent variables describe previously on subsection 3.1. Our empirical models are the following SAR and SDM presented on equations (3) and (4), respectively.

$$R_{it} = \rho \sum_{j=1}^{N} w_{ij}\, R_{jt} + BM_{it}\beta_1 + DP_{it}\beta_2 + ROE_{it}\beta_3 + KZ_{it}\beta_4 + \varepsilon_{it} \tag{3}$$

$$\begin{aligned} R_{it} = \rho \sum_{j=1}^{N} w_{ij}\, R_{jt} + BM_{it}\beta_1 + DP_{it}\beta_2 + ROE_{it}\beta_3 + KZ_{it}\beta_4 \\ + \sum_{j=1}^{N} w_{ij}\,(BM_{it}\theta_1 + DP_{it}\theta_2 + ROE_{it}\theta_3 + KZ_{it}\theta_4) + \varepsilon_{it} \end{aligned} \tag{4}$$

where w_{ij} is an element of one of the spatial weights matrices W_1 or W_2, R is the quarterly stock return; the set of independent variables consists of *ROE*, Dividend-price ratio (*D/P* ratio), book-to-market ratio (*B/M* ratio) and the financial constraint dummies (*KZ*). We calculate these variables as described in section 3.1. For each model, we also calculate the AIC criteria and apply a Hausman test to verify which model (fixed or random-effect) is more appropriate to the panel sample.

Since the key-point of spatial is the accurate choice of the spatial weight matrix for establishing the relationship between the spatial units, we use two criteria for this work: sectoral activity information and technological intensity for the Brazilian companies listed on

[13] A SAR model is nested in the SDM model when θ=0.

the Sao Paulo Stock Exchange. Belonging to a specific sector is a simple form to construct a proximity matrix[14]. We consider the companies spatial correlated if they operate on the same activity sector or if they operate in the same technological sector. This choice standardize the spatial weight variable between periods and smooth the Elhorst (2014) estimation procedure for panel data.

Therefore, we name the spatial weight matrix with sectoral proximity, as W_1, and the second matrix with the technological intensity, as W_2, both are time invariant. The final spatial weight matrices are quadratic and row-normalized. Its elements establish a binary relationship among spatial units (companies). We suppose company i as an influential factor on company j if both belong to the same activity sector and attribute a spatial weight equal to $\omega_{i,j} = \omega_{j,i} = 1$, otherwise the weights are $\omega_{i,j} = \omega_{j,i} = 0$. In spatial econometrics, we cannot say one spatial unit is correlated to itself, thus, $\omega_{i,i} = \omega_{j,j} = 0$, which indicates the main diagonal elements are equal to zero. These matrices allow a variability to the number of companies as competitors or cooperators accordingly the companies included on the database and its respective sector of activity or technological intensity.

To interpret the parameters correctly, one cannot use the same principal of traditional econometrics. On spatial econometric models, the interpretation is fundamental. Using the reduced form of the model (2), since the SAR model is nested in it, we can find the average effects of the spatial estimations. This form shows the effects produced on company i because of changes on the other companies as a result of their spatial relationship. LeSage and Pace (2009, p. 33) affirm "the parameters estimates contain a wealth of information on relationships among the observations".

Any change on an observation's exploratory variable can affect all the spatial units direct or indirectly. Thus, any interpretation has to use marginal effects for the partial derivatives. LeSage and Pace (2009) and Elhorst (2014) suggest two types of marginal effects known as direct and indirect effects. The first ones measure the impact of a change on an independent variable k for company i on the dependent variable of the same company. The indirect effects results of the change on an independent variable k for company j on the dependent variable of all the units. To find the average effects of the spatial estimations, we use the reduced form of equation (2) and derivate the marginal effects (5) using the Elhorst (2014) procedures

$$\begin{aligned}\begin{bmatrix}\frac{\partial E(y)}{\partial x_{ik}} & \cdots & \frac{\partial E(y)}{\partial x_{nk}}\end{bmatrix} &= \begin{bmatrix}\frac{\partial E(y_1)}{\partial x_{ik}} & \cdots & \frac{\partial E(y_1)}{\partial x_{nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(y_n)}{\partial x_{ik}} & \cdots & \frac{\partial E(y_n)}{\partial x_{nk}}\end{bmatrix} \\ &= (\boldsymbol{I} - \rho \boldsymbol{W})^{-1} \begin{bmatrix}\beta_k & w_{12}\theta_k & \cdots & w_{1n}\theta_k \\ w_{21}\theta_k & \beta_k & \cdots & w_{2n}\theta_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}\theta_k & w_{n2}\theta_k & \cdots & \beta_k\end{bmatrix}\end{aligned} \tag{5}$$

Elhorst (2014) and LeSage and Pace (2009) consider the direct effects for each spatial unit as the average of the main diagonal elements of the coefficient's matrix on equation (5), while the indirect effects are the off-diagonal elements (reflecting cross-partial derivatives)

[14] The technological intensity variable follow the sectorial classification of Cavalcante (2014) with four categories of innovative intensity that involves (1) high technological intensity; (2) medium-high technological intensity; (3) medium-low technological intensity; and (4) low technological intensity. We include a fifth category to aggregate Construction, and Agricultural and Fishing.

from each row. The authors suggest the summarized measure of these average marginal effects to understand the variable behavior by using the following expressions for the average direct, average indirect and average total effects

- Average direct impact: refers to the change on the i^{th} spatial unit of x_k on y_i, (company's own stock return), comprehending the main diagonal elements of the matrix in (5). That is $n^{-1}tr[(\boldsymbol{I_{NT}} - \rho(\boldsymbol{I_T} \otimes \boldsymbol{W}))^{-1}[\boldsymbol{I_N}\beta + (\boldsymbol{I_T} \otimes \boldsymbol{W})\theta]$;
- Average total impact: refers to the variation of only one spatial unit on all the spatial units. We calculate $n^{-1}\boldsymbol{\iota_n'}[(\boldsymbol{I_{NT}} - \rho(\boldsymbol{I_T} \otimes \boldsymbol{W}))^{-1}[\boldsymbol{I_N}\beta + (\boldsymbol{I_T} \otimes \boldsymbol{W})\theta]\boldsymbol{\iota_n}$; and
- Average indirect impact is the difference between the total average effect and the average direct effect and represents the feedback impacts on the global and local spatial system. It is all the off-diagonal elements on equation (5).

4. Empirical results

Table 1 summarize the statistical measures for our sample sectors indication mean and standard deviations for financial characteristics and technological intensity. Our results indicate that the sample consists of companies belonging to sectors such as Electricity, Steel and Metal, and Textile industry. Almost 30% of the companies have financial problems and were classified as constrained financially by the index KZ. Using the sectors of activity as a classification instrument, five sectors have most of its companies classified as financial constrained. Agriculture, Mining, Paper and Pulp and Telecommunications consist of a higher number of companies with financial problems, while Construction, Electronics, and Software and Data are in the opposite situation with more unconstrained companies. We cannot neglect to mention the set of companies that is neither financial constrained nor unconstrained corresponds to half of the sample and belongs to Textile industry, Industrial tools, Steel and Metal and Chemistry sectors (Table 1).

For the sectors' characteristics, Chemistry and Industrial tools, which are more innovative than others, the average stock returns are negative, and they experience worst opportunities for future investment by having a higher dividend payment. This can also be a reflex of the period analyzed which involves, mainly, the effects of the international crisis of 2008.

Although, Mazzucato and Tancioni (2012) indicate that the higher the innovation's uncertainty, the higher is the volatility of the company' stock returns, especially in technological change periods and these two sectors develop expensive basic researches. Moreover, Czarnitzki and Hotternrott (2012) suggest that innovation usually seek internal funding as its main financial resource since its uncertainty makes the search process for external funding more difficult. External funding demands a stable cash flow, but the innovative companies do not have this characteristic, especially the ones that make basic research or radical innovations.

Table 1 show that sectors with constrained firms are responsible for higher stock returns, highlighting Telecommunications, Paper and Pulp, and Nonmetal minerals. Fazzari et al. (2000) indicate that financial constrained companies keep a stock of cash rationally to protect themselves from possible delays, cancellations or complications of investment projects, which can be relate to the uncertainty of the innovative process. On the other hand, the Software and data sector has 5.1% of average stock return, the highest ROE and the third biggest investment opportunity, measure as the inverse of the book-to-market ratio. In addition, Steel and Metal, Textile industry and Electricity, the three biggest sectors on the sample, have an average stock return of 3.9%, 4.6% and 2.5% respectively.

Table 1 – Statistical summary for the sectors and their characteristics – 2007-2014

	Size (million R$)		**Sales (million R$)**		**Stock return**		**ROE**		**BM (Ln)**		**DP (Ln)**		**Innovative intensity**	**FC**
	Mean	**Stand. dev.**	**Mean**	**Stand. dev.**	**Mean**	**Stand. dev.**	**Mean**	**Stand. dev.**	**Mean**	**Stand. dev.**	**Mean**	**Stand. dev.**		
Agriculture and Fishing	1.43	1.51	0.23	0.33	1.10%	27.4%	-5.759	17.556	-0.31	1.484	-4.776	1.220	-	Yes
Food and Beverage	14.10	19.60	7.79	14.00	3.60%	33.8%	7.024	61.222	0.275	2.379	-2.485	1.531	Low	Middle
Construction	4.77	4.59	0.96	1.27	0.70%	33.0%	3.374	12.123	1.199	1.216	-2.106	1.589	-	No
Electronics	1.64	1.86	1.18	2.05	2.30%	34.4%	9.356	56.235	0.841	1.169	-0.104	1.393	High	No
Electricity	14.20	30.10	3.26	4.85	2.50%	32.8%	9.895	25.048	0.384	2.167	-0.715	1.449	High	Middle
Industrial tools	2.61	3.33	1.04	1.63	-0.30%	26.5%	4.695	9.024	0.757	1.007	-0.723	1.450	High	Middle
Mining	91.20	124.00	21.10	33.20	-2.60%	29.3%	25.487	147.147	0.201	1.237	-1.881	1.589	Low	Yes
Nonmetal minerals	0.54	0.31	0.31	0.27	5.30%	35.8%	6.599	32.260	0.812	0.510	-1.048	2.024	Low	Middle
Paper and Pulp	9.94	9.60	1.68	1.78	5.30%	28.3%	3.757	14.577	2.134	1.270	-1.366	0.986	Low	Yes
Oil and gas	150.00	267.00	45.50	86.60	0.80%	28.9%	-9.503	1417.727	0.513	1.542	-2.785	6.195	Low	Yes
Chemistry	6.42	13.20	3.34	7.62	-1.10%	24.2%	0.35	51.148	0.641	0.952	-0.707	1.388	High	Middle
Steel and Metal	11.10	21.20	4.09	9.38	4.60%	73.6%	-5.878	174.594	0.605	1.524	-0.619	1.324	Low	Middle
Software and data	4.06	4.09	2.02	1.77	5.10%	14.9%	66.904	129.162	-0.571	0.991	-2.595	0.685	High	No
Telecommunications	20.30	23.50	7.10	8.20	12.80%	119.8%	4.281	359.270	-1.11	2.987	-0.222	1.241	High	Yes
Textile industry	1.24	1.37	0.65	0.89	4.60%	55.3%	-0.211	258.165	1.148	1.708	-1.112	1.490	Low	Middle
Vehicles and Parts	3.13	5.97	1.40	2.52	4.40%	57.3%	0.359	87.352	0.847	1.587	-1.237	1.385	High	Middle

Source: database sample.

Note: size is the total assets of a company and sales is the sales revenue. The classification of innovative intensity sectors follows the proposition of OECD and the Cavalcante (2014)'s adaptation for the Brazilian case. These considerations are based on the industrial sectors and, therefore, do not include Agriculture and Construction sectors. FC represents financial constraint. We consider "Yes" as a higher presence of companies that are financial constrained, "No" for the financial unconstrained companies and "Middle" as the ones with median KZ index.

Size and sales can illustrate the importance of each branch of activity. One can see that, using this sample, the companies of Oil and gas and Mining sectors are the bigger ones and are responsible for the higher sales revenue of the sample but have financial difficulties for our financial constraint index. On the other hand, Nonmetal minerals, Textile Industry, Electronics and Agriculture and Fishing have smaller size relatively to the other sectors. For the sales revenue, Chemistry and Mining have the lowest stock return but, surprisingly, have a higher level of sales revenue on the period possibly as a response to the commodities' international prices. On the other hand, the other sectors have a lower level of this variable especially Telecommunications and Nonmetal Minerals, which have some type of financial restrictions (Table 1).

We use sectoral information to create the spatial weight matrices. Tables A.2 and A.3 on appendix A inform the linkages' distribution among companies for W_1 and W_2, respectively the sectorial and the technological intensity matrices, considering the sample employed. It is relevant to note that the elements of the spatial weight matrices are binary measures of the participation on a sector of activity or a technological intensity sector. The most important fact about these matrices is the non-existence of "islands" amid the companies. For the complete sample with the multiple imputation procedure, the highest number of linkages consists of 33 links between companies for the W_1 and 52 links amongst companies for the W_2. There is merely two cases where there is only one link (or one neighbor) for the sector of activity matrix whilst the lowest linkage on the technological matrix is 21 spatial units' connections. On the other hand, for the reduced sample, the highest number of connections for matrix W_1 consists of 22 links with only four companies having one link, while matrix W_2 has a maximum of 39 spatial linkages.

We present the spatial models estimated on table 2 using the empirical models from equations (3) and (4). Following the literature for spatial econometrics for financial data, we estimate the SAR and SDM models and adopt a microdata analysis for the Brazilian companies. Asgharian et al. (2013) and other authors provide evidences of a spatial dependence amidst global stock markets with these two models and we aim to understand the spatial dependence among Brazilian companies listed on Sao Paulo Stock Exchange. Since the Hausman tests reject the assumption of a better fit for the random-effect model, we present only the results for the fixed-effect models. Moreover, to simplify the analysis, we discuss only the results presented on the SAR models since their AIC criteria are the smallest ones vis-à-vis the SDM models, but all the analysis are extended to this last model type.

All models indicate a positive and statistical significant spatial dependence parameter. This suggests the commoving of Brazilian stock returns varying from 9.3% to 19.6% when considering sectorial and technological proximity measures. Therefore, a favorable stock return for one company on a specific sector can improve the stock return of a competitor on the same sector. For this reason, the consideration of this effect is important for an investor when deciding which equities will participate of his/her portfolio. Also, our findings reinforce the existence of a spatial dependence for Brazilian companies of the Fernandez (2011)'s work and the suggestions of Leary and Roberts (2014) regarding the existence of externalities and their effects on changes to one firm affecting the outcome at another firm. Leary and Roberts (2014, p. 155) show that "the primary channel through which peer firms may influence financial policy is via actions (i.e., peer firms' policy choices), as opposed to characteristics". We translate this channel as the belonging to the same sectoral or technological intensity measure. Gong and Weng (2016) also indicate the existence of financial contagion between stock returns for the Chinese companies and reinforce this same analysis for the Brazilian sample.

Table 2 – Estimated parameters of various models for the two samples

	Missing imputed				Reduced sample			
	Matrix W1		Matrix W2		Matrix W1		Matrix W2	
	SAR	SDM	SAR	SDM	SAR	SDM	SAR	SDM
ρ	0.131*** (0.025)	0.128*** (0.025)	0.196*** (0.048)	0.182*** (0.046)	0.102*** (0.027)	0.093*** (0.027)	0.103* (0.055)	0.070 (0.055)
σ^2_e	0.062*** (0.005)	0.062*** (0.005)	0.062*** (0.005)	0.062*** (0.005)	0.054*** (0.006)	0.054*** (0.006)	0.054*** (0.006)	0.054*** (0.006)
β coeffs.								
Constraint (dummy)	-0.043** (0.017)	-0.035** (0.018)	-0.044** (0.018)	-0.039** (0.017)	-0.013 (.018)	-0.011 (0.018)	-0.013 (0.018)	-0.011 (0.018)
Unconstraint (dummy)	-0.040*** (0.014)	-0.043*** (0.014)	-0.040*** (0.014)	-0.043*** (0.014)	-0.024* (0.013)	-0.029** (.012)	-0.024* (0.013)	-0.03** (0.012)
ROE	4.5E-05* (2.6E-05)	4.6E-05* (2.6E-05)	4.5E-05* (2.6E-05)	4.4E-05* (2.6E-05)	-4.6E-05 (3.5E-05)	-4.7E-05 (3.6E-05)	-4.6E-05 (3.6E-05)	-4.8E-05 (3.5E-05)
Leverage	3.0E-04 (3.7E-04)	3.0E-04 (3.6E-04)	3.0E-04 (3.7E-04)	2.9E-04 (3.7E-04)	-2.2E-04 (3.2E-04)	-2.2E-04 (3.1E-04)	-2.1E-04 (3.2E-04)	-2.4E-04 (3.1E-04)
BM (ln)	-0.019*** (0.005)	-0.020*** (0.005)	-0.019*** (0.005)	-0.020*** (0.005)	-0.044*** (0.008)	-0.046*** (0.008)	-0.045*** (0.008)	-0.046*** (0.008)
DP (ln)	-0.016*** (0.006)	-0.017*** (0.006)	-0.016*** (0.006)	-0.016*** (0.006)	-0.056*** (0.015)	-0.055*** (0.016)	-0.056*** (0.015)	-0.056*** (0.015)
θ coeffs.								
Constraint (dummy)	-	-0.087** (0.041)	-	-0.118 (0.084)	-	-0.118** (0.055)	-	-0.203** (0.098)
Unconstraint (dummy)	-	0.002 (0.041)	-	0.011 (0.105)	-	0.009 (.036)	-	-0.04 (0.065)
ROE	-	-2.2E-05 (1.5E-05)	-	-1.1E-04 (7.7E-05)	-	1.4E-04 (1.3E-04)	-	2.6E-05 (2.0E-04)
Leverage	-	-5.6E-04 (6.2E-04)	-	-8.9E-04 (11.E-03)	-	2.2E-04 (9.1E-04)	-	5.0E-04 (1.2E-03)
BM (ln)	-	0.010 (0.009)	-	0.018 (0.017)	-	-0.012 (0.012)	-	-0.011 (0.019)
DP (ln)	-	0.003 (0.008)	-	-0.009 (0.017)	-	-0.046 (0.029)	-	-0.078 (0.052)
Obs.	5146	5146	5146	5146	4030	4030	4030	4030
AIC	308.88	308.94	316.49	320.28	-300.38	-300.08	-289.94	-291.31
Hausman	21.51**	31.93***	82***	109.37***	32.15***	46.13***	24***	31.72***
R^2	0.017	0.013	0.018	0.011	0.022	0.018	0.022	0.014
Mean of fixed-effects	-0.002	0.02	-0.0005	0.017	0.053	0.11	0.053	0.154

Note: the SAR model we estimate is

$$R_{it} = \rho \sum_{j=1}^{N} w_{ij}\, R_{jt} + BM_{it}\beta_1 + DP_{it}\beta_2 + ROE_{it}\beta_3 + KZ_{it}\beta_4 + \varepsilon_{it}$$

For the SDM model, we use

$$R_{it} = \rho \sum_{j=1}^{N} w_{ij}\, R_{jt} + BM_{it}\beta_1 + DP_{it}\beta_2 + ROE_{it}\beta_3 + KZ_{it}\beta_4 + \sum_{j=1}^{N} w_{ij}\,(BM_{it}\theta_1 + DP_{it}\theta_2 + ROE_{it}\theta_3 + KZ_{it}\theta_4) + \varepsilon_{it}$$

where *wij* is an element of the spatial weights matrix *W*, *R* is the quarterly stock return for each company over the period analyzed; the set of independent variables is described in section 3.1. We control for leverage since there is a correlation with ROE for the missing imputation sample. Leverage is the ratio between total assets and book value. Matrix W_1 consists of the sectoral activity measure and matrix W_2 is the technological intensity measure. R^2 is the goodness-of-fit. ***, **, and * represents statistical significance at the 1%, 5%, and 10% level, respectively.

A negative commoving on stock returns presents itself for the financial constrained firms, although the results for the reduced sample are inconclusive and not statistical significant. We suggest there is an important common restriction factor on stock returns for these firms and some of these indications have a clear relationship with the period considered on the analysis that corresponds to the Great Recession and its developments. Lamont et al. (2001) inform that firms with financial problems must compensate their investors by offering positive returns with the increase of financial constraints. There is a positive and statistical significant effect for the return on equity, the profitability variable, for the multiple imputation sample. Thus, an increase on the profitability of the firm will benefit the investor's investment decision if these companies are in his/her portfolio, even though the economic extent is smaller than the other variables.

One can also conclude the importance of the value fundamentals as B/M ratio, and the D/P ratio to the stock return of one company. The D/P ratio (dividend-price ratio) is a good forecaster of stock returns, since the lower than one this ratio is the bigger the investment and, therefore, the future stock return. On the other hand, the inverse of the B/M ratio (book-to-market ratio) is a good indicator of the growth opportunities. Companies with a higher dividend payment and book value will have the lowest stock returns through all the models estimated.

Since LeSage and Pace (2009) and Elhorst (2014) suggest the use of the marginal effects known as direct and indirect effects as the correct form to understand the spatial econometrics results, table 3 describes these information for all the models and considering each spatial weight matrices. The direct effects measure the impact of a change on a specific independent variable, as B/M ratio or KZ dummies, for one company on its dependent variable. The indirect effects involve the change on a specific independent variable for company A on the dependent variable of all the units, that is, a spillover effect. An important aspect is that the coefficients from the reduced sample are relatively higher for most variables than the multiple imputation sample. We indicate this fact already in the information provided on table A.1 with the statistical summary for these samples. The only difference occurs with the financial constrained variable for the average bands of KZ index that are lower for the reduced sample.

The main effect is the direct one with almost 90% of the total effect for all variables. Therefore, the knowledge of the financial characteristics of some company can support the investor decisions and improve the understanding of the shocks on their own stock returns. Companies that are on either tails of the KZ index's distribution (constrained and unconstrained firms) have a higher and statistically significant reduction of stock return that can vary from 4.0 to 4.4%. On the other hand, the increase of 1% on the book value of a company decrease its stock return in 1.9% or 4.5%. Therefore, companies with lower opportunity to growth on the Brazilian market have lower stock return. This result is consistent with Gong and Weng (2016) since they also found evidence of a negative, statistically significant, relation to individual stock returns on the Chinese market. Finally, the dividend policy is essential for the favorable stock returns since an increase of 1% on the dividend-price ratio can decrease its stock return in 1.6% and 5.6%, respectively for the imputed and the reduced sample. For the imputed sample, the return on equity is positive and statistically significant, but its economic magnitude is tiny whilst for the reduced sample, this variable is not statistically important.

Table 3 – Direct, indirect and total marginal effects estimated

	Missing imputed				**Reduced sample**			
	Matrix W1		**Matrix W2**		**Matrix W1**		**Matrix W2**	
	SAR	**SDM**	**SAR**	**SDM**	**SAR**	**SDM**	**SAR**	**SDM**
Direct Effect								
Constraint	-0.044***	-0.037**	-0.044***	-0.041**	-0.024*	-0.013	-0.013	-0.012
(dummy)	(0.017)	(0.017)	(0.017)	(0.017)	(0.012)	(0.018)	(0.018)	(0.018)
Unconstraint	-0.040***	-0.043***	-0.040***	-0.043***	-0.013	-0.029**	-0.024**	-0.030**
(dummy)	(0.014)	(0.014)	(0.014)	(0.014)	(0.018)	(0.012)	(0.012)	(0.012)
ROE	4.6E-05*	4.7E-05*	4.6E-05***	4.4E-05*	-4.7E-05	-4.55E-05	-4.6E-05	-4.9E-05
	(2.4E-05)	(2.5E-05)	(2.4E-05)	(2.5E-05)	(3.4E-05)	(3.4E-05)	(3.4E-05)	(3.4E-05)
BM (ln)	-0.019***	-0.020***	-0.019***	-0.019***	-0.044***	-0.046***	-0.044***	-0.046***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)
DP (ln)	-0.016***	-0.017***	-0.016***	-0.016***	-0.056***	-0.055***	-0.056***	-0.056***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.015)	(0.015)	(0.015)	(0.014)
Leverage	2.9E-04	2.9E-04	2.9E-04	2.8E-04	-2.1E-04	-2.06E-04	-2.1E-04	-2.3E-04
	(3.5E-04)	(3.5E-04)	(3.5E-04)	(3.5E-04)	(2.9E-04)	(2.9E-04)	(2.9E-04)	(2.9E-04)
Indirect Effect								
Constraint	-0.007**	-0.102**	-0.011**	-0.148	-0.002	-0.123**	-0.002	-0.222**
(dummy)	(0.003)	(0.045)	(0.006)	(0.106)	(0.002)	(0.06)	(0.003)	(0.109)
Unconstraint	-0.006**	-0.005	-0.010**	-0.024	-0.003*	0.008	-0.003	-0.044*
(dummy)	(0.002)	(0.048)	(0.004)	(0.134)	(0.002)	(0.04)	(0.002)	(0.07)
ROE	6.8E-06*	-1.8E-05	1.2E-05	-1.2E-04	-5.26E-06	1.46E-04	-5.7E-06	2.8E-05
	(3.8E-06)	(1.7E-05)	(7.3E-06)	(9.2E-05)	(4.1E-06)	(1.3E-04)	(5.7E-06)	(2.1E-04)
BM (ln)	-0.003***	0.008	-0.005**	0.018	-0.005***	-0.018	-0.005	-0.015
	(0.001)	(0.010)	(0.002)	(0.021)	(0.002)	(0.013)	(0.003)	(0.020)
DP (ln)	-0.002***	0.001	-0.004**	-0.014	-0.006**	-0.057**	-0.007	-0.090*
	(0.001)	(0.008)	(0.002)	(0.02)	(0.002)	(0.029)	(0.004)	(0.055)
Leverage	4.3E-05	-5.9E-04	7.1E-05	-1.0E-03	-2.38E-05	2.20E-04	-2.5E-05	-5.2E-04
	(5.3E-05)	(6.8E-04)	(9.1E-05)	(1.3E-03)	(3.5E-05)	(9.3E-04)	(4.3E-05)	(1.2E-03)
Total Effect								
Constraint	-0.050**	-0.139***	-0.055**	-0.189*	-0.015	-0.136**	-0.015	-0.234
(dummy)	(0.020)	(0.048)	(0.022)	(0.108)	(0.020)	(0.062)	(0.021)	(0.11)
Unconstraint	-0.046***	-0.049	-0.050***	-0.067	-0.027	-0.021	-0.027**	-0.074
(dummy)	(0.016)	(0.049)	(0.018)	(0.132)	(0.014)	(0.042)	(0.014)	(0.07)
ROE	5.2E-05*	2.9E-05	5.7E-05*	-7.7E-05	-5.21E-05	1.01E-04	-5.2E-05	-2.1E-05
	(2.8E-05)	(3.4E-05)	(3.1E-05)	(1.0E-04)	(3.7E-05)	(1.4E-04)	(3.8E-05)	(2.2E-04)
BM (ln)	-0.022***	-0.012	-0.024***	-0.002	-0.049***	-0.064***	-0.050***	-0.061***
	(0.006)	(0.011)	(0.006)	(0.022)	(0.009)	(0.015)	(0.01)	(0.022)
DP (ln)	-0.018***	-0.016	-0.019***	-0.030	-0.062***	-0.113***	-0.063***	-0.146***
	(0.007)	(0.010)	(0.007)	(0.02)	(0.017)	(0.026)	(0.017)	(0.052)
Leverage	3.4E-04	-3.1E-04	3.7E-04	-7.4E-04	-2.33E-04	1.41E-05	-2.3E-04	-7.5E-04
	(4.0E-04)	(7.5E-04)	(4.4E-04)	(1.3E-03)	(3.3E-04)	(9.8E-04)	(3.3E-04)	(1.3E-03)

Note: Matrix W_1 consists of the sectoral activity measure and matrix W_2 is the technological intensity measure. We control for leverage since there is a correlation with ROE for the missing imputation sample. Leverage is the ratio between total assets and book value. R^2 is the goodness-of-fit. ***, **, and * represents statistical significance at the 1%, 5%, and 10% level, respectively.

The feedback effect for the spatial system occurs on the indirect effects. Here we can contribute to the literature debate by identifying two main feedbacks on stock return for company *i*: a negative effect of other companies that have financial constraints and a negative effect from the financial fundamentals of competitors or suppliers. Leary and Roberts (2014) said peer effects are essential to companies in the same industries. For instance, an oil spill of a company has noticeable repercussions for its industry via the stimulus on future regulations. This occurs when we consider matrix W_1, but not for matrix W_2 and its ability to gather different sectors on the same technological intensity. Therefore, we believe knowledge is the key to capture better stock returns for the investors. If a company belongs to a baseline group consisting of companies that have financial problems, then it may contribute to decrease the stock return of a competitor on 0.7% for the imputed sample. Already, for the technological proximity, we conclude that financial problem can be a response for the innovative investment process and, hence, will bring lower opportunities to growth and lower stock returns for the short run (a decrease of 1.1% for the imputed sample). The unconstrained companies have the same problems but with lower values since the period analyzed is critical to the Brazilian companies listed on Sao Paulo Stock Exchange.

For the second type of feedback, competitors with a higher dividend payment can negatively influence the stock returns of the companies in the baseline group since the investor can see the relationship amongst them as an indicator of lower expected stock returns for the group. This is also the conclusion we make for the B/M ratio. Competitors with a higher book value – or that lost some market value on the period – can penalize the baseline group with a decrease from 0.3% to 0.5% on stock returns as an indication of the decrease in opportunity growth. The reduced sample is responsible for the biggest feedback reductions of the stock return in baseline groups. This means that 130 companies on the reduced sample, when aggregate by branch of activity (matrix W_1), are more susceptible to have a 0.5% or 0.64% decrease in their stock return if the sectoral group is known as a higher dividend distributor.

5. Conclusions

In this paper, we have tested for spatial dependence in a panel of 166 Brazilian companies over the period of 2007-2014. We use two economic distance measures for the construction of the spatial weight matrices: branch of activity and technological intensity of the sector. To our knowledge, this is the first time the spatial econometrics is applied to micro econometric analysis of financial data in Brazil. International empirical literature has shown the existence of spatial dependence on financial analysis and its importance for the construction of portfolios.

Our results indicate a spatial dependence in the Brazilian companies listed on the stock exchange for two distance measures and its positive effect on the stock returns. Hence, the knowledge of boom periods for the competitors can positively improve the stock return of a company in the same baseline group. Therefore, companies in the same branch of activity (or the same technological intensity of it sector) can benefit themselves by the good phase of competitors, obtaining positively greater stock returns not only for the maintaining of their financial foundations, but by the interaction with the companies of their group.

Contrariwise, the B/M ratio and the D/P ratio are important financial fundamentals that need consideration by the investor if a higher stock return is their main decision. This is also an indication of the risk of a portfolio behavior with the companies from the same group. Our results reveal that companies with more investment opportunities and less dividend payment have increases on their stock returns as a result of the spillover of companies with the same characteristics.

We have two main limitations: the construction of the spatial weight matrices since it is difficult to create a measure of spatial dependence for financial data, and the period considered for the analysis. The international crisis from 2008/2009 had great influence on the stock returns for the Brazilian companies and was able to reduce the Brazilian capital market's returns for either the financial constrained and unconstrained companies counted on this paper. We suggest future studies seek different strategies to identify competitors and customer/supplier relationships amongst other industries and the inclusion of an extended period to understand the companies listed on Sao Paulo Stock Exchange.

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Appendix A

Table A.1 – Imputation missing data for the spatial analysis

	Incomplete data		Missing imputation		Reduced sample	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
KZ index	1.283	0.7976	1.283	0.7976	1.252	0.8272
BM (Ln)	0.6257	1.8561	0.5989	1.8566	0.763	1.653
DP (Ln)	-1.2389	1.9496	-1.2213	1.9604	0.368	0.873
Stock return (ln)	-0.0163	0.2860	-0.0157	0.2856	-0.0131	0.2727
ROE	4.078	258.105	4.032	258.076	3.65	126.55

Source: database sample.

Table A.2 – Spatial units' distribution for matrices W_1 and W_2 for sample with 166 companies

W_1	**Spatial links**	1	2	3	4	6	7	12	18	19	32
	Companies	2	6	12	5	7	16	26	19	40	33
W_2	**Spatial links**	21	22	30	36	52					
	Companies	22	23	31	37	53					

Source: database sample.

Table A.3 – Spatial units' distribution for matrices W_1 and W_2 for sample with 130 companies

W1	**Spatial links**	1	2	3	4	5	6	10	14	15	16	18	22
	Companies	4	6	4	5	18	7	11	2	14	17	19	23
W2	**Spatial links**	16	18	22	30	39							
	Companies	17	19	23	31	40							

Source: database sample.