INTERRELATIONSHIPS BETWEEN THE STOCK RETURNS OF BRAZILIAN COMPANIES THAT MAKE UP THE SÃO PAULO STOCK EXCHANGE INDEX

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Abstract

The objective of this paper was to verify the interrelationships between the stock returns of 33 Brazilian companies that make up the São Paulo Stock Exchange Index (IBOVESPA), from January 2006 to June 2018, using the principal components analysis (PCA), applied on the residuals of the VAR-GARCH model. In general, the results of this study revealed the presence of interrelation between the stock returns which compose the IBOVESPA, and that the interdependence and the correlation pattern vary over time, which can directly impact the investment decisions of economic and financial agents, especially concerning the diversification of their asset portfolios.

Keywords: Financial market; Brazil; dependent data; principal component analysis; financial econometrics.

JEL: C55; C58; G11

1 INTRODUCTION

The capital market has an important role in the development of any economy. However, regarding Brazil, the benefits from this market were late, since the country faced a long period of high inflation and economic instability, which led to negative effects on the stock market. The Real Plan was a milestone for the Brazilian stock market and started a vigorous growth pattern, especially from 2003 onwards (Padmanabhan, 2015). According to Nunes, Costa, and Meurerii (2005), such growth led to an increase in the capitalization of the stock market, both in terms of turnover and allocative efficiency levels. Furthermore, the Brazilian stock market has attracted the attention of investors and companies due to showing itself as an opportunity for foreign investors who seek to diversify their portfolios. This behavior can also be observed for internal investors.

Unlike most developed countries, the Brazilian stock market is heavily concentrated in a small number of companies. The most representative sectors of the São Paulo Stock Exchange Index (IBOVESPA) – considering the portfolio on July 4, 2018 – were the following: banking; oil and gas extraction; metal mining; generation, transmission and distribution of electricity;

and beverage industry. Therefore, any negative effect on the companies that make up these sectors can cause significant negative impacts on the IBOVESPA and the Brazilian economy in general. To Hermann and Martins (2012), stock market growth is a positive indicator for the economy, creating favorable expectations for both the issuing companies and for the stock acquirers. However, even with relevant positive externalities, the stock market is not risk-free, as any other segment of the financial market. According to Hermann and Martins (2012), resource losses may happen to individual investors and financial institutions and, depending on the proportion of losses, trigger a series of contagion effects, i.e., impacts on other investors and institutions, segments of the financial market, and even on the non-financial sector.

To Jubert et al. (2008), to diversify their investments, global investors focus their attention on the dynamics of international markets. In the case of investors focused on the Brazilian market, the sectorial approach is paramount in reducing the risk of stock portfolios. Furthermore, it is expected that stocks from companies that operate in the same economic activity present similar behaviors. This is because the companies of the same sector are generally affected by the same factors of the competitive environment and guided by the same legislation. Therefore, sector diversification is crucial for the investor dedicated to a given market, and who seeks to reduce non-systematic risks. Baca, Garbe, and Weiss (2000), in a study of the seven major asset markets in the world, argue that the influence of country-specific components under the variation of stock returns has declined, while the impact of sectoral components has remained relatively constant or increased.

Over the last two decades, the debates on financial integration have intensified, especially when global economic crises occur. According to Billio et al. (2015), to measure the co-movements (interrelationships) and to verify the evolution over time of the financial markets is fundamental, since such correlations tend to guide economic agents (politicians and investors) in their future decisions. In terms of empirical analysis of the interrelationships in the financial markets, two main sets of studies can be cited: 1. those based on the evolution models of financial assets, which assume that financial markets are efficient; and 2. studies on the analysis of the evolution of the correlations and co-movements of the prices of the traded assets. To Fuinhas, Marques and Nogueira (2014), at the global level, the degree of financial integration enables a perception about the behavior of the capital flow between the economies (countries); thus, being crucial in the understanding of the co-movement of markets. In this case, the analysis of the behavior of the correlations between the asset prices (or stock prices) becomes an important tool to evaluate the co-movements (interrelationships) in the financial markets.

In Brazil, few studies have dealt with the interrelations between the financial indexes and the stock returns of the companies of the São Paulo Stock Exchange (BOVESPA), especially about to econometric research. Among the studies, one can cite Jubert et al. (2008), who analyzed the univariate volatility pattern of the following Brazilian market stock indexes: IBOVESPA, Electrical Energy Index (IEE), Corporate Sustainability Index (ISE), Industrial Index (INDX) and Telecommunications Index (ITEL). The authors used conditional heteroscedasticity models of the GARCH family. Medeiros (2012), using a univariate conditional heteroscedasticity approach, analyzed the volatility of four sectoral financial indexes of BOVESPA: IEE, ITEL, Financial Index (IFNC) and INDX. Ferreira and Mattos (2012) analyzed the contagion effect of the subprime crisis on IBOVESPA and some sectoral market indices, based on the study of the covariance pattern estimated between Brazilian and US stock market indices. The empirical analysis was based on the multivariate GARCH-BEKK models. It is also worth noting that some studies (e.g., Kamogawa et al., 2006; Andrade, 2015) that adopted the PCA technique in the context of the Brazilian stock market did not consider the problems arising from data dependence.

To the best of our knowledge, there are no studies that verify the interrelationship between the stocks of companies that make up the IBOVESPA portfolio. Thus, this study examined the correlation between the stock returns of 33 companies that make up the IBOVESPA, from January 2006 to June 2018, through of the principal components analysis (PCA)[1]. It should be noted that, among the studies that adopt PCA, a common feature in the time domain is to neglect data dependence. However, in its classical form, this technique assumes that the data are independent (Anderson, 2003; Johnson & Wichhern, 2007). According to Jolliffe (2002), the use of PCA in multivariate time series requires some care in its application, especially for series that show more than weak dependence. To Matteson and Tsay (2011) and Hu and Tsay (2014), in multivariate time series, the principal components are contemporaneously uncorrelated. However, lagged cross-correlations may be nonzero, condition-

1 Principal component analysis (PCA) is one of the techniques used to evaluate the co-movements (interrelationships) of financial markets. According to Volosovych (2011), few articles have used the PCA technique, individually or paired to other techniques, to measure financial integration. Some examples are: Nellis (1982), Gagnon and Unferth (1995), Mauro, Sussman, and Yafeh (2002), Bordo and Murshid (2006), among others.

al correlations may be nonzero, and cross-correlations of nonlinear transformations such as the square process may be nonzero. Then, in this study, PCA is applied on the residuals of the VAR-GARCH model.

Furthermore, since most of the existing studies limit the use of PCA to the calculation of the principal components over a given time (Volosovych, 2011), the analyses were segmented as follows: 1. from 01/02/2006 to 05/20/2008, i.e., before the most acute effects of the American subprime crisis; 2. from 05/21/2008 to 12/31/2009, i.e., the beginning of the subprime crisis in Brazil, until the stock market, in terms of IBOVESPA, reached a similar level before the crisis; 3. from 01/04/2010 to 01/20/2016, in which IBOVESPA maintained levels well above the worst moments of the subprime crisis, but with oscillations (positive and negative) and downward trend – this period was characterized by intense anti-corruption efforts in Brazil, with the beginning of the so-called "Operation Car Wash"; and 4. from 01/21/2016 to 06/29/2018, i.e., a new recovery of the Brazilian stock market after IBOVESPA showed its lowest value (01/20/2016) after the subprime crisis due to political and economic problems. In this period, the impeachment of the president of Brazil occurred. According to Hu et al. (2008) and Tam (2014), the interdependence between financial markets may vary over time, since each period presented specific factors that may change the correlations between the stock returns, such as crises, political and economic events, environmental events, natural movement of financial markets, among others.

This article is structured as follows. In addition to this introduction, Section 2 describes the classical principal component analysis (PCA). The results and discussions are shown in Section 3. Finally, the final considerations are presented in Section 4.

2 PRINCIPAL COMPONENT ANALYSIS (PCA)[2]

The main objective of PCA is to explain the variance-covariance structure of a variable set using some of linear combinations of these variables. Although, in general, components are required to reproduce the total variability

2 Item based on Johnson and Wichern (2007).

of the system, generally, most of the original data can be accounted for a small number of principal components.

Algebraically, the principal components are linear combinations of p random variables $Y_1, Y_2, ..., Y_p$. Geometrically, these linear combinations represent the selection of a new coordinate system, by the rotation of the original system, with $Y_1, Y_2, ..., Y_p$ being the axis of the coordinates. The new axes demonstrate directions with maximum variability and provide a simpler and more parsimonious covariance structure.

The principal component technique depends only on the covariance matrix (Σ) or the correlation matrix (ρ) of $Y_1, Y_2, ..., Y_p$. The development of PCA does not require the assumption of multivariate normality. However, inferences can be made from the sample components when the population follows normal multivariate distribution.

Consider the random vector $Y' = [Y_1, Y_2, ..., Y_p]$, with covariance matrix given by Σ, with eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0$. Suppose the linear combinations,

$$\begin{aligned} X_1 &= a_1'Y = a_{11}Y_1 + a_{12}Y_2 + \ldots + a_{1p}Y_p \\ X_2 &= a_2'Y = a_{21}Y_1 + a_{22}Y_2 + \ldots + a_{2p}Y_p. \\ &\vdots \\ X_p &= a_p'Y = a_{p1}Y_1 + a_{p2}Y_2 + \ldots + a_{pp}Y_p \end{aligned} \tag{1}$$

By adopting some algebraic properties, one obtains

$$Var(X_i) = a_i'\Sigma a_i,\ i = 1,2,\ ...,\ p, \tag{2}$$

$$Cov(X_i,\ X_k) = a_i'\Sigma a_k,\ i,\ k = 1,2,\ ...,\ p. \tag{3}$$

The principal components are the linear combinations $X_1, X_2, ..., X_p$ whose variances given in Equation (2) are the largest possible. In this case, the first component is the linear combination with the maximum variance. That is, it maximizes $Var(X_1) = a_1'\Sigma a_1$. It is clear that the $Var(X_1) = a_1'\Sigma a_1$ can be raised by multiplying any a_1 by some constant. To eliminate this indeterminacy, it is convenient to restrict attention to coefficient vectors of length equal to one. Then, it is defined:

First principal component = linear combination of $a_1'Y$ that maximizes $Var(a_1'Y)$, subject to $a_1'a_1 = 1$;

Second principal component = linear combination of $a_2'Y$ that maximizes $Var(a_2'Y)$, subject to $a_2'a_2 = 1$ and $Cov(a_1'Y, a_2'Y) = 0$.

In the i-th step:

i-th principal component = linear combination of $a_i'Y$ that maximizes $Var(a_i'Y)$, subject to $a_i'a_i = 1$ and $Cov(a_i'Y, a_k'Y) = 0$, for $k < i$.

Result 1. Let Σ be the covariance matrix associated with the random vector $Y' = [Y_1, Y_2, \ldots, Y_p]$. Let Σ have eigenvalue-eigenvector pairs (λ_1, e_1), (λ_2, e_2), …, (λ_p, e_p), in which $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0$. Then, the i-th principal component is given by,

$$X_i = e_i'Y = e_{i1}Y_1 + e_{i2}Y_2 + \cdots + e_{ip}Y_p,\ i = 1,2, \ldots, p. \tag{4}$$

Then,

$$Var(X_i) = e_i'\Sigma e_i = \lambda_i,\ i = 1,2, \ldots, p, \tag{5}$$

$$Cov(X_i, X_k) = e_i'\Sigma e_k = 0,\ i \neq k. \tag{6}$$

It is worth mentioning that, if some λ_i are equal, the choice of the corresponding coefficient vector e_i and, hence, X_i is not unique.

For Result 1, the principal components are uncorrelated and have variances equal to the eigenvalues of the covariance matrix Σ.

Result 2. Let $Y' = [Y_1, Y_2, \ldots, Y_p]$ have covariance matrix Σ, with eigenvalue-eigenvector pairs $(\lambda_1, e_1), (\lambda_2, e_2), \ldots, (\lambda_p, e_p)$, in which $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0$. Let $X_1 = e_1' Y, X_2 = e_2' Y, \ldots, X_p = e_p' Y$ be the principal components. So,

$$\sigma_{11} + \sigma_{22} + \cdots + \sigma_{pp} = \Sigma_{i=1}^{p} VAR(Y_i) = \lambda_1 + \lambda_2 + \cdots + \lambda_p = \Sigma_{i=1}^{p} VAR(X_i). \qquad (7)$$

By Result 2,

$$\text{total population variance} = \sigma_{11} + \sigma_{22} + \cdots + \sigma_{pp} = \lambda_1 + \lambda_2 + \cdots + \lambda_p, \qquad (8)$$

and consequently, the proportion of the total variance due to the k-th main component is given by:

$$\left(\begin{array}{c} \textit{Proportion of the total} \\ \textit{population variance due to the} \\ k - \textit{th principal component} \end{array} \right) = \frac{\lambda_k}{\lambda_1 + \lambda_2 + \cdots + \lambda_p}, \; k = 1,2, \ldots, p. \qquad (9)$$

Additionally, each component of the coefficient vector $e_i' = [e_{i1}, \ldots, e_{ik}, \ldots, e_{ip}]$ must also be inspected. The e_{ik} magnitude measures the importance of the k-th variable in the i-th principal component, independent from the other variables. In particular, e_{ik} is proportional to the correlation coefficient between X_i and Y_k.

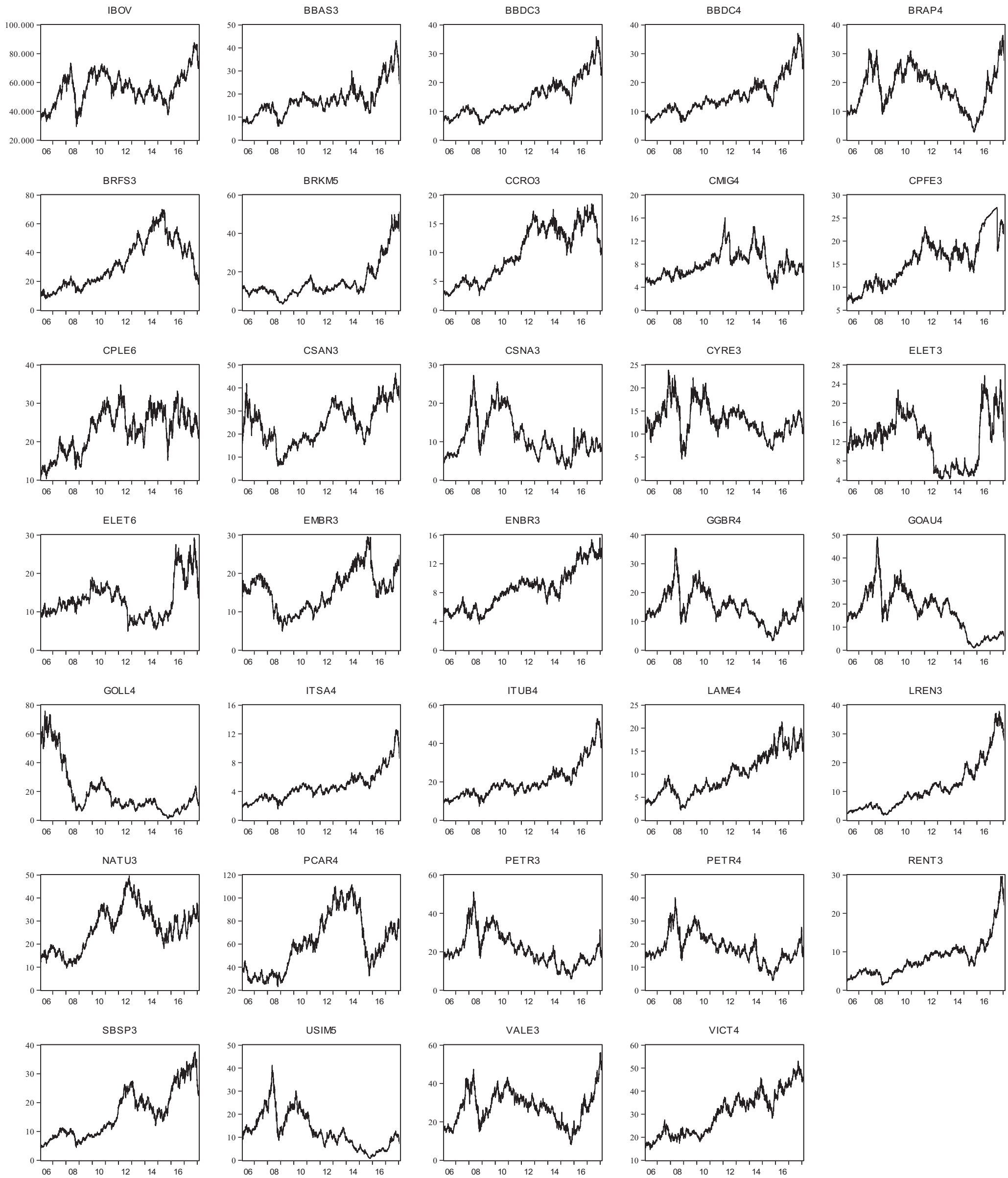
3 RESULTS AND DISCUSSIONS

3.1. Variables

The data of this research refer to the adjusted daily closing values (end-of-session quotations) of 33 company stocks that compose the São Paulo Stock Exchange Index (IBOVESPA). The analysis comprised the period from January 2006 to June 2018, with daily frequency. It must be noted that, considering the portfolio on 04/04/2018, the IBOVESPA consisted of 67 stocks (common – ON and preferred – PN). Since many of these stocks do not have some available information and/or became part of IBOVESPA after June 2006, this study only used 33 company stocks, which represented 56.86% of the theoretical amount of the index in the period in question. The data were collected from Investing.com and BM&FBOVESPA and correspond to: Banco do Brasil (BBAS3, ON NM); Bradesco (BBDC3, ON EJ N1); Bradesco (BBDC4, PN EJ N1); Bradespar (BRAP4, PN N1); BRF AS (BRFS3, ON NM); Brasken (BRKM5, PNA N1); CCR SA (CCRO3, ON NM); Cemig (CMIG4, PN N1); CPFL Energia (CPFE3, ON NM); Copel (CPLE6, PNB N1); Cosan (CSAN3, ON NM); Companhia Siderúrgica Nacional (CSNA3, ON); Cyrela Realt (CYRE3, ON NM); Eletrobras (ELET3, ON N1); Eletrobras (ELET6, PNB N1); Embraer (EMBR3, ON EJ NM); Energias BR (ENBR3, ON NM); Gerdau (GGBR4, PN N1); Gerdau Metalurgia (GOAU4, PN N1); Gol (GOLL4, PN N2); Itausa (ITSA4, PN N1); Itauunibanco (ITUB4, PN ED N1); Lojas Americanas (LAME4, PN N1); Lojas Renner (LREN3, ON EJ NM); Natura (NATU3, ON NM); Pão de Açúcar – CBD (PCAR4, PN N1); Petrobras (PETR3, ON N2); Petrobras (PETR4, PN N2); Localiza (RENT3, ON EJ NM); Sabesp (SBSP3, ON NM); Usiminas (USIM5, PNA N1); Vale (VALE3, ON NM); and, Telefônica Brasil (VIVT4, PN EJ).

Figure 1

Evolution of the stock value from January 2006 to June 2018



Source: Prepared by the authors based on research data.

The evolution of stock values over the period can be seen in Figure 1. In addition to the 33 stocks, the IBOVESPA index is also shown. It should be noted that the stocks showed great volatility, undergoing growth and decreasing phases, according to economic conditions, whether global or national. The crisis that began in mid-2007 in the United States (subprime crisis), for example, affected several world economies in terms of economic growth, employment, etc., as well as the financial market. The impact of the crisis was mainly observed in Brazil in 2008 and 2009, as can be seen in the graph refers to the IBOVESPA index (IBOV). The IBOVESPA reached its lowest value on 10/27/2008. After that, the index presented growth due to economic recovery, achieving the highest value on 04/11/2010. However, as a result of global economic facts and internal political problems, as of 04/11/2010, the Brazilian financial market presented great swings, with a downward trend of the IBOVESPA, which led to a very low index value on 01/20/2016. The market then started to grow again.

One of the assumptions of classical principal component analysis is that the data are stationary. Because stock values are usually non-stationary, they are often turned into returns. In this study, the following tests proved the non-stationarity of the series: Augmented Dickey-Fuller – ADF (Dickey & Fuller, 1981); Phillips-Perron – PP (Phillips & Perron, 1988); and, Kwiatkowski-Phillips-Schmidt-Shin – KPSS (Kwiatkowski et al., 1992). Here, the stationary processes were defined as $r_t = \text{In}(y_{t-1})$, in which y_t is the vector of daily values of stocks. Table 1 summarizes the basic descriptive statistics of stock returns (r_t). For several returns, the distributions appear to be asymmetric, since there are positive and negative estimates of skewness. All return series have heavy tails and show a strong deviation from normality. Also, the Jarque-Bera (JB) test rejected the null hypothesis of normality at 5% significance. According to Maldelbrot (1963) and Fama (1965), excess kurtosis and non-normality are stylized facts regarding financial returns.

Table 1

Descriptive statistics of daily returns (*rt*), from January/2006 to June/2018

Returns	Mean	Median	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	P-value
BBAS3	0.00050	0.00000	0.18826	-0.23789	0.02737	-0.10885	9.25248	5120.94	0.00000
BBDC3	0.00043	0.00000	0.15465	-0.13926	0.02102	0.16205	7.14593	2262.60	0.00000
BBDC4	0.00045	0.00000	0.19989	-0.14056	0.02179	0.35262	8.39831	3877.79	0.00000
BRAP4	0.00042	0.00000	0.15377	-0.21083	0.02797	-0.01920	6.06373	1228.25	0.00000
BRFS3	0.00027	0.00000	0.28095	-0.27267	0.02563	0.08241	20.48675	40010.60	0.00000
BRKM5	0.00045	0.00000	0.19393	-0.22043	0.02622	0.28466	8.65664	4228.76	0.00000
CCRO3	0.00042	0.00000	0.17932	-0.15415	0.02288	-0.03663	7.46851	2613.12	0.00000
CMIG4	0.00017	0.00000	0.13742	-0.23639	0.02481	-0.88506	13.15070	13890.58	0.00000
CPFE3	0.00037	0.00000	0.11604	-0.18597	0.01836	-0.32654	9.36202	5351.32	0.00000
CPLE6	0.00024	0.00000	0.15557	-0.18226	0.02261	-0.15095	7.23349	2356.78	0.00000
CSAN3	0.00027	0.00000	0.20662	-0.15857	0.02710	-0.13016	7.14821	2260.20	0.00000
CSNA3	0.00019	0.00000	0.19628	-0.22951	0.03337	0.18791	7.21182	2339.39	0.00000
CYRE3	0.00004	0.00000	0.28930	-0.19807	0.03028	-0.02104	9.21892	5060.20	0.00000
ELET3	0.00013	0.00000	0.40076	-0.23534	0.02969	0.80944	17.20001	26724.15	0.00000
ELET6	0.00022	0.00000	0.27824	-0.22415	0.02764	0.36046	11.40496	9310.50	0.00000
EMBR3	0.00016	0.00000	0.20293	-0.16783	0.02281	-0.04216	10.13990	6670.58	0.00000
ENBR3	0.00034	0.00000	0.14458	-0.11628	0.02047	-0.02490	6.07562	1237.93	0.00000
GGBR4	0.00014	0.00000	0.16886	-0.16135	0.02829	0.06995	5.61265	895.62	0.00000
GOAU4	-0.00017	0.00000	0.17671	-0.20955	0.03056	-0.07851	6.85545	1948.00	0.00000
GOLL4	-0.00053	-0.00163	0.40764	-0.24360	0.03867	0.72384	12.82558	12905.12	0.00000
ITSA4	0.00055	0.00000	0.22432	-0.12279	0.02220	0.42445	9.55168	5710.24	0.00000
ITUB4	0.00050	0.00000	0.21004	-0.12942	0.02255	0.44590	9.27981	5263.59	0.00000
LAME4	0.00052	0.00000	0.24718	-0.17398	0.02536	0.24503	10.20113	6815.95	0.00000
LREN3	0.00086	0.00000	0.19236	-0.17985	0.02589	0.09174	7.27502	2395.49	0.00000
NATU3	0.00028	0.00000	0.13671	-0.14780	0.02298	0.19792	5.75682	1014.84	0.00000
PCAR4	0.00025	0.00000	0.14170	-0.11467	0.02077	0.15708	5.85917	1082.46	0.00000
PETR3	0.00007	0.00000	0.14966	-0.16154	0.02851	-0.00172	6.57545	1672.56	0.00000
PETR4	0.00009	0.00045	0.15086	-0.17148	0.02819	-0.15192	6.99026	2095.23	0.00000
RENT3	0.00075	0.00000	0.24095	-0.20599	0.02630	0.02025	11.47698	9401.80	0.00000
SBSP3	0.00055	0.00053	0.15574	-0.16152	0.02364	-0.09088	7.04961	2149.90	0.00000
USIM5	-0.00004	0.00000	0.30092	-0.17598	0.03435	0.39058	7.92629	3254.94	0.00000
VALE3	0.00038	0.00000	0.13769	-0.20552	0.02723	-0.05410	6.67924	1772.59	0.00000
VICT4	0.00033	0.00000	0.08765	-0.08350	0.01709	-0.05307	5.09213	574.13	0.00000

Source: Prepared by the authors based on research data.

As previously mentioned, the classical PCA technique assumes that data are independent. However, financial returns tend to present temporal correlation (serial or cross) and conditional heteroscedasticity (volatility). Preliminary analyses indicated that returns (r_t) show autocorrelation (autocorrelation function) and cross-correlation (cross-correlation function). Thus, the VAR model, using the Akaike information criterion, was adopted to deal with this problem. Here, the VAR(1) model was sufficient to remove the serial and cross correlations. However, the ARCH-LM test (Engle, 1982) and the autocorrelation functions of squared residuals of the VAR(1) model (μ_t) revealed the presence of conditional heteroscedasticity. Therefore, in addition to using the VAR filter (for temporal correlation), a GARCH filter was used to filter the conditional heteroscedasticity of the returns. In this case, the PCA technique was applied on the residuals (ε_t) of the VAR(1)-GARCH(1,1) model, wherein the GARCH part, the BEKK method was used (for details, see Engle & Kroner, 1995; Bauwens, Laurent, & Rombouts, 2006; Lütkepohl, 2005).

3.2. Interrelationships between the stock returns

The period from 01/02/2006 to 05/20/2008 was the first to be analyzed, i.e., before the most acute effects of the subprime crisis on the Brazilian economy. Table 2 shows the initial eigenvalues **XX** for this period, considering the filtered data. PCA allows the calculation of as many components as the number of original variables; thus, 33 components (and eigenvalues) were extracted from the data set. There are several criteria to determine the number of components to be retained (see Jolliffe, 2002)[3]. According to Kaiser's rule, for example, only components with eigenvalues **XX** greater than 1 (one) are considered significant, concerning retention; the other components are disregarded. In this case, any principal component (PC) with an eigenvalue less than 1 (one) has a variance of less than 1 (one) and contains less information than one of the original variables; thus, retaining it is not worth it (for details

3 It is important to say that there are several methods to determine the total number of components that best explain the set of original variables (see Jolliffe, 2002). Bai and Ng (2003) and Lam and Yao (2012), for example, developed interesting approaches to identify the number of factors in temporal correlation data. However, these methods were not applied here, because the data present conditional heteroscedasticity and they led to an ambiguous dimensional-reduction regarding the economic interpretation of the components. Kaiser's rule present good results. According to Jolliffe (2002), the number of principal components required to represent a data set may be greater or less than the number indicated by the estimated PCA model. The main idea is that different goals lead to different needs related to how many components should be retained.

of the Kaiser's rule, see Jolliffe (2002)). Therefore, based on Kaiser's rule, five (5) principal components were considered to represent the stock returns (considering that residuals (ε_t) were used in the estimation of the principal components). For example, the first PC explained 44.43% of the total variance of the observed variables.

For information purposes, if the original data were considered in the principal component estimates, without considering the proposed filters (differentiation, temporal correlation, and conditional heteroscedasticity), only four components would be retained by Kaiser's rule, and the first component would represent about 66.67% of the total variance of the observed variables (the four retained components would explain 92.19% of the total variance). Also, the components generated from the original data presented temporal correlation (serial and cross-correlation). Therefore, the application of the PCA technique to non-stationary data, with temporal correlation and conditional heteroscedasticity, tends to generate misleading (or spurious) results, since a large percentage of the variability explanation of the data set was directed to the first principal components and the generated components were temporally correlated, contrary to one of the classical PCA hypotheses.

Table 2

Initial eigenvalues considering the filtered data for the period from 01/02/2006 to 05/20/2008

Components	Initial eigenvalues	% of variation	% cumulative
1	14.66062	0.44426	0.44426
2	1.58922	0.04816	0.49242
3	1.20894	0.03663	0.52905
4	1.17338	0.03556	0.56461
5	1.04329	0.03161	0.59623
6	0.91631	0.02777	0.62399
7	0.87533	0.02653	0.65052
8	0.85326	0.02586	0.67637
9	0.75584	0.02290	0.69928
10	0.72681	0.02202	0.72130
11	0.70313	0.02131	0.74261
12	0.68647	0.02080	0.76341
13	0.66925	0.02028	0.78369
14	0.64028	0.01940	0.80309
15	0.60770	0.01842	0.82151
16	0.60268	0.01826	0.83977
17	0.55361	0.01678	0.85655
18	0.55043	0.01668	0.87323
19	0.52297	0.01585	0.88908
20	0.49837	0.01510	0.90418
21	0.46500	0.01409	0.91827
22	0.44328	0.01343	0.93170
23	0.43398	0.01315	0.94485
24	0.40048	0.01214	0.95699
25	0.36491	0.01106	0.96805
26	0.28330	0.00858	0.97663
27	0.22930	0.00695	0.98358
28	0.13453	0.00408	0.98766
29	0.11105	0.00337	0.99102
30	0.10021	0.00304	0.99406
31	0.08601	0.00261	0.99666
32	0.07930	0.00240	0.99907
33	0.03078	0.00093	1.00000

Source: Prepared by the authors based on research data.

The relation between returns and components is expressed by the coefficients of the matrix of loadings. Components with large coefficients (in absolute value) for a variable are closely related to this variable. Furthermore, since the estimated components are uncorrelated, the loadings of the components represent the unique contribution of each component and can be interpreted as the correlations between the components and the original variables. To Jollife (2002) the rotation of the components in the F-dimensional space can facilitate the analysis, since the rotation focuses on transforming the components to make them more interpretable. This study used the varimax method, which attempts to minimize the number of variables with high loadings on a single component.

From Table 3 (matrix of loadings), it can be observed that in the period from 01/02/2006 to 05/20/2008, with some exceptions, each component is associated with a group of stock returns of companies that make up a given sector. The first component, for example, is strongly related to the industrial sector companies such as Companhia Siderúrgica Nacional (CSNA3), Gerdau (GGBR4 and GOAU4), Petrobras (PETR3 and PETR4), Usiminas (USIM5) and Vale (VALE3). The presence of Bradespar (BRAP4) in the first component must be highlighted; although Bradespar is an investment company, its portfolio is mainly composed of Vale S.A. stocks, which may have contributed to direct BRAP4 to the first component. The second component is highly correlated with returns from companies such as Cosan (CSAN3) and Cyrela (CYRE3), linked to the energy, infrastructure and construction segments. Also, the stock returns of Lojas Renner (LREN3) and Natura (NATU3) are relevant in the second component. These companies have a significant weight in the composition of IBOVESPA, being linked to the consumer sector, which is deeply affected during crises, for example. The third component is mainly represented by financial sector companies: Banco do Brasil (BBAS3), Bradesco (BBDC3 and BBDC4), Itausa (ITSA4) and Itauunibanco (ITUB4). Regarding the fourth component, it is represented by state-owned enterprises of the electric sector such as Cemig (CMIG4), Copel (CPLE6) and Eletrobras (ELET3 and ELET6). Finally, the fifth component is associated with Embraer (EMBR3) and Telefônica (VICT4).

Table 3

Matrix of loadings with varimax rotation for the period from 01/02/2006 to 05/20/2008

	Components				
	1	2	3	4	5
BBAS3	0.19	0.37	0.54	0.24	0.16
BBDC3	0.35	0.25	0.72	0.19	0.14
BBDC4	0.41	0.31	0.73	0.22	0.16
BRAP4	0.64	0.34	0.31	0.11	0.23
BRFS3	0.17	0.29	0.08	0.21	0.47
BRKM5	0.10	0.26	0.34	0.34	0.41
CCRO3	0.17	0.44	0.18	0.17	0.34
CMIG4	0.35	0.25	0.25	0.53	0.23
CPFE3	0.29	0.44	0.14	0.27	0.39
CPLE6	0.27	0.26	0.27	0.50	0.25
CSAN3	0.26	0.58	0.11	0.23	0.04
CSNA3	0.64	0.33	0.19	0.23	0.22
CYRE3	0.12	0.57	0.27	0.26	0.12
ELET3	0.20	0.22	0.21	0.84	0.11
ELET6	0.18	0.26	0.20	0.84	0.11
EMBR3	0.08	-0.09	0.25	-0.02	0.69
ENBR3	0.35	0.27	0.11	0.19	0.38
GGBR4	0.62	0.37	0.26	0.24	0.28
GOAU4	0.58	0.42	0.23	0.25	0.26
GOLL4	0.05	0.06	0.43	0.26	0.31
ITSA4	0.36	0.38	0.65	0.26	0.15
ITUB4	0.39	0.34	0.71	0.24	0.16
LAME4	0.23	0.40	0.29	0.17	0.34
LREN3	0.19	0.65	0.17	0.16	0.11
NATU3	0.16	0.60	0.17	0.13	-0.02
PCAR4	0.32	0.27	0.34	0.19	0.28
PETR3	0.85	0.05	0.17	0.16	0.08
PETR4	0.85	0.11	0.19	0.19	0.10
RENT3	0.11	0.51	0.33	-0.05	0.25
SBSP3	0.31	0.09	0.21	0.37	0.30
USIM5	0.54	0.45	0.19	0.33	0.19
VALE3	0.73	0.30	0.28	0.07	0.23
VICT4	0.26	0.18	0.02	0.17	0.64

Source: Prepared by the authors based on research data.

Table 4 presents the initial eigenvalues and Table 5 the matrix of loadings for the period from 05/21/2008 to 12/31/2009, i.e., from the beginning of the subprime crisis in Brazil, until the stock market, in terms of IBOVESPA, reached a level similar to that registered before the crisis[4]. Considering Kaiser's rule, four (4) components were retained to represent the 33 stock returns[5]. Moreover, some characteristics observed in the estimates deserve attention: i) in the period before the crisis, the first five components explained 59.62% of the data set variability. After the crisis, four components accounted for 63.79%; (ii) before the subprime crisis, the second component was represented (in terms of correlation) by six companies. In the period from 05/21/2008 to 12/31/2009, this number grew to nine companies; iii) considering a 0.5 cutoff point for component loadings to define a high correlation between the stock return and a principal component, it should be noted that, before the crisis, there were 24 companies in this situation. After the crisis, even with a smaller number of components (four), 25 companies had a component load equal to or greater than 0.5. This may indicate a higher correlation among the 33 stocks that make up the analysis during the crisis period. It is worth remembering that during the subprime crisis, the classification of companies by sector was not as clear as before the crisis, when considering each component.

4 Estimates were made considering the differentiation, temporal correlation and conditional heteroscedasticity filters.

5 Here, if the original data were considered without considering the proposed filters (differentiation, temporal correlation and conditional heteroscedasticity), only three components would be retained by the Kaiser's Rule, and the first component would represent about 76.54% of the total variance of the observed variables (the three retained components would explain 90.95% of the total variance). Results can be provided upon request.

Table 4

Initial eigenvalues for the period from 05/21/2008 to 12/31/2009

Components	Initial eigenvalues	% of variation	% cumulative
1	16.77340	0.50828	0.50828
2	1.92513	0.05834	0.56662
3	1.33024	0.04031	0.60693
4	1.02039	0.03092	0.63785
5	0.97262	0.02947	0.66733
6	0.89577	0.02714	0.69447
7	0.81858	0.02481	0.71928
8	0.77988	0.02363	0.74291
9	0.74662	0.02262	0.76553
10	0.72449	0.02195	0.78749
11	0.63858	0.01935	0.80684
12	0.61028	0.01849	0.82533
13	0.59565	0.01805	0.84338
14	0.57964	0.01756	0.86095
15	0.54314	0.01646	0.87741
16	0.48450	0.01468	0.89209
17	0.46491	0.01409	0.90618
18	0.43131	0.01307	0.91925
19	0.37957	0.01150	0.93075
20	0.33069	0.01002	0.94077
21	0.30757	0.00932	0.95009
22	0.29786	0.00903	0.95912
23	0.26469	0.00802	0.96714
24	0.23042	0.00698	0.97412
25	0.22176	0.00672	0.98084
26	0.18074	0.00548	0.98632
27	0.14159	0.00429	0.99061
28	0.09356	0.00284	0.99344
29	0.07345	0.00223	0.99567
30	0.06391	0.00194	0.99760
31	0.03125	0.00095	0.99855
32	0.02649	0.00080	0.99935
33	0.02130	0.00065	1.00000

Source: Prepared by the authors based on research data.

Table 5

Matrix of loadings with varimax rotation for the period from 05/21/2008 to 12/31/2009

	Components			
	1	2	3	4
BBAS3	0.41	0.27	0.61	0.27
BBDC3	0.37	0.27	0.71	0.33
BBDC4	0.40	0.26	0.75	0.32
BRAP4	0.81	0.29	0.30	0.14
BRFS3	0.18	0.28	0.54	0.06
BRKM5	0.31	0.39	0.27	0.36
CCRO3	0.17	0.41	0.22	0.35
CMIG4	0.24	0.73	0.18	0.10
CPFE3	0.22	0.65	0.25	0.23
CPLE6	0.30	0.68	0.24	0.11
CSAN3	0.45	0.24	0.17	0.27
CSNA3	0.77	0.30	0.23	0.32
CYRE3	0.44	0.21	0.35	0.48
ELET3	0.17	0.74	0.12	0.31
ELET6	0.22	0.76	0.14	0.31
EMBR3	0.22	0.26	0.22	0.49
ENBR3	0.22	0.57	0.20	0.27
GGBR4	0.77	0.35	0.22	0.30
GOAU4	0.75	0.36	0.22	0.32
GOLL4	0.16	0.10	0.22	0.64
ITSA4	0.35	0.27	0.76	0.30
ITUB4	0.36	0.27	0.77	0.29
LAME4	0.40	0.44	0.44	0.25
LREN3	0.35	0.37	0.41	0.20
NATU3	0.28	0.51	0.26	-0.06
PCAR4	0.21	0.51	0.39	0.17
PETR3	0.82	0.19	0.35	0.07
PETR4	0.82	0.21	0.34	0.07
RENT3	0.41	0.20	0.19	0.45
SBSP3	0.31	0.43	0.44	0.15
USIM5	0.72	0.34	0.25	0.27
VALE3	0.84	0.22	0.32	0.14
VICT4	0.14	0.50	0.33	-0.27

Source: Prepared by the authors based on research data.

It should be noted that some stock returns already presented a significant correlation before the subprime crisis, especially considering the sectors of the Brazilian economy. However, there was a general increase in correlations during the crisis. This may be due to the contagion effect that takes place early in a crisis and the herding behavior that dominates its latter stages. The apparent high correlation during crisis periods implies that the diversification gained by holding a portfolio composed of several companies' stocks declines, since all stock markets are commonly exposed to systematic risk.

These characteristics are the same as those found in the studies on the interrelationship between the financial markets of different countries. According to Forbes and Rigobon (2001), in the case of countries, some economies already have some pre-existing integration, and during a period of turbulence, this integration (relation) tends to be strengthened. Moreover, such strengthening may be sufficient to cause breaks in the structure of the transmission of shocks between countries. This is characterized as a "contagion effect", i.e., shocks occurring in one economy affect the economy of another country, regardless of the situation of macroeconomic fundamentals between these countries. Chiang et al. (2007) describes that systemic financial crises with international effects have two specific phases: 1. the first phase is characterized by a massive increase in the degree of co-movements among international stock market returns during the crisis ("contagion effect"), and 2. the second is based on the relatively high correlation between country returns observed in the post-shock period ("herding effect").

Table 6 shows the initial eigenvalues and Table 7 the matrix of loadings for the period from 01/04/2010 to 01/20/2016, in which the IBOVESPA maintained levels well above the worst moments of the subprime crisis, but with oscillations (positive and negative) and a downward trend. By Kaiser's Rule, it is observed that the number of components to be retained for analysis is equal to six (6). This period was characterized by intense anti-corruption efforts in Brazil, specifically from March 17, 2014, with the beginning of the so-called "Operation Car Wash". This operation has been investigating corruption at the state-controlled oil company, Petrobras, which is one of the largest companies in the IBOVESPA index. "Operation Car Wash" caused Petrobras's stocks (PETRE and PETR4) to drop sharply between 2014 and 2016, showing great volatility. This may have contributed to Petrobras (PETRE and PETR4) moving from the first to the fifth principal component. Also, there was a reduction of the explanation percent of the first component when compared to the previously analyzed periods. Between 01/04/2010 and 01/20/2016 the first component represented 37.7% of the IBOVESPA variability.

The strengthening of the banking sector concerning their representativeness in the IBOVESPA variability was an important change that occurred after the subprime crisis. The companies of this sector were inserted in the third component before the crisis and during its period. After the crisis, these companies moved to the second component. It is worth recalling that Banco do Brasil (BBAS3), Bradesco (BBDC3 and BBDC4), Itausa (ITSA4) and Itauunibanco (ITUB4) have a great influence on the composition of IBOVESPA, and that the sector has had high profits in Brazil in recent years, even in the period of crisis. Consequently, the increasing participation of the sector in the IBOVESPA variability is justified.

Another important change after the subprime crisis is the greater number of companies with a factorial loading greater than 0.5, when compared to the previous periods. Naturally, the largest number of retained components (six) contributed to this. Moreover, companies that did not present high correlations with the first components before and during the crisis presented high loadings values after the crisis, especially the companies related to the consumer sector: BRF SA (BRFS3), Lojas Americanas (LAME4), Pão de Açúcar – CBD (PCAR4) and Localiza (RENT3).

Table 6

Initial eigenvalues for the period from 01/04/2010 to 01/20/2016

Components	Initial eigenvalues	% of variation	% cumulative
1	12.44136	0.37701	0.37701
2	2.26120	0.06852	0.44553
3	1.77513	0.05379	0.49932
4	1.32491	0.04015	0.53947
5	1.07696	0.03264	0.57211
6	1.05290	0.03191	0.60401
7	0.91293	0.02766	0.63168
8	0.85247	0.02583	0.65751
9	0.82407	0.02497	0.68248
10	0.76518	0.02319	0.70567
11	0.74286	0.02251	0.72818
12	0.72126	0.02186	0.75004
13	0.70408	0.02134	0.77137
14	0.67710	0.02052	0.79189
15	0.65772	0.01993	0.81182
16	0.63878	0.01936	0.83118
17	0.61962	0.01878	0.84996
18	0.60840	0.01844	0.86839
19	0.57289	0.01736	0.88575
20	0.54507	0.01652	0.90227
21	0.51751	0.01568	0.91795
22	0.48416	0.01467	0.93262
23	0.41905	0.01270	0.94532
24	0.39201	0.01188	0.95720
25	0.37978	0.01151	0.96871
26	0.28437	0.00862	0.97733
27	0.26756	0.00811	0.98543
28	0.15255	0.00462	0.99006
29	0.09233	0.00280	0.99285
30	0.08289	0.00251	0.99537
31	0.07265	0.00220	0.99757
32	0.04466	0.00135	0.99892
33	0.03559	0.00108	1.00000

Source: Prepared by the authors based on research data.

Table 7

Matrix of loadings with varimax rotation for the period from 01/04/2010 to 01/20/2016

	Components					
	1	2	3	4	5	6
BBAS3	0.19	0.67	0.30	0.19	0.16	0.09
BBDC3	0.19	0.78	0.29	0.19	0.15	0.20
BBDC4	0.22	0.81	0.28	0.18	0.18	0.20
BRAP4	0.68	0.17	0.23	0.13	0.36	0.10
BRFS3	0.12	0.20	0.23	0.11	0.06	0.57
BRKM5	0.40	0.11	0.21	0.13	0.07	0.32
CCRO3	0.04	0.12	0.49	0.23	0.14	0.27
CMIG4	0.10	0.08	0.19	0.64	0.12	0.14
CPFE3	0.06	0.12	0.27	0.62	0.15	0.30
CPLE6	0.11	0.05	0.28	0.64	0.17	0.18
CSAN3	0.14	0.27	0.40	0.16	0.20	0.22
CSNA3	0.77	0.20	0.18	0.18	0.13	0.08
CYRE3	0.25	0.31	0.53	0.21	0.02	0.09
ELET3	0.24	0.30	0.08	0.76	0.05	-0.09
ELET6	0.22	0.28	0.07	0.78	0.00	-0.11
EMBR3	0.24	0.13	-0.03	0.09	-0.05	0.67
ENBR3	0.05	0.05	0.29	0.59	0.00	0.19
GGBR4	0.81	0.17	0.16	0.10	0.08	0.23
GOAU4	0.80	0.16	0.15	0.13	0.09	0.23
GOLL4	0.28	0.21	0.41	0.13	0.13	-0.03
ITSA4	0.23	0.81	0.28	0.20	0.14	0.17
ITUB4	0.23	0.82	0.29	0.18	0.15	0.17
LAME4	0.22	0.23	0.69	0.18	0.00	0.12
LREN3	0.17	0.17	0.71	0.17	0.03	0.08
NATU3	0.10	0.09	0.54	0.19	0.15	-0.01
PCAR4	0.12	0.22	0.50	0.10	0.23	0.14
PETR3	0.31	0.30	0.19	0.21	0.78	0.10
PETR4	0.31	0.30	0.20	0.20	0.78	0.09
RENT3	0.18	0.20	0.58	0.15	0.00	0.12
SBSP3	0.13	0.14	0.19	0.44	0.20	0.31
USIM5	0.76	0.13	0.20	0.15	-0.03	0.02
VALE3	0.69	0.17	0.17	0.10	0.38	0.10
VICT4	0.11	0.14	0.20	0.18	0.26	0.45

Source: Prepared by the authors based on research data.

Table 8 shows the matrix of loadings for the period from 01/21/2016 to 06/29/2018, i.e., a new recovery of the Brazilian stock market after the IBOVESPA showed its lowest value after the subprime crisis (01/20/2016), due to political and economic problems. By Kaiser's rule, five (5) components were retained to represent the 33 stock returns. In this period, the value of Petrobras's stocks (PETR3 and PETR4) grew and the company became part of the first component again. It should be noted that Vale (VALE3) moved to the third component, possibly due to environmental accidents, especially after November 2015.

In this period, the companies in the banking sector moved to the first component, showing once again the importance of the sector to IBOVESPA. Additionally, the second component is especially correlated with the companies of the consumer sector, namely: BRF SA (BRFS3), Lojas Americanas (LAME4), Lojas Renner (LREN3), Natura (NATU3), Pão de Açúcar – CBD (PCAR4) and Localiza (RENT3).

Table 8

Matrix of loadings with varimax rotation for the period from 01/21/2016 to 06/29/2018

	Components				
	1	2	3	4	5
BBAS3	0.73	0.33	0.25	0.21	0.00
BBDC3	0.72	0.44	0.18	0.14	0.08
BBDC4	0.76	0.42	0.22	0.14	0.03
BRAP4	0.10	0.21	0.83	0.00	0.24
BRFS3	0.05	0.59	0.17	-0.04	0.18
BRKM5	0.15	0.22	0.17	-0.04	0.46
CCRO3	0.40	0.56	0.17	0.12	-0.07
CMIG4	0.44	0.44	0.21	0.34	0.02
CPFE3	0.16	0.48	0.11	0.13	0.12
CPLE6	0.45	0.44	0.23	0.25	0.16
CSAN3	0.45	0.27	0.20	0.05	0.30
CSNA3	0.33	0.28	0.73	0.13	0.11
CYRE3	0.56	0.37	0.24	0.17	-0.04
ELET3	0.24	0.21	0.15	0.90	0.06
ELET6	0.25	0.21	0.11	0.89	0.09
EMBR3	0.01	0.03	0.05	0.11	0.73
ENBR3	0.26	0.50	0.16	0.24	0.04
GGBR4	0.30	0.17	0.79	0.14	0.04
GOAU4	0.36	0.17	0.76	0.16	-0.05
GOLL4	0.46	0.30	0.18	0.17	-0.12
ITSA4	0.73	0.45	0.18	0.12	0.03
ITUB4	0.75	0.44	0.20	0.13	0.04
LAME4	0.41	0.62	0.14	0.08	-0.02
LREN3	0.34	0.65	0.12	0.09	0.08
NATU3	0.15	0.60	0.21	0.12	0.00
PCAR4	0.41	0.48	0.15	0.11	0.11
PETR3	0.70	0.09	0.32	0.12	0.37
PETR4	0.73	0.13	0.32	0.15	0.29
RENT3	0.35	0.51	0.11	0.09	0.04
SBSP3	0.40	0.39	0.10	0.16	0.19
USIM5	0.37	0.20	0.67	0.17	-0.14
VALE3	0.04	0.16	0.83	-0.03	0.28
VICT4	0.32	0.51	0.08	0.11	0.23

Source: Prepared by the authors based on research data.

4 CONCLUSIONS

This study examined the correlation between the stock returns of 33 companies that make up the IBOVESPA, from January 2006 to June 2018, using principal components analysis applied on the residuals of the VAR-GARCH model.

It should be emphasized that the application of the classical principal component analysis to the original data, i.e., disregarding the proposed filters (differentiation, temporal correlation and conditional heteroscedasticity), generated spurious and misleading results, which corroborates the assumption that the PCA technique should be applied on stationary, and independent data.

The main results demonstrated that:

a) The period from 01/02/2006 to 05/20/2008: companies of the industrial sector were the ones that most determined the IBOVESPA variability, with emphasis on the companies: Companhia Siderúrgica Nacional (CSNA3), Gerdau (GGBR4 and GOAU4), Petrobras (PETR3 and PETR4), Usiminas (USIM5) and Vale (VALE3);

b) The period from 05/21/2008 to 12/31/2009: during the subprime crisis, in general, there was a higher correlation among the 33 stock returns. It is worth recalling that the classification of companies by sector during this period, in terms of each component, is not as clear as before the crisis. There were no major changes in terms of the representativeness of companies in the IBOVESPA variability;

c) The period from 01/04/2010 to 01/20/2016: Petrobras (PETR3 and PETR4) moved from the first to the fifth principal component, which can be explained by the corruption at the state-controlled oil company. An important change that occurred after the subprime crisis was the strengthening of the banking sector about their representativeness in the IBOVESPA variability;

d) The period from 01/21/2016 to 06/29/2018: consolidating their position, the companies of the banking sector moved to the first component, in terms of representativeness of the IBOVESPA variability.

Furthermore, it is significant to highlight that the results of this research are in agreement with Hu et al. (2008) and Tam (2014), i.e., the interdependence between financial markets may vary over time. The segmentation in four periods enabled the identification of several differences, since each period presented specific factors that may change the correlations between the stock returns, such as crises, political and economic events, environmental events, natural movement of financial markets, among others.

Additionally, it is important to say that the interdependence between stock returns reveals that the positive or negative effects may be spread among the analyzed stock returns and the IBOVESPA index, which can directly impact the investment decisions of economic and financial agents, especially concerning the diversification of their asset portfolios. For example, the apparent high correlation during crisis periods implies that the gain of the diversification by holding a portfolio composed of several companies' stocks declines, since the stock markets are commonly exposed to systematic risk.

In short, the results of this study reveal that there was an interrelation among the stock returns that compose the IBOVESPA, and that the interdependence and the correlation pattern vary over time. This information is crucial, since, for Castro and Brandão (2008), shocks in the financial market tend to have a significant impact on the real side of the economy. Crises in the financial market may reduce bank financing, increase the costs of taking credit, create difficulties in the capital market, reduce the level of savings, reduce consumption, among others. These problems are propagated to the real side of the economy, affecting the level of economic activity and, consequently, investment decisions.

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INTER-RELAÇÕES ENTRE O RETORNO DAS AÇÕES DE EMPRESAS BRASILEIRAS QUE COMPÕEM O ÍNDICE DA BOLSA DE VALORES DE SÃO PAULO

Resumo

O objetivo deste artigo foi verificar as inter-relações entre o retorno das ações de 33 empresas brasileiras que compõem o Índice da Bolsa de Valores de São Paulo (IBOVESPA), de janeiro de 2006 a junho de 2018, utilizando a análise de componentes principais (PCA), aplicada aos resíduos do modelo VAR-GARCH.

De maneira geral, os resultados deste estudo revelaram a presença de inter-relação entre os retornos das ações que compõem o IBOVESPA, e que a interdependência e o padrão de correlação variam ao longo do tempo, o que pode impactar diretamente as decisões de investimento dos agentes econômicos e financeiros, principalmente no que se refere à diversificação de suas carteiras de ativos.

Palavras-chave: Mercado financeiro; Brasil; dados dependentes; principal componente de análise; econometria financeira.

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