ISSN 1808-057X
DOI: 10.1590/1808-057x201805770

ORIGINAL ARTICLE

Misvaluation and behavioral bias in the Brazilian stock market

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Received on 04.30.2017 – Desk acceptance on 06.13.2017 – 2nd version approved on 11.27.2017 – Ahead of print on 09.17.2018
Associate Editor: Fernanda Finotti Cordeiro Perobelli

ABSTRACT

The study sought to apply the model developed by Gokhale et al. (2015) to identify the existence of overreaction and behavioral biases in the Brazilian stock market and analyze its performance as an investment strategy on the São Paulo Stock, Commodities, and Futures Exchange (BM&FBOVESPA) in the short term and long term, as well as test its robustness with time window simulations. The impacts of behavioral finance on capital markets can affect economic decisions, perpetuate or increase asset pricing anomalies, and in more extreme and persistent situations contribute to the formation of bubbles that can compromise the entire financial system of a country**.** The study pioneers an innovative methodology in the Brazilian stock market for identifying behavioral biases and obtaining abnormal returns and higher returns than the Ibovespa. The research uses the model developed by Gokhale, Tremblay, and Tremblay (2015) in three samples with quotations data for Brazilian publicly-traded companies that compose the Ibovespa and IBrA in the period from 2005 to 2016. With the R statistical software, the Fundamental Valuation Index (FVI) was calculated for each sample share and each year. From the FVI index, the undervalued shares were identified, indicating that the sales price does not reflect their economic fundamentals, and portfolio simulations were carried out for investment over three months or the next year. The results indicate the possible existence of overreaction and behavioral biases in the Brazilian stock market, which lead to the possibility of higher abnormal returns than those of the Ibovespa. Similar to the US market, at the end of the 2006-2016 period simulated portfolios yielded more than 274%, while the Ibovespa yielded approximately 80%. The robustness tests attest to the effectiveness of the model. The various investment portfolios, simulated over different time horizons, yielded more than the Ibovespa on average. The study also confirmed the assumptions of Gokhale, Tremblay, and Tremblay (2015) regarding the model's inadequacy for short-term strategies.

Keywords: behaviorial finance, misvaluation, behavioral bias, Brazilian stock market, Market Model.

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1. INTRODUCTION

The Efficient Market Hypothesis (EMH) is based on the assumption that share prices reflect all available information in a context in which market agents are rational and there are no transaction costs (Famas, 1970). However, even under the assumption that market agents are rational, market constraints and psychological factors involving investors can lead to the occurrence of valuation or devaluation bias in share prices (Gokhale, Tremblay & Tremblay, 2015).

Thus, even in competitive markets, distortions in asset prices can occur, indicating that they do not reflect their economic fundamentals. In certain periods, asset prices can be above or below their equilibrium values; in both cases, this bias is expected to be corrected over the course of the transactions that take place immediately afterwards. In any case, the existence of overvaluation or undervaluation – that is, misvaluation – can present an opportunity for investor gains.

Various studies have found indications that quotation prices do not always follow the EMH assumptions regarding the immediate adjustment of prices to all available information (Aguiar, Sales & Sousa, 2008; Costa, 1994; De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993; Gokhale et al., 2015; Rabelo & Ikeda, 2004). In more extreme and persistent situations, the formation of positive or negative bubbles can even occur [for example, Leone and Medeiros (2015) and Leybourne, Kim, and Taylor (2007)]. Thus, the existence of misvaluation may persist for longer periods of time.

This study uses the innovative model developed by Gokhale et al. (2015) (GTT from here on) in the Brazilian stock market to detect overreaction resulting from investor behavior and identify undervalued shares among the companies listed on the São Paulo Stock, Commodities, and Futures Exchange (BM&FBOVESPA) in the period from 2005 to 2016. It also analyzes the GTT model as a strategy for investing in shares in the Ibovespa and IBrA indices in the short and long term, as well as testing its robustness with time window simulations.

For the research, three samples were elaborated with companies belonging to the Ibovespa and the IBrA in the period from 2005 to 2016 and two groups of tests were carried out. In the first group, the GTT model was applied to the companies from the Ibovespa and from the IBrA in the same ways as in the original work of Gokhale et al. (2015). In the second group, portfolios and time windows were simulated to test the robustness of the model and its performance in the short and long term.

The GTT model for estimating asset price misvaluation was developed based on the Market Model and adapted to capture traders' systematic behavioral errors. The method consists of initially measuring share returns by estimating the α and β coefficients using the ordinary least squares (OLS) method. Then, based on the modified market model, the structure of the standard error is broken down into two components: one that consists of white noise and another that captures behavioral tendencies. The distance between the return obtained in the market model and the return based on the modified market model from Gokhale et al. (2015) indicates whether a share is poorly valued.

The results found in this study demonstrate the existence of misvaluation in the period from 2005 to 2016. Also, the simulation of a portfolio identifying undervalued shares each year presented substantially higher returns than those of the Ibovespa in the year immediately after, indicating the strategy's potential for gains. The cumulative return on the simulated portfolios at the end of the 2006-2016 period was more than 274%, while the Ibovespa yielded approximately 80%. The complementary tests for the Ibovespa, with simulations of various investment portfolios, proved the robustness of the strategy based on the GTT model; for example, at 10% significance, portfolios simulated for 12 months [12 months calculating the Fundamental Valuation Index (FVI) and three months of return] yielded 7.3% more than the Ibovespa on average.

In relation to applying the method to the IBrA shares, the results were not satisfactory. Finally, confirming the assumptions of Gokhale et al. (2015), the short-term portfolios (12-week calculation period and three weeks of return) presented a result that was 5.84% lower than that of the Ibovespa on average.

The article is composed of this Introduction and four more sections. Section 2 presents the concepts related to misvaluation and behavioral bias, as well as presenting and discussing the modified model from Gokhale et al. (2015). Section 3 describes the data and how the methodology is carried out. Section 4 analyzes the results and the last section presents the conclusions.

2. THEORETICAL FRAMEWORK

2.1 Misvaluation and Behavioral Bias

A market is efficient when the prices of the assets traded in it always fully reflect the available information (Fama, 1970). However, the EMH is contested by various studies that provide evidence that investors can present irrational behaviors and react in an exaggerated way to new information, whether good or bad, creating opportunities for abnormal gains (Costa, 1994; De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993; Kimura, 2003; Leone & Medeiros, 2015; Piccoli, Souza, Silva & Cruz, 2015; Shiller, 2003).

Thus, even when investors are rational, constraints and noise can cause valuation biases or poor share or security price valuations. In contrast, psychological factors involving investors, such as optimism, can produce irrational behaviors and also affect the efficiency of the markets (Gokhale et al., 2015).

De Bondt and Thaler (1985), for example, verified whether exaggerated movements in American share prices were followed by price movements in the opposite direction. The authors used portfolios formed of shares that had made losses or extreme gains in the previous five-year period and calculated returns in the following three years. The results indicated average abnormal returns of 19.6% for the portfolio based on losing shares and an average loss of 5% in relation to the market for the portfolios formed of winning shares.

Kimura (2003) notes that these exaggerated movements, identified by De Bondt and Thaler (1985), are called overreaction and occur when financial variables such as prices and volatilities deviate excessively from their intrinsic values due to news that provokes euphoria or gloom among investors.

Jegadeesh and Titman (1993) sought to examine whether price reactions to common factors and specific company information affect strategies with winning and losing portfolios. The evidence found by the authors indicates that specific firm information provokes exaggerated asset price reactions; in contrast, investors are late to react in relation to common news. According to Kimura (2003), this phenomenon is called underreaction in the literature and enables the development of "moment strategies" in which the investor buys assets with above-average past performance and sells assets with below-average past performance.

The model from Gokhale et al. (2015) aims to identify shares impacted by the overreaction phenomenon. This behavioral phenomenon was explored by De Bondt and Thaler (1985) to develop the investment strategy known as "contrarian" (Kimura, 2003). However, the model from Gokhale et al. (2015) does not use the lowest or highest return in the past to select the investment portfolio, but instead the efficient frontier analysis technique and breakdown of the Market Model error, as will be better explored in section 2.2.

In Brazil, Costa (1994) applied the model used by De Bondt and Thaler (1985) to detect exaggerated investor reactions, analyzing the period from 1972 to 1989. The results found suggested the existence of a significant exaggerated reaction effect in the Brazilian market, consistent with the American market. The difference in returns between the winning and losing portfolios was 25.69% after 12 months of calculation. After 24 months, the portfolio formed by the "losing" shares obtained a 17.63% higher average return than the market return.

Santos and Santos (2005) discussed the existence or not of rationality in the formation of assets prices and indicate the existence of conflict between rational thinking and human limitations or idiosyncrasies in decision-making, relating other factors that can influence the fluctuation of share prices, such as errors in processing information, beliefs and values, a short-term or long-term outlook, and the influence of market analysts.

Within this context, Aguiar et al. (2008) carried out empirical tests to investigate the occurrence of overreaction and underreaction phenomena in the Brazilian stock market, using a model based on fuzzy set theory, which is closely related with behavioral finance theory, applied to financial indicators from two sets of shares: one from the oil and gas sector and the other from the textile sector, related to the period from 1994 to 2005. The results indicated that the market has informational inefficiencies, given that there is significant evidence of overreaction and underreaction, thus being inconsistent with the EMH.

Gomes, Mól, and Souto (2015) also used the fuzzy behavioral model to analyze the existence of overreaction and underreaction in the first and second line assets of the Brazilian stock market, with a sample composed of 132 assets, 59 being first line and 73 being second line, in the period from 2004 to 2011. The results suggest momentaneous (short-term) deviations from the EMH, in the semi-strong form, as well as opposing heuristics for the first and second line assets, showing non-symmetrical behavioral effects for these categories of assets.

Leone and Medeiros (2015) found indications of the presence of misvaluation, detecting that security prices do not always immediately react to all available information (EMH assumptions) and identifying undervalued prices for NASDAQ shares in the period from February 1973 to June 1992 (negative bubble) and overvalued prices in the period from December 1998 to July 2001 (positive bubble).

However, despite the evidence of share misvaluation caused by behavioral bias (Aguiar et al., 2008; Dourado & Tabak, 2014), Pimentel (2015) indicates other specific factors of the Brazilian capital market, such as market concentration, high interest rates, and high volatility, which can interfere in the share pricing dynamic and in the returns forecasting models.

2.2. Market Model and Stochastic Frontier for Identifying Misvaluation

The model developed and used by Gokhale et al. (2015) to identify misvaluation of shares is based on the Market Model and the literature on technical efficiency and economic efficiency, with the use of efficient frontier analysis and econometric modeling.

The Market Model is a variant of the Capital Asset Pricing Model (CAPM), which is one of the models used to analyze risk and returns for shares (Richardson, Tuna & Wysocki, 2010). Based on the Market Model, Gokhale et al. (2015) initially assumes that investors are rational and there is no misvaluation and that the market return on share *i* at time *t* is given by the following linear relationship:

$$R_{it} = \alpha_i + \beta_i R_{mt} + v_{it} \tag{1}$$

in which R_{mt} is the market return of a portfolio of shares and v_{it} is the error term that represents white noise with an average of 0 and finite and constant variance. According to Gokhale et al. (2015), the Market Model has been widely used in event studies to determine the effect of unexpected information over share returns. The abnormal returns (AR) in the post-event period correspond to the difference between the observed returns and the returns expected if the event had never occurred:

$$AR_{i\tau} = R_{i\tau} - (\hat{\alpha}_i + \hat{\beta}_i R_{m\tau}) \tag{2}$$

in which the alpha and beta parameters are estimated with a least squares regression.

The innovation offered by Gokhale et al. (2015) was the modification of the traditional market model to take into consideration traders' systematic behavioral errors. The problem with the traditional approach is that the OLS over/underestimates the returns on shares in the presence of undervaluation or overvaluation in the market. Thus, Gokhale et al. (2015) developed a market model with a composite error term, as shown in equation 3:

$$R_{it} = \alpha_i + \beta_i R_{mt} + v_{it} + \mu_{it} \tag{3}$$

where $\varepsilon_{it} = v_{it} + \mu_{it}$. The first term, v_{it}, has a normal distribution and is associated with the Market Model. The second term, μ_{it}, is a one-tailed error term associated with behavioral biases that cause misvaluation, which is the focus of this study. It is generally assumed that this term is independent and identically distributed (i.i.d.), half-normal, and that the two error terms are independent from each other. When μ_{it} is positive, there is evidence of overvaluation; that is, the share returns are higher than the returns based on the company's economic fundamentals. The opposite occurs when this μ_{it} term is negative and there is evidence of undervaluation of the assets. When the value of this error term is 0, there is no evidence of behavioral biases and the Market Model can be used.

The model defined by Gokhale et al. (2015) enables the fundamental value of the returns to be estimated as the difference between the market value and the error associated with the trading bias:

$$R_{it}^* = R_{it} - \mu_{it} = R_{it} = \alpha_i + \beta_i R_{mt} + v_{it} \tag{4}$$

The expected value of the fundamental returns is given by:

$$E(R_{it}^*) = E(R_{it} - \mu_{it}) = \alpha_i + \beta_i R_{mt} \tag{5}$$

Expression 5 indicates that in the presence of misvaluation there is some distancing between the market value observed and the fundamental values, so that:

$$\mu_{it} = R_{it} - R_{it}^* \tag{6}$$

To estimate the composite error, as previously described, the maximum likelihood method is used. The undervaluation and overvaluation models are estimated separately. In the case of undervaluation, it is assumed that $\mu_{it} \sim N^{+}(0, \sigma_{\mu}^{2})$; in the case of overvaluation, $\mu_{it} \sim N^{-}(0, \sigma_{\mu}^{2})$.

The log-likelihood function is given by:

$$\ln L(\alpha, \beta, \sigma_v, \sigma_\mu) = -T \ln(\sigma) + \frac{T}{2} \ln(\frac{2}{\pi}) + \sum_{t=1}^{T} \left\{ \ln \Phi \left[\frac{s.\, \varepsilon_{it} \lambda}{\sigma} \right] - \frac{1}{2} \left[\frac{\varepsilon_{it}}{\sigma} \right]^2 \right\} \quad (7)$$

in which T = number of periods, σ_v^2 = variance of v_{it}, σ_μ^2 = variance associated with the normal distribution from which the half-normal derives, $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$; $\lambda = \sigma_u / \sigma_v$; $\Phi(.)$ = cumulative standard normal distribution, and s = model specification indicator, with 1 for overvaluation and -1 for undervaluation. Using the maximum likelihood method, it is possible to obtain the estimates for the variances, the coefficients of the model, and the standard errors, and with this estimate the value of μ_{it} or misvaluation (Greene, 2008).

The null hypothesis of inexistence of misvaluation or $\sigma_\mu = 0$ can be verified with a one-tailed likelihood ratio test (Coelli, 1995). If the null hypothesis is rejected, there is overvaluation with $\mu_{it} > 0$ and undervaluation when $\mu_{it} < 0$, as according to expression 6. This presents two advantages in relation to the Market Model: it considers the possibility of separating the systematic biases of the white noise terms and enables the valuation bias to be formally tested.

The magnitude of the valuation bias is measured by the FVI developed by Gokhale et al. (2015), which is defined with the average of the estimated bias:

$$FVI_{i=} \sum_{t=1}^{T} \frac{\hat{\mu}_{it}}{T} \quad (8)$$

in which if the value of expression 8 is positive, the return is overvalued; if it is negative, it is undervalued, and if it is equal to 0, it corresponds to the fundamental values of expression 1. In addition, the higher the absolute value of the FVI, the greater the size of the valuation bias.

One limitation of using the GTT model as an investment strategy, according to Gokhale et al. (2015), is that the FVI does not identify the exact change of tendency point for a share; that is, it determines whether a share is undervalued or overvalued. Thus, using the model may present negative results for short-term investment strategies.

3. METHODOLOGICAL PROCEDURES

3.1 Samples and Data

This study used data on the companies and indices listed on the BM&FBOVESPA in the period from 2005 to 2016. The data were obtained from the Economatica database and from the BM&FBOVESPA website. Data on daily closing quotations were gathered for the listed companies that formed part of at least one of the theoretical portfolios from the Ibovespa and the IBrA, as well as closing quotations and theoretical portfolio compositions for the indices themselves.

The Ibovespa was chosen as a reference for market return when applying the GTT model because this index reflects the performance of the shares that are best known by investors in the Brazilian stock market and that would be impacted by behavioral effects, causing overreaction or underreaction. The use of the IBrA as a reference for market return aimed to verify the performance of the model in a wider set of shares, known or not by the investors. In this case, the expected behavior is that the GTT model does not produce such efficient results, since investors would not be able to identify opportunities resulting from overreaction or underreaction of shares due to the large number of shares to monitor.

Three samples were elaborated for this study. The first was based on the Ibovespa theoretical portfolios, published in the last four months of each year in the period from 2005 to 2016 and composed of 115 companies that formed part of at least one of the portfolios during the period of the study. To test robustness, a second Ibovespa sample was used, considering the theoretical compositions from every four-month periods and composed of 122 companies. The third sample was constructed based on the IBrA theoretical portfolios in the period from 2011 to 2016, composed of 189 companies. In this sample only the theoretical portfolios from the last four months of each year were used.

The adjustments described by Serra, Saito, and Fávero (2016) were carried out in the three samples in relation to the companies that changed name/trading code during the analysis period. After extracting the data from Economatica, the data were transferred to the R statistical software (R Core Team, 2016).

3.2 Back Testing

To identify misvaluation and investment opportunities in the Brazilian market, two types of simulations were carried out. In the first, the FVI values for each share in the Ibovespa and IBrA samples in the period analyzed were calculated annually, similar to Gokhale et al. (2015). In addition, for each share the likelihood ratio test was also carried out annually in order to verify the significance of the estimated models. To estimate the regression models with stochastic frontier analysis, the likelihood ratio tests, and the values of the inefficiency components used in the FVI calculation, the *sfa* and *lrtest* functions from the Frontier package of the R statistical software (R Core Team, 2016), developed in 2013 by Tim Coelli and Arne Henningsen, were used, respectively. The aim was to test whether identifying misvaluation provided a medium-term investment strategy. For this, 1%, 5%, and 10% undervalued securities were identified and the portfolios were compiled at the start of each year based on the identification of misvaluation from the year immediately before. The portfolios were composed in equal amounts for each share. As in Gokhale et al. (2015), only the cases of undervaluation were considered in the investment strategy.

At the end of each year, a new portfolio was compiled, repeating this procedure. This strategy considers that the valuation bias could be eliminated with time. In the years in which no share was identified as undervalued by the model, the Special Custodial and Clearing System (Selic) rate was used as a reference, based on the idea that the investor, in this case, would liquidate the shares in their portfolio and invest in fixed income, more specifically in government bonds, receiving the Selic rate as a return. In addition, forming a portfolio with a smaller number of shares will probably result in a higher level of risk. This was also not considered here, despite the deviations from the returns on the chosen portfolios being lower than the deviation from the Ibovespa in the period analyzed.

The transaction costs, such as brokerage and fees (settlement, registration, and exchange), were considered to calculate the return in the investment strategy. For this, an investment portfolio in the amount of R$ 100 thousand and fixed brokerage fee of R$ 10.00 were simulated, in the same way as in Teixeira and Oliveira (2010). In relation to the BM&FBOVESPA rates (registration, settlement, and exchange), a percentage of 0.0345% was used for each purchase or sale, as foreseen in Annex II of Circular Letter n. 70/2008-DP of October 27, 2008 (BM&FBOVESPA, 2008).

The second group of simulations was only carried out with the Ibovespa sample, which considered all the theoretical portfolios from every four months during the period. The IBrA was not used because this index only started to be published in May of 2011, which made compiling a significant number of portfolios unfeasible. Windows were analyzed in this test, similar to the study from Jegadeesh and Titman (1993), with 12-month calculation intervals and calculating the return in the following three months. To form the portfolios, the initial reference date for calculating the FVI was altered monthly and the period for calculating the returns was limited to the three months subsequent to the date of calculating the FVI. There was no overlapping of calculation periods in each portfolio individually.

The use of this calculation methodology enabled the simulation of various investment portfolios using the model from Gokhale et al. (2015). Portfolios were simulated in which the method was applied for 12, 24, 36, 48, and 60 months. The tests were carried out with greater and non-usual confidence intervals (1%, 5%, 10%, 15%, 20%, and 25%) in an attempt to better understand the behavior of the FVI.

The results obtained from the two types of tests were compared with each other and also with the Ibovespa and IBrA returns in the same period. These results are presented and commented on in the next section.

4. RESULTS

4.1 Analysis of Applying the GTT Methodology for the Ibovespa

Initially, the test that Gokhale et al. (2015) carried out in the American market was repeated for the Brazilian market. The results of applying the GTT model in the first sample of Ibovespa data indicate evidence of overreaction in every year of the period analyzed, with the exception of 2006, in which no undervalued security was identified, at least at 1%, 5%, and 10% statistical significance. Examples of values calculated annually for each company of the FVI and the p-values of the likelihood ratio tests in the period from 2005 to 2009 can be verified in Annex 1.

Table 1 demonstrates the results of applying the GTT model in the period from 2006 to 2016. The Ibovespa returns, the average returns of each portfolio compiled at a 10%, 5%, and 1% level of significance, the quantity of assets that were undervalued, and the cumulative factor (1 + rate of return) are presented.

Table 1
Annual and cumulative returns on the portfolios and on the Bovespa Index (Ibovespa) – 2006-2016

1% Portfolio	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Average return (%)	13.2	26.7	-66.4	82.4	31.5	-27.1	-0.4	-4.1	0.1	-4.6	32.5
Quantity of shares	0	3	1	3	2	2	6	9	4	5	6
Cumulative factor	1.13	1.43	0.48	0.88	1.16	0.84	0.84	0.81	0.81	0.77	**1.0183**
											1.83%
5% Portfolio											
Average return (%)	13.2	26.7	-29.0	103.1	22.1	1.9	2.7	-7.8	5.7	-10.6	26.4
Quantity of shares	0	3	3	8	5	4	9	19	6	11	8
Cumulative factor	1.13	1.43	1.02	2.07	2.52	2.57	2.64	2.43	2.57	2.30	**2.907**
											190.7%
10% Portfolio											
Average return (%)	52.8	26.7	-34.7	103.1	13.5	12.7	9.7	-5.6	1.7	-13.4	24.9
Quantity of shares	1	3	4	8	7	7	11	24	8	16	13
Cumulative factor	1.53	1.94	1.26	2.57	2.91	3.28	3.60	3.40	3.46	2.99	**3.742**
											274.2%
Ibovespa											
Average return (%)	32.9	43.7	-41.2	82.7	1.0	-18.1	7.4	-15.5	-2.9	-13.3	38.9
Cumulative factor	1.33	1.91	1.12	2.05	2.07	1.70	1.82	1.54	1.49	1.30	**1.8002**
											80.02%

Source: *Elaborated by the authors.*

The results presented show that the two portfolios exceeded the Ibovespa in almost every year of the period analyzed. In the case of the 10% portfolio, the cumulative return at the end of the period was almost 274.54%, while the Ibovespa yielded approximately 80.02%. In the case of the 5% portfolio, the total cumulative return in the period was approximately 190%. The results are in line with the results found by Gokhale et al. (2015).

Figure 1 compares the annual Ibovespa cumulative returns with the annual cumulative returns on the portfolios compiled based on the composite error (stochastic frontier) model used in this study, at 10%, 5%, and 1% levels of significance.

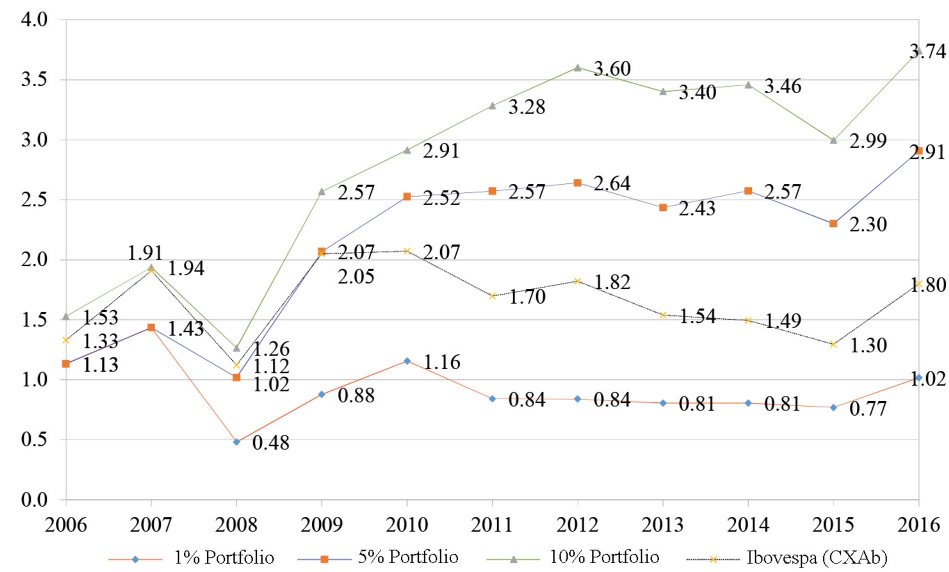

Figure 1 *Comparison of the cumulative factors of the Bovespa Index (Ibovespa) with the 10%, 5%, and 1% significant portfolios – 2006-2016*
Source: *Elaborated by the authors.*

4.2 Analysis of Applying the GTT Methodology for the IBrA

To test another proxy for the market portfolio, the IBrA was used instead of the Ibovespa. The IBrA aims to offer a broad overview of the Brazilian stock market and measures the average performance of all the assets traded on the BM&FBOVESPA that meet the minimum liquidity and trading criteria (BM&FBOVESPA, 2017). In this case, the investment strategy is not expected to produce such efficient results, due to the quantity of companies in the IBrA being higher with many of them being unknown to most investors, which can delay the investors' reaction time, reducing the return derived from the taking advantage of the overreaction effects.

The results of applying the model in the period from 2012 to 2016 are presented in Table 2, revealing a large number of shares with evidence of undervaluation (at a 10%, 5%, or 1% level of significance) in the period analyzed, with this number being considerably higher in 2013.

Table 2
Annual and cumulative returns on the portfolios and on the Índice Brasil Amplo (IBrA) – 2012-2016

1% Portfolio	**2012**	**2013**	**2014**	**2015**	**2016**
Average return (%)	-9.6	-15.5	-20.9	-22.3	35.7
Quantity of shares	13	19	12	11	10
Cumulative factor	0.90	0.76	0.60	0.47	0.64
					-36.24%
5% Portfolio					
Average return (%)	-0.8	-14.9	-15.0	-18.8	27.1
Quantity of shares	22	35	18	20	14
Cumulative factor	0.99	0.84	0.72	0.58	0.74
					-25.93%
10% Portfolio					
Average return (%)	4.78	-12.45	-16.76	-13.37	28.46
Quantity of shares	28	44	24	30	22
Cumulative factor	1.05	0.92	0.76	0.66	0.85
					-15.02%
IBrA					
Average return (%)	13.65	-3.55	-3.07	-12.69	36.87
Cumulative factor	1.14	1.10	1.06	0.93	1.27
					26.96%

Source: *Elaborated by the authors.*

Figure 2 compares the cumulative annual returns on the IBrA with the cumulative annual returns on the portfolios compiled based on the composite errors (stochastic frontier) model used in this study, at 10%, 5%, and 1% levels of significance.

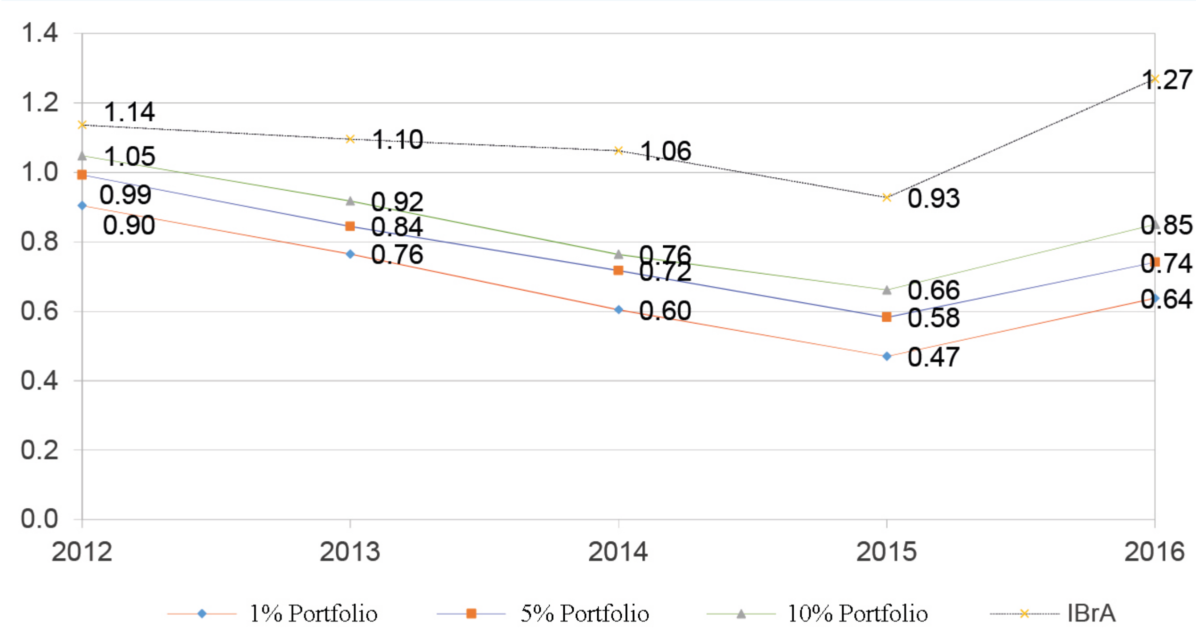

Figure 2 *Comparison of the cumulative factors of the Índice Brasil Amplo (IBrA) with the 10%, 5%, and 1% significant portfolios – 2012-2016.*
Source: *Elaborated by the authors.*

The results presented in Table 2 and in Figure 2 show that the portfolios compiled using the IBrA as a proxy for market returns did not exceed the Ibovespa in any of the years of the period analyzed. In the case of the 10% portfolios, the final cumulative return for the period was negative by approximately -15.02%, which is much below the cumulative return on the IBrA (26.96%). In the case of the 5% portfolios, the total cumulative return in the period was negative by approximately -25.90%.

The evidence found by Gomes et al. (2015), such as opposing heuristics for the first and second line assets, that is, non-symmetrical behavioral effects for these categories of assets, may be a possible explanation for the negative results of applying the GTT model with IBrA assets.

4.3 Analysis of Applying the GTT Methodology for the Ibovespa – Simulation of Windows

To test the robustness of the GTT model, investment in various portfolios with multiple time horizons was simulated. Initially, the FVI was calculated for a period of 12 months and the return in the following three months, with rebalancing of the portfolio carried out quarterly. Table 3 shows the result of the average cumulative returns (gross and net of brokerage) on the portfolios, with half-normal distribution, and with a time horizon of 12, 24, 36, 48, and 60 months, for 1%, 5%, 10%, 15%, 20%, and 25% levels of significance, as described in item 3.2.

The results show that, in the longest portfolios, especially in the 60-month ones, the average returns tend to be higher, so that in these portfolios the difference for the Ibovespa tends to be greater.

Table 3
Cumulative returns (gross and net) with quarterly rebalancing and moving windows, estimated cost of brokerage, and cumulative return on the Bovespa Index (Ibovespa) – Half-normal distribution

Level of significance (%)	Time horizon of the portfolios (months)	Gross return (average) (%)	Brokerage (average) (%)	Net return (average) (%)	Ibovespa return (average) (%)	Difference return net (-) Ibovespa (average) (%)
1.0	12	3.6	0.0309	3.4	6.8	-3.4
	24	-3.8	0.0314	-4.0	6.6	-10.6
	36	-11.7	0.0315	-12.0	5.9	-17.9
	48	-18.2	0.0314	-18.6	9.4	-28.0
	60	-23.5	0.0306	-24.0	7.5	-31.5
5.0	12	11.3	0.0564	11.0	6.8	4.2
	24	8.4	0.0580	7.9	6.6	1.4
	36	6.4	0.0590	5.6	5.9	-0.3
	48	10.0	0.0595	8.9	9.4	-0.4
	60	11.7	0.0585	10.4	7.5	2.9
10.0	12	14.5	0.0747	14.1	6.8	7.3
	24	16.6	0.0766	15.9	6.6	9.4
	36	20.4	0.0773	19.3	5.9	13.4
	48	30.6	0.0774	29.1	9.4	19.7
	60	37.5	0.0766	35.5	7.5	28.0
15.0	12	12.1	0.0879	11.8	6.8	5.0
	24	13.2	0.0894	12.5	6.6	5.9
	36	16.3	0.0898	15.1	5.9	9.2
	48	26.1	0.0896	24.4	9.4	15.0
	60	31.0	0.0890	28.8	7.5	21.2
20.0	12	11.0	0.0988	10.6	6.8	3.8
	24	11.7	0.1003	10.8	6.6	4.2
	36	14.7	0.1009	13.4	5.9	7.5
	48	24.2	0.1010	22.3	9.4	12.9
	60	28.8	0.1004	26.4	7.5	18.9
25.0	12	9.9	0.1057	9.4	6.8	2.6
	24	8.5	0.1073	7.6	6.6	1.1
	36	10.1	0.1082	8.7	5.9	2.8
	48	17.5	0.1084	15.6	9.4	6.2
	60	20.4	0.1080	17.9	7.5	10.4

Source: *Elaborated by the authors.*

With relation to the level of significance, the results of the simulations reveal that the 10% level is the one that presents the highest average portfolio returns that most exceed the Ibovespa. For example, for the 10% level, the 60-month portfolios obtained an average gain of 28 percentage points more than the Ibovespa. The results for the 1% and 5% levels of significance were generally poorer than for the other levels.

Table 4 shows the results of the same simulations, however with the truncated normal distribution. Although slightly poorer, the results are generally similar to those of the half-normal distribution, with the longer portfolios (48 to 60 months) being the best performing ones, at a 15% level of significance.

Table 4

Cumulative returns (gross and net) with quarterly rebalancing and moving windows, estimated cost of brokerage, and cumulative return on the Bovespa Index (Ibovespa) – Truncated normal distribution.

Level of significance (%)	Time horizon of the portfolios (months)	Gross return (average) (%)	Brokerage (average) (%)	Net return (average) (%)	Ibovespa return (average) (%)	Difference return net (-) Ibovespa (average) (%)
1.0	12	8.1	0.0318	8.0	6.8	1.2
	24	3.6	0.0323	3.3	6.6	-3.2
	36	-5.2	0.0328	-5.6	5.9	-11.5
	48	-12.0	0.0326	-12.5	9.4	-21.9
	60	-20.3	0.0318	-20.8	7.5	-28.3
5.0	12	9.1	0.0573	8.8	6.8	2.0
	24	3.9	0.0587	3.4	6.6	-3.2
	36	0.5	0.0595	-0.2	5.9	-6.1
	48	2.5	0.0596	1.5	9.4	-7.9
	60	1.3	0.0583	0.1	7.5	-7.4
10.0	12	12.1	0.0690	11.8	6.8	5.0
	24	11.7	0.0705	11.1	6.6	4.5
	36	13.9	0.0710	13.0	5.9	7.1
	48	21.5	0.0709	20.2	9.4	10.8
	60	25.7	0.0698	24.0	7.5	16.5
15.0	12	13.1	0.0787	12.8	6.8	6.0
	24	14.4	0.0802	13.8	6.6	7.2
	36	18.1	0.0806	17.0	5.9	11.1
	48	28.4	0.0805	26.9	9.4	17.5
	60	34.8	0.0796	32.8	7.5	25.3
20.0	12	12.3	0.0886	11.9	6.8	5.2
	24	12.6	0.0900	11.9	6.6	5.3
	36	15.0	0.0906	13.8	5.9	7.9
	48	24.0	0.0905	22.3	9.4	12.9
	60	28.3	0.0899	26.1	7.5	18.5
25.0	12	10.9	0.0940	10.5	6.8	3.8
	24	11.6	0.0958	10.7	6.6	4.2
	36	14.3	0.0971	13.0	5.9	7.1
	48	23.0	0.0974	21.2	9.4	11.8
	60	27.2	0.0972	24.8	7.5	17.3

Source: *Elaborated by the authors.*

Table 5 shows the results of the cumulative returns with annual rebalancing of the portfolios, using the truncated normal distribution as an alternative to quarterly rebalancing, whose results were presented in tables 3 and 4.

The results of Table 5 show that at a 10% level of significance and in the portfolios with longer periods, much higher returns than those of the Ibovespa are obtained, as well as higher returns than those obtained with quarterly rebalancing.

For example, in the portfolios with 60 periods and with 10% significance for the FVI, the portfolios obtained an average return of 62.8 percentage points more than the Ibovespa. In addition, in these simulations with annual rebalancing there was less variability in the average cumulative returns on the portfolios, so that it was possible to beat the Ibovespa in practically every simulation.

Table 5
Cumulative returns (gross and net) with annual rebalancing and moving windows, estimated cost of brokerage, and cumulative return on the Bovespa Index (Ibovespa) – Truncated normal distribution

Level of significance (%)	Time horizon of the portfolios (months)	Gross return (average) (%)	Brokerage (average) (%)	Net return (average) (%)	Ibovespa return (average) (%)	Difference return net (-) Ibovespa (average) (%)
1.0	12	21.4	0.0500	21.3	6.8	14.5
	24	31.0	0.0565	30.8	6.6	24.2
	36	43.2	0.0613	42.9	5.9	37.0
	48	44.0	0.0619	43.6	9.4	34.2
	60	50.7	0.0621	50.2	7.5	42.7
5.0	12	15.6	0.0950	15.4	6.8	8.6
	24	20.5	0.1067	20.1	6.6	13.6
	36	30.5	0.1145	29.9	5.9	24.0
	48	34.8	0.1169	34.0	9.4	24.6
	60	42.7	0.1167	41.7	7.5	34.2
10.0	12	20.4	0.1238	20.1	6.8	13.3
	24	30.5	0.1383	29.9	6.6	23.4
	36	45.4	0.1473	44.6	5.9	38.7
	48	55.7	0.1506	54.6	9.4	45.2
	60	71.8	0.1504	70.3	7.5	62.8
15.0	12	19.4	0.1410	19.0	6.8	12.2
	24	28.3	0.1569	27.7	6.6	21.1
	36	42.9	0.1666	42.0	5.9	36.1
	48	51.9	0.1705	50.7	9.4	41.3
	60	65.9	0.1705	64.3	7.5	56.8
20.0	12	19.2	0.1572	18.8	6.8	12.0
	24	28.4	0.1743	27.8	6.6	21.2
	36	43.0	0.1850	42.0	5.9	36.1
	48	51.9	0.1897	50.5	9.4	41.1
	60	65.9	0.1901	64.1	7.5	56.6
25.0	12	18.4	0.1711	18.0	6.8	11.2
	24	27.3	0.1883	26.6	6.6	20.0
	36	41.3	0.1994	40.2	5.9	34.3
	48	50.2	0.2043	48.7	9.4	39.3
	60	63.9	0.2050	62.0	7.5	54.4

Source: *Elaborated by the authors.*

4.4 Other Tests

The GTT model was used to detect possible overvaluation in the Brazilian stock market in the period of the study. However, the returns obtained with the portfolios compiled based on these estimations were lower than the Ibovespa returns in the period analyzed; that is, the market model with the composite error used in this study, both with the proxy for the Ibovespa and with the proxy for the IBrA, were unable to adequately capture the possible overvaluations of the shares included in the sample used. This fact could be the object of future studies to understand the reasons for which the GTT model did not obtain satisfactory performance in detecting the overvaluation of assets.

Finally, the GTT model was tested as a short-term investment strategy. The FVI was calculated for a period of 12 weeks and the return was measured in the following three weeks, also in windows. 522 portfolios were simulated for 12 months each, from 2005 to 2016. The average return on the portfolios was negative by 5.84% in relation to the Ibovespa return, at 10% significance and considering transaction costs. The FVI was also calculated for the very short term (four-week calculation period and one week for return) at 10% significance and considering transaction costs; the average return on the portfolios was negative by 18.7%. This evidence confirms the assumptions of Gokhale et al. (2015), who indicated negative performance with the application of the model for short-term investment strategies, given that the model does not identify a share's change of tendency point, but instead merely communicates whether it is undervalued or overvalued.

5. FINAL REMARKS

This article discussed applying the GTT model for evaluating assets in the Brazilian capital market. The model captures the systematic errors of behavioral traders and detects undervaluation biases in share prices.

The results found were consistent with the results of applying the same method for American companies belonging to the DOW 30 Index and confirmed the expectations that the composite errors model would be able to capture possible behavioral biases that could be causing misvaluation in the Brazilian stock market.

The performances of the portfolios compiled based on this model much exceeded the market portfolio (Ibovespa) in the period analyzed. In the case of the portfolio based on the FVI at 10% significance, the final cumulative return for the period from 2006 to 2016 was approximately 274%, while the Ibovespa yielded approximately 80%.

The model was not adequate when the IBrA was used as a reference for the market portfolio. The cumulative return on the annual portfolios, at 10% significance, was negative by approximately -15.02%, while the IBrA yielded 26.96% in the period. In the case of the 5% portfolio, the total cumulative return in the period was negative by approximately -25.93%.

The time windows study demonstrated the possibility of using the methodology indicating average positive returns in relation to the Ibovespa, both in the quarterly calculation of the return and in the annual calculation of the return. For example, at 10% significance, portfolios simulated for 12 months (12 months of FVI calculation and three months of return) yielded 7.3% more than the Ibovespa on average.

The tests of the models in the short term confirmed the assumptions of Gokhale et al. (2015) and presented unsatisfactory results. For the FVI calculation for 12 weeks and return calculation in three weeks, the simulated portfolios presented a negative average return of 5.84% in relation to the Ibovespa, at 10% significance and considering transaction costs.

Finally, applying the methodology to identify episodes of overvaluation in the Brazilian market presented inconsistent results and is not viable as an investment strategy.

Subsequent studies could deepen the analysis of the model by modifying the frequency of the data analyzed, with intraday returns and the compilation of monthly or weekly portfolios, varying the calculation period and the period for determining returns. The effects of moments of economic crises on the GTT model could also be the object of new studies (Piccoli et al., 2015).

Other possibilities include estimating the overvaluation model in parallel with the undervaluation one, thus adopting a mixed buy and sell strategy and observing the returns obtained in these models (contrarian strategy), and using another alternative pricing model to the market model in order to improve the adjustment of the model and obtain a better estimation of the error component associated with misvaluation.

REFERENCES

Aguiar, R. A., Sales, R. M., & Sousa, L. A. D. (2008). Um modelo Fuzzy comportamental para análise de sobre-reação e sub-reação no mercado de ações brasileiro. *RAE– Revista de Administração de Empresas*, *48*(3), 8-22.

Bolsa de Valores, Mercadorias e Futuros de São Paulo (2008). *Ofício Circular nº 70/2008-DP. Alteração na Política de Tarifação de Produtos e Serviços da BM&FBOVESPA*. Retrieved from http://www.bmfbovespa.com.br/pt_br/regulacao/oficios-e-comunicados/.

Bolsa de Valores, Mercadorias e Futuros de São Paulo (2017). Índices amplos. Retrieved from http://www.bmfbovespa.com.br/pt_br/produtos/indices/indices-amplos/.

Coelli, T. (1995). Estimators and hypothesis tests for a stochastic frontier function. A Monte Carlo analysis. *Journal of Productivity Analysis*, *6*(3), 247-268.

Coelli, T., & Henningsen, A. (2017). Frontier: Stochastic Frontier Analysis. R package version 1.1-2. Retrieved from https://CRAN.R-Project.org/package=frontier.

Costa, N. C. A., Jr. (1994). Overreaction in the Brazilian stock market. *Journal of Banking & Finance*, *18*(4), 633-642.

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, *40*(3), 793-805.

Dourado, G. A., & Tabak, B. M. (2014). Teste da hipótese de mercados adaptativos para o Brasil. *Revista Brasileira de Finanças*, *12*(4), 517-553.

Fama, E. F. (1970). Efficient capital markets: a review of theory and empirical work. *The Journal of Finance*, *25*(2), 383-417.

Gokhale, J., Tremblay, C. H., & Tremblay, V. J. (2015). Misvaluation and behavioral bias in financial markets. *Journal of Behavioral Finance*, *16*(4), 344-356.

Gomes, A., Mól, A., & Souto, M. (2015). Análise da sobre-reação e sub-reação nos ativos de primeira e segunda linha do mercado acionário brasileiro. *Revista Universo Contábil*, *11*(3), 85-109.

Greene, W. H. (2008). The econometric approach to efficiency analysis. In Fried, H. O., Lovell, C., & Schmidt S. S (Eds.), *The measurement of productive efficiency and productivity growth* (pp. 92-250). New York/NY: Oxford University.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: implications for stock market efficiency. *The Journal of Finance*, *48*(1), 65-91.

Kimura, H. (2003). Aspectos comportamentais associados às reações do mercado de capitais. *RAE–eletrônica*, *2*(1), 1-14.

Leone, V., & de Medeiros, O. R. (2015). Signalling the Dotcom bubble: a multiple changes in persistence approach. *The Quarterly Review of Economics and Finance*, *55*(2015), 77-86.

Leybourne, S., Kim, T. H., & Taylor, A. R. (2007). Detecting multiple changes in persistence. *Studies in Nonlinear Dynamics and Econometrics*, *11*(3), 1-32.

Piccoli, P. G. R., Souza, A., da Silva, W. V., & Cruz, J. A. W. (2015). Revisitando as estratégias de momento: o mercado brasileiro é realmente uma exceção? *Revista de Administração*, *50*(2), 183-195.

Pimentel, R. C. (2015). Lucros inesperados, retorno das ações e risco no mercado de capitais brasileiro. *Revista Contabilidade & Finanças*, *26*(69), 290-303.

R Core Team (2016). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Retrieved from https://www.R-project.org/.

Rabelo, T. S., Jr., & Ikeda, R. H. (2004). Mercados eficientes e arbitragem: um estudo sob o enfoque das finanças comportamentais. *Revista Contabilidade & Finanças*, *15*(34), 97-107.

Richardson, S., Tuna, İ., & Wysocki, P. (2010). Accounting anomalies and fundamental analysis: a review of recent research advances. *Journal of Accounting and Economics*, *50*(2), 410-454.

Santos, J. O. D., & Santos, J. A. R. D. (2005). Mercado de capitais: racionalidade *versus* emoção. *Revista Contabilidade & Finanças*, *16*(37), 103-110.

Serra, R. G., Saito, A. T., & Fávero, L. P. L. (2016). Nova metodologia do Ibovespa, betas e poder explicativo dos retornos das ações. *Revista de Contabilidade e Organizações*, *10*(27), 71-85.

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *The Journal of Economic Perspectives*, *17*(1), 83-104.

Teixeira, L. A., & Oliveira, A. L. I. (2010). A method for automatic stock trading combining technical analysis and nearest neighbor classification. *Expert Systems with Applications*, *37*(10), 6885-6890.

ANNEX 1

Undervaluation model and likelihood ratio test – Bovespa Index (Ibovespa) – 2005-2009

	2005		2006		2007		2008		2009	
Share	**p-value**	**FVI**	**p-value**	**FVI**	**p-value**	**FVI**	**p-value**	**FVI**	**p-value**	**FVI**
ABEV3	0.000	-200.3[a]	0.499	-0.6	0.001	-121.9[a]	0.499	-1.6	0.023	-110.7[a]
ACES4	1.000	-31.3	0.499	-0.7	0.499	-0.5	1.000	-28.3		
ALLL11	1.000	-35.5	1.000	-39.6	1.000	-33.1	0.198	-204.8	0.499	-1.9
ALLL3			0.499	-4.1	0.499	-2.1	0.499	-4.3	0.006	-451.3[a]
AMBV4	0.499	-1.2	0.499	-2.0	0.137	-100.7	0.299	-123.4	0.010	-128.6*
ARCE3	0.499	-2.0	1.000	-34.6	1.000	-32.0				
ARCZ6	0.499	-1.9	0.499	-0.8	1.000	-31.4	0.001	-309.2*	0.499	-2.4
BBAS3	1.000	-33.6	0.499	-1.0	1.000	-30.4	0.499	-3.3	0.013	-141.4**
BBDC3	1.000	-33.0	0.499	-1.7	0.499	-0.8	0.387	-97.2	0.081	-94.7[a]
BBDC4	1.000	-30.4	0.499	-0.6	0.385	-52.6	1.000	-32.0	0.006	-107.4*
BISA3			0.499	-0.8	0.499	-2.1	0.019	-243.9[a]	0.499	-0.9
BNCA3	0.499	-0.8	1.000	-40.3	0.116	-131.4	0.499	-0.8	0.001	-102.6[a]
BRAP4	1.000	-31.7	0.499	-1.0	0.216	-84.9	1.000	-35.3	0.499	-0.9
BRFS3			0.499	-0.8	1.000	-39.2	0.499	-1.6	0.499	-1.2
BRKM5	1.000	-35.0	1.000	-36.8	1.000	-34.4	0.499	-2.1	0.499	-1.5
BRML3					0.260	-192.7	0.499	-2.0	0.162	-161.1
BRTP3	0.095	-147.6***	0.001	-228.4*	1.000	-40.5	1.000	-40.0	0.000	-308.9[a]
BRTP4	1.000	-32.9	1.000	-32.4	1.000	-32.5	0.115	-240.2	0.499	-3.4
BTOW3					0.003	-219.5*	0.375	-148.8	0.499	-1.3
BVMF3							0.499	-4.2	0.475	-64.6
CCRO3	0.150	-124.3	0.324	-137.8	0.101	-142.2	0.499	-1.7	1.000	-37.4
CESP6			1.000	-29.4	1.000	-39.4	0.000	-379.8*	1.000	-35.9
CIEL3									0.499	-1.0
CLSC4	1.000	-34.9	1.000	-32.7	0.499	-0.7	0.289	-99.8	0.499	-0.8
CMET4	0.422	-70.8	0.499	-1.9						
CMIG4	0.499	-2.8	0.499	-2.5	0.499	-1.0	0.004	-203.9*	0.317	-89.2
CPFE3	1.000	-31.7	0.439	-59.9	0.499	-0.9	0.011	-182.6**	0.117	-95.9
CPLE6	1.000	-34.9	1.000	-31.9	0.351	-84.9	0.196	-143.9	0.213	-92.9
CRTP5	1.000	-33.8	0.499	-1.3						
CRUZ3	0.499	-1.9	1.000	-36.5	1.000	-36.0	0.499	-1.5	1.000	-32.2
CSAN3	0.500	-0.9	0.500	-5.2	0.181	-166.0	0.017	-298.4**	0.499	-2.0
CSNA3	0.499	-1.4	0.499	-0.7	0.499	-1.0	0.499	-0.9	0.499	-1.3
CSTB4	0.116	-157.7								
CTIP3									0.234	-205.3
CYRE3	0.499	-1.0	0.157	-200.8	0.499	-2.0	0.025	-272.8**	0.169	-181.6
DASA3	1.000	-40.5	1.000	-5.2	1.000	-35.0	0.499	-2.1	1.000	-30.4
DTEX3					0.160	-258.0	0.004	-277.7[a]	0.499	-0.6
DURA4	1.000	-39.0	0.499	-2.5	0.224	-124.1	0.389	-151.5	0.300	-137.3
EBTP4	0.499	-1.4	1.000	-37.0	0.499	-0.9	0.499	-2.8	0.499	-1.0
EGIE3	0.499	-1.8	1.000	-35.6	0.499	-1.6	0.499	-1.9	0.480	-59.3
ELET3	1.000	-36.0	1.000	-38.4	1.000	-33.7	0.499	-1.1	1.000	-35.5
ELET6	1.000	-34.3	1.000	-36.4	1.000	-30.8	0.499	-1.6	0.499	-0.7
ELPL4			1.000	-26.7	0.499	-1.8	0.264	-156.1	1.000	-32.2
EMBR3	0.499	-2.0	1.000	-34.2	0.176	-100.0	0.499	-1.7	0.499	-2.6
EMBR4	1.000	-32.4	0.482	-54.9						
ENBR3	0.499	-0.9	0.499	-3.1	0.053	-147.5[a]	0.499	-1.4	1.000	-30.2
EQTL3							0.499	-2.1	1.000	-34.3
ESTC3							0.281	-230.5	0.499	-2.4
EVEN3					0.499	-1.8	0.499	-2.6	0.499	-3.9
FIBR3									0.499	-1.5
GFSA3			0.499	-0.8	0.499	-1.9	0.027	-306.3**	0.499	-1.9
GGBR4	0.499	-0.7	0.499	-1.4	0.500	-1.6	0.275	-117.7	0.499	-1.2
GOAU4	1.000	-30.3	0.499	-1.1	0.394	-63.4	0.365	-103.0	0.500	-1.8
GOLL4	0.499	-1.8	0.499	-1.1	1.000	-39.6	0.499	-1.8	0.499	-1.6

ANNEX 1

Cont.

	2005		2006		2007		2008		2009	
Share	**p-value**	**FVI**	**p-value**	**FVI**	**p-value**	**FVI**	**p-value**	**FVI**	**p-value**	**FVI**
HGTX3			0.499	-1.3	0.499	-1.0	0.499	-3.1	0.499	-2.1
HYPE3							0.274	-192.3	0.371	-129.7
ITSA4	0.499	-1.2	0.499	-1.1	0.499	-0.8	1.000	-40.6	0.151	-96.7
ITUB4	0.499	-2.3	1.000	-2.9	0.499	-0.7	1.000	-40.9	0.062	-109.8***
JBSS3					0.050	-220.8[a]	0.499	-3.6	0.499	-2.7
KLBN4	1.000	-35.1	1.000	-33.0	0.176	-127.5	0.499	-1.6	0.499	-1.4
LAME4	1.000	-35.8	0.499	-1.6	1.000	-35.0	0.499	-1.5	1.000	-34.8
LIGT3	0.499	-1.8	0.002	-254.4*	0.307	-110.0	0.499	-1.0	0.326	-85.8
LREN3	0.499	-0.7	0.499	-1.2	0.126	-160.9	0.009	-307.1*	0.499	-3.3
MMXM3			0.499	-0.4	0.378	-110.5	0.499	-2.7	0.499	-1.4
MRFG3					0.499	-1.0	0.000	-292.2[a]	0.499	-1.7
MRVE3					0.499	-1.2	0.455	-138.2	0.299	-172.8
MULT3					0.023	-262.0[a]	0.207	-180.8	1.000	-37.3
NATU3	0.499	-1.2	0.499	-1.6	0.010	-173.4**	0.499	-2.2	0.018	-137.4**
NETC4	0.499	-2.8	1.000	-32.9	0.035	-164.8**	0.026	-248.4**	0.499	-2.8
OGXP3							0.499	-2.9	1.000	-6.3
OIBR4	0.499	-0.6	1.000	-31.9	1.000	-32.6	0.243	-195.6	0.117	-138.3
PCAR4	0.235	-101.3	1.000	-35.1	0.499	-1.1	1.000	-40.6	0.499	-1.0
PDGR3					0.075	-184.4[a]	0.499	-6.6	1.000	-8.2
PETR3	0.358	-77.3	0.287	-78.0	0.499	-0.4	1.000	-39.4	0.499	-1.0
PETR4	0.135	-97.9	0.301	-65.8	0.499	-0.4	1.000	-36.7	0.499	-0.8
POMO4	1.000	-31.2	0.499	-0.7	1.000	-37.9	0.499	-2.7	0.499	-1.5
PRGA4	0.500	-6.2	0.048	-332.9[a]						
PRML3							0.499	-3.7	0.499	-0.8
PTIP4	1.000	-33.3	1.000	-31.7	0.116	-125.9				
RADL3					0.232	-223.8	0.499	-1.8	1.000	-38.9
RDCD3					0.499	-0.4	0.499	-4.7	0.096	-192.9***
RENT3	1.000	-31.8	0.499	-1.6	0.499	-1.4	0.105	-275.2	1.000	-39.6
RSID3	0.499	-2.6	0.274	-167.2	0.499	-1.6	0.108	-288.6	0.037	-208.5**
SANB11									0.499	-1.1
SBSP3	1.000	-32.5	1.000	-34.8	0.499	-3.2	0.499	-3.2	1.000	-38.1
SDIA4	0.331	-108.3	0.499	-3.3	1.000	-35.7	0.000	-404.1*	0.499	-1.2
SUZB5	1.000	-33.4	1.000	-34.6	1.000	-30.5	0.187	-143.2	0.499	-1.1
TAMM4	0.413	-121.7	0.499	-0.8	0.150	-150.3	0.499	-6.2	0.499	-1.1
TCOC4	1.000	-37.4	0.499	-1.1						
TCSL4	1.000	-34.0	1.000	-39.8	1.000	-33.7	0.499	-1.9	1.000	-39.5
TESA3					0.499	-1.1	0.499	-2.2	0.499	-1.0
TIMP3	0.016	-215.8[a]	0.111	-172.9	0.499	-1.1	0.375	-161.8	0.079	-170.9[a]
TMAR5	0.499	-0.8	1.000	-30.8	1.000	-31.7	0.323	-162.7	0.499	-3.2
TMCP4	1.000	-37.6	0.499	-1.1	1.000	-35.2	1.000	-33.1	1.000	-35.4
TNLP3	0.499	-1.0	0.004	-227.6*	1.000	-39.6	0.499	-1.6	0.392	-84.6
TNLP4	0.499	-0.5	0.499	-1.1	0.499	-0.7	0.499	-1.6	0.499	-3.0
UBBR11	1.000	-32.0	0.499	-1.1	0.499	-0.7	0.499	-2.1	0.390	-127.8
USIM3	1.000	-36.9	1.000	-37.9	1.000	-4.4	0.499	-1.7	0.499	-3.5
USIM5	1.000	-31.1	0.499	-0.9	0.499	-1.5	1.000	-41.0	1.000	-31.4
VALE3	1.000	-28.8	0.499	-1.3	0.087	-95.1***	1.000	-34.0	0.291	-65.9
VALE5	0.499	-1.1	0.432	-48.2	0.154	-74.6	0.499	-1.3	0.465	-36.3
VCPA4	0.499	-0.8	1.000	-32.9	1.000	-31.9	0.141	-205.4	0.287	-206.8
VIVO4	1.000	-39.3	0.499	-1.8	0.499	-1.2	0.372	-141.4	0.368	-95.2
VIVT4	1.000	-32.1	0.499	-1.0	0.243	-102.4	0.388	-104.9	0.499	-1.3

, **, *: 1%, 5%, and 10% significant, respectively; a: asset not participating in the Ibovespa portfolio in the year in question.*
FVI = Fundamental Valuation Index.
Source: *Elaborated by the authors.*