Rating changes and the impact on stock prices

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Abstract

Purpose – The objective of this study is to analyze the impact of changes in credit ratings on the long-term return of Brazilian firms.

Design/methodology/approach – We conducted an event study to measure how stock prices in the Brazilian stock exchange (B3) react to rating upgrades and downgrades by Moody's and S&P.

Findings – Our sample presents positive and significant returns measured by the BHAR for ratings downgrades and non-significant ones for upgrades. Our data also show the important role of the previous rating in explaining these results in a non-linear fashion.

Originality/value – Our research makes an important contribution to the theory of market efficiency, analyzing the degree of information present in the announcements of credit ratings changes. We also present results for Brazilian companies, correcting gaps pointed out in previous methodologies.

Keywords – Credit ratings; Stock market; Event study; Market efficiency

1 Introduction

The informational content of corporate rating changes is a topic that has long been debated in the literature. Pinches and Singleton (1978) and Glascock, Davidson, and Henderson (1987) find no significant unanticipated effects on stock prices of companies having their risk ratings downgraded. Papers published afterwards that study larger and more frequent (monthly and daily) databases find strong evidence that downgrades have an impact on short- and long-term stock returns (Griffin & Sanvicente (1982), Followill & Martell (1997), Dichev & Piotroski (2001), Norden & Weber (2004), and Linciano (2004)). Other authors, such as Holthausen and Leftwich (1986), Hand, Holthausen, and Leftwich (1992), and Dichev and Piotroski (2001), also verify that rating upgrades do not have significant impacts. Goh and Ederington (1993) find interesting results in the form of negative impacts on prices after downgrades due to falling profits, and positive impacts in terms of price increases after downgrades due to increased leverage.

This empirical evidence on the impact of increased bankruptcy risk on stock prices is controversial as to the direction in which it operates. It is known as the "distress puzzle." Some studies show a positive relationship between increased default risk and the rate of return on the stock, while others find the opposite result.

For example, Vassalou and Xing (2004), Chava and Purnanandam (2010), and Friewald, Wagner, and Zechner (2014) find evidence of increased profitability for higher credit risk securities. In these cases, the risk of default is measured by using the methodology proposed in Merton (1974). The empirical results in Friewald et al. (2014) document that measuring credit risk by credit default swap (CDS) spreads and building portfolios by buying high-credit risk companies and selling low-credit risk companies yields a positive alpha after controlling for standard risk factors. They use data from between 2001 and 2010, including the 2008 crisis.

On the other hand, there are several articles documenting a negative relationship between stock returns and increased default risk, such as those of Hand, Holthausen, and Leftwich (1992), Dichev (1998), Dichev and Piotroski (2001), Griffin and Lemmon (2002), and most recently by Campbell, Hilscher, and Szilagyi (2008), Avramov, Chordia, Jostova, and Philipov (2009), and Vassalou and Xing (2013). In these articles, however, the increase in risk is measured by rating changes published by rating agencies (Moody's and S&P) and by credit-risk metrics based on historical data such as Z-Score and O-Score, as suggested by Altman (1968) and Ohlson (1980), respectively.

Positive results appear to be in line with the efficient market theory, as investors demand higher returns on riskier assets, except if we consider default risk as a systematic risk and therefore not diversifiable. In this sense, Vassalou and Xing (2014) demonstrate that the risk of default is systematic and even partially captured by the factors that generate the price formation anomalies pointed out in Fama and French (1992). Articles that find a negative relationship between profitability and increased risk of default appear to be in conflict with the efficient market hypothesis: after all, rating agencies publish their results after analyzing public data and meetings held at the companies. Even if the company could pass on private information at these meetings, these effects would be short-term, which contradicts several long-term results previously mentioned, for example by Dichev and Piotroski (2001), who find abnormal returns of 10% to 14% one year after the rating downgrade. Vassalou and Xing (2013) explain this apparent contradiction by the fact that when the rating change announcement occurs, the affected company changes its risk behavior, thus creating an inverted V effect on default risk metrics by using the default model in Merton (1974). For example, downgraded companies seek to reduce risk and thus expected returns will be lower than for comparable companies.

Another academic argument to justify the apparent contradiction claims that the controversial results of the distress puzzle can be explained by the methodology chosen. Thus, traditional event study methodologies such as the one proposed by Campbell, Lo, and Mackinlay (1997) use CAR (cumulative abnormal return) and fail to capture part of the variations in return explained by other factors such as company size, rating, and book-to-market ratio. To correct this bias, Dichev and Piotroski (2001) propose the use of the buy and hold returns (BHAR) methodology, following Barber and Lyon (1996). This methodology compares the return on securities with changes in their credit risk with comparable corporate portfolios by using metrics for size, book-to-market ratio, and credit risk. Even so, the long-term results are preserved. Subsequently, Jorion and Zhang (2006) find a moderating effect of the previous credit rating, which shows that this metric should be included in the models to avoid omitted variable bias. Therefore, with the inclusion of previously omitted variables, we expect more consistent results.

Almost all these articles analyze results in the US market, especially because the coverage of emerging countries by rating agencies is more recent. In this sense, Benjamin EE (2008) publishes one of the pioneering studies on emerging countries. He finds a significant negative abnormal return in the long run for downgrades, but which is smaller in the case of emerging countries. Freitas and Minardi (2013) find similar results for Latin American countries using the methodology of Campbell, Lo, and Mackinlay (1997). They also find results which are not significant for rating upgrades.

For this article, we studied a database covering 161 rating changes in Brazil, issued by the Moody's and S&P agencies until 2018. Following a methodology compatible with that used by Dichev and Piotroski (2001), we generated 27 control portfolios and found significant negative results for downgrades. The ratings had impacts ranging from 4.35% in 6 months to up to 24.95% in 12 months. We also detected larger impacts for lower rated companies, compatible with the moderating effect in Jorion and Zhang (2006). Not only do we innovate in terms of the methodology used, but also in the use of more data on rating fluctuations, which have increased in frequency due to the recent economic crisis the country has faced.

Our data also demonstrate that the moderating effect of ratings is not linear as it shows quadratic behavior. Therefore, the results of rating changes for companies in the middle of the risk spectrum are less economically significant than for companies with low or high credit risk. Friewald et al. (2014) had already documented this inverted U pattern, but for bankruptcy probabilities measured by the CDS (credit default swap) spread of corporate long-term securities. Our work is the first that we are aware of that detects this nonlinear effect for rating changes, which could be explained by the investor's concern about lowering the prices of companies in the middle of the risk spectrum more intensely than those of lower or higher credit risk companies. In the former this is possibly because the downgrade is still far from being a problem of increased default risk; and in the case of companies with high-credit risk it is because their prices have already been fully reduced due to the high speculative level they represent. The disciplining effect of rating changes pointed out by Vassalou and Xing (2003) also appears to be more effective for companies with ratings at the end of the risk spectrum, thus generating greater adjustments and therefore lower expected returns over the medium and long term. The fact that long-term setbacks are greater than short-term ones is also compatible with the time it takes for the company to generate effective risk mitigation measures.

In addition to their academic significance, the findings of this paper have an impact on the market as they may suggest an easy-to-implement investment strategy for stock managers, or

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investors who buy or sell companies that have their ratings downgraded or upgraded (not necessarily in that order). For example, Avramov, Chordia, Jostova, and Philipov (2013) show that it is possible to make abnormal gains by short selling portfolios composed of companies with downgraded ratings in the US market and our article documents similar effects for Brazilian companies.

The remainder of this paper is organized as follows. The second section discusses the literature review. The third section describes the methodology. The fourth section discusses the results obtained. The fifth section presents the conclusion.

2 Literature Review

The usual empirical tests to measure the impact of rating shifts analyze changes in stock prices before, around, and after the announcements of these rating shifts. They apply the event study methodology. If rating changes bring relevant new information to the market, a price reaction is expected after the announcement. Similarly, considering that agencies primarily formulate ratings using available public information, changes in ratings should not have an impact on stock prices because they already reflect all informational content in accordance with the efficient market hypothesis.

Dichev and Piotroski (2001) point out that one motivation for studying the effect of rating changes stems from "the fact that existing research offers only sporadic and somewhat contradictory evidence on this issue." In fact, arbitrariness in choosing how to model and to conduct statistical tests has not enabled the literature to create a standard - there is no single ideal methodology for event studies. There has been a great deal of disagreement among the authors of academic studies on the subject so far, as they have used different timeframes, criteria to select companies, rating agencies, abnormal return measures, sample filters, and their subsequent applications. For studies on different markets,

countries, and years, we have attached Table A-1, which is a summary of those studies, their sample characteristics, and their main results.

Most papers find significant negative abnormal returns for downgrades, but they do not find significant abnormal returns following upgrades. Vassalou and Xing (2003, 2004) dispute this conclusion, which was somewhat consolidated as standard in the literature, presenting two anomalies that made no sense from the behavioral point of view of individuals in financial markets. First, the magnitude of the impact of rating changes should be the same for downgrades and upgrades, because if ratings bring new relevant information to the market, it should react regardless of the direction of the change. Second, the abnormal return for downgraded stocks should be positive, as downgrades imply higher credit risk and investors require higher returns as the risk of the investment rises. The authors conducted a study to find the reason for the persistence of these anomalies. After performing statistical tests and cross-sectional regression analyses, they concluded that such anomalies were specific to the method used to compute the abnormal return, which until then disregarded a biasing factor. The level of credit risk was verified as being a highly significant explanatory variable for stock returns and, therefore, it should be incorporated in the methodology.

The non-incorporation of the credit risk level variable in the model was presented as a cause of the anomalies present in the results obtained so far in the literature. Vassalou and Xing (2003, 2004) are pioneers of this reasoning, and two other relevant studies continued to develop it further. Norden and Weber (2004) develop a study that reveals, among other conclusions, that the rating before and after the change influences the magnitude of the abnormal return. Jorion and Zhang (2006) are more emphatic in addressing anomalies, and develop a study focused primarily on the importance of the pre-change rating variable, concluding in parallel with Norden and Weber (2004) that lower past ratings are

associated with higher effects on stock returns for both downgrades and upgrades.

Vassalou and Xing (2003, 2004) show that changes in the default likelihood index (DLI) have inverted V behavior around the date of the announcement of a risk rating change. They provide it as a possible explanation for the change in company behavior after the announcement. They also note that the intensity of this inverted V is dependent on the previous rating level, suggesting nonlinear behavior regarding this risk rating prior to the announcement.

It was found that the effect of rating changes on share prices depends on the pre- and post-change rating level - the lower the previous rating the larger the impact on prices. Thus, an additional channel for the return analysis should be included. In this way the bias between the impact of lowering and raising ratings is reduced. Since the previous rating level itself can be considered a measure of credit risk, it can be inferred that all of these authors complemented each other by generally pointing to the same conclusion: stocks with a higher risk are expected to generate higher returns. This implies a bias that may explain why downgrades have so far shown a larger impact on prices. Due to an intrinsic feature of rating distributions, downgrades occur more often for companies that were previously worse off than companies that receive upgrades, as companies that receive rating upgrades are generally at better credit risk levels, and the associated abnormal return is lower. On the other hand, it can be argued that the effect of downgrades is greater because companies voluntarily disclose good news, but they are more reluctant to publish bad news. Furthermore, it is argued that rating agencies apply more rigor and resources to detect deteriorations in credit quality than improvements, as it is more damaging to their reputation not to foresee serious credit problems if they materialize (e.g. as in the subprime crisis).

Thus, as in Vassalou and Xing (2003, 2004), it is common to see, in recent literature, that type of challenge in previous methodologies and the authors suggest changes in the model for event studies. Another issue is that most papers have applied the traditional event study methodology as explained by Campbell, Lo, and Mackinlay (1997), namely: the use of cumulative abnormal return (CAR); a time span that encompasses not only a period after the event has occurred, but also a period around and prior to the event (although the specific choice is arbitrary); and little attention is paid to choosing the reference portfolio to measure abnormal return. However, Barber and Lyon (1996) conducted a study on the empirical power and specification of the statistical tests used in event studies to detect abnormal stock market returns, and concluded by proposing adjustments to improve the significance of the tests. First, the abnormal return should be measured by the buy-and-hold (BHAR) methodology, as opposed to the traditional CAR one, as "CARs are biased predictors of BHARs" that potentially lead to incorrect inferences and do not correspond to the appropriate value of investing in a stock over time. Second, abnormal returns should not be measured based on a reference portfolio (e.g. the market index), as it promotes three types of bias (listing, rebalancing, and skewness), but rather based on different portfolios grouped in terms of the size and book-to-market of companies, conditioning the abnormal return to their portfolio.

The adjustments proposed above were only implemented by Dichev and Piotroski (2001), who developed one of the most relevant studies in the recent literature, focused on the long term, and which serves as the best reference for the development of this study. It is worth mentioning the work of Freitas and Minardi (2013), which despite addressing Latin America as a whole, presented individual analyses by country using the traditional CAR methodology. Brazil represented a large part of the sample and had great relevance in the study. Thus, their work is the one that most closely resembles our article, although it is positioned in a different fashion.

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3 Methodology

In line with the methodology of Dichev and Piotroski (2001), an empirical study will be conducted to analyze whether changes in credit ratings significantly affect short- and long-term stock returns, in this case exclusively for Brazilian companies. To validate the hypothesis of this significant impact, abnormal returns will be tested within six months and one year after the announcement of the rating change, including the moderating effect in Jorion and Zhang (2006).

3.1 Data

Data were collected for all rating upgrades and downgrades (disregarding revisions, withdrawals, and affirmations) by Moody's and S&P of Brazilian companies traded on the B3, which make up the Bovespa Index, until the end of 2018.

The Ibovespa is composed of companies that together represent 85% of the B3 tradability index, the Brazilian stock exchange, as well as individually meeting other volume, liquidity, and size criteria (e.g. being present in 95% of trading sessions and not being classified as penny stocks). Therefore, the decision taken to restrict rating changes only to companies that make up the index was to mitigate very low liquidity stocks with low representativeness, which could have biased returns due to several factors regarding the characteristics of small companies, as well as the lack of enough data to compare with the reference portfolio at very lagged dates, given that the first rating change occurred in 1998.

The rating change database was provided by Bloomberg, and a filter was applied to include only those of the issuer type, i.e. the ratings of the companies as a whole and not of individual securities issued. A second filter was applied exclusively to S&P ratings, which separates the issuer ratings into short-term and long-term, including only the latter. Filters were applied for three reasons. First, there are many occurrences of different ratings for different securities of the same company, which would make the analysis difficult. Second, long-term issuer ratings are best suited for this study because they reflect the company's overall long-term ability to meet its financial obligations. Third, issuer ratings are more abundant than individual bond ratings. This is important for the results to be representative of the market, especially for Brazil, whose coverage by the agencies is still recent and relatively scarce, and, therefore, the sample size is smaller compared to that of more developed countries.

Finally, multiple rating changes that occurred on the same date for the same company, or within one year, were excluded, so as not to bias their return. This exclusion significantly reduced the database but did not compromise the conclusion of this work: if it were not made, these companies would only have greater weight in the final result. Changes in the rating of companies that did not have a corresponding reference portfolio on the date were also excluded.

After applying the filters, the database presented 161 observations, of 36 companies in the index. Figure 1 shows the amount of rating changes over the period studied. There are few changes in the rating of Brazilian companies between 1999 and 2010 and from 2011 this amount increases, peaking at 28 changes in 2017, following the pattern of downgrades received by Brazil from major international agencies after 2014.
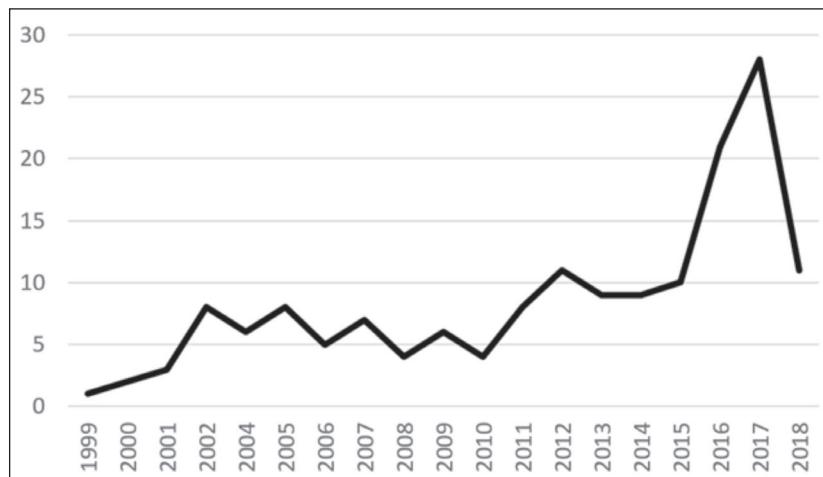
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Figure 1. Evolution of the amount of rating changes for Brazilian companies from 1999 to 2018.

The use of rating upgrades and downgrades as a measure of default risk is implicitly based on the assumption that all assets within a rating category share the same default risk and that it is impossible for a company to experience changes in its probability of default without also experiencing a rating change. Table 1 summarizes the magnitude of all Moody's and S&P rating downgrades and rating upgrades in the final sample during the period cited, as in Dichev and Piotroski (2001). The columns represent the pre-change rating class and the rows represent the post-change rating class. The class nomenclature used is taken from S&P, bearing in mind that although they vary between agencies, they are equivalent. For example, S&P class AA is rated AA +, AA, and AA- and is equivalent to Moody's class Aa, which is rated Aa1, Aa2, and Aa3. The number in each cell represents the number of observations that had their initial and final ratings. The diagonal of the matrix captures the rating changes within the same class.

The main diagonal of the matrix contained in Table 1 contains 105 observations, i.e. 65.2% of the rating changes occurred within the same rating class. Of the 56 changes between different classes, 53 (94.6%) occurred by a magnitude of 1 class (e.g. from BB to BBB). Of the 56 changes between different classes, 42 were downgrades (75%) and 14 were upgrades (25%).

Additionally, 50 post-change ratings were above or equal to the BBB class, i.e. 31.1% of post-change ratings are investment grade, while the rest are speculative. Finally, 26 ratings (16.2%) were changed from speculative to investment grade, and the opposite occurred only 7 times (4.4%).

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Table 1

Moody's rating and S&P rating class changes matrix.

	Final Rating								
	AAA	AA	A	BBB	BB	B	CCC	CC	C, D
Initial Rating									
AAA	0	0	0	0	0	0	0	0	0
AA	0	0	0	0	0	0	0	0	0
A	0	0	1	2	0	0	0	0	0
BBB	0	0	4	36	7	0	0	0	0
BB	0	0	2	24	59	5	0	0	0
B	0	0	0	0	9	7	0	0	0
CCC	0	0	0	0	1	2	2	0	0
CC	0	0	0	0	0	0	0	0	0
C, D	0	0	0	0	0	0	0	0	0

From the first date of the rating changes of the database used here, on January 15, 1999, the closing price, market capitalization, book-to-market, and issuer rating of the shares of all Ibovespa companies were collected, one year and six months after the date on which the last rating change in the sample occurred. These data are used to compose the reference portfolios used in the abnormal return calculation and were provided by Economatica. If a company is not rated by at least one of the two rating agencies (Moody's and S&P) or it has no book-to-market on the date of a particular rating change, it will not be included in the reference portfolio on that date.

3.2 Measurement of abnormal returns

The abnormal return of companies that had their rating changed was measured one year and six months after the announcement of the change. As suggested by Barber and Lyon (1996), the methodology for calculating abnormal return will be BHAR.

First, the one-year buy-and-hold return (252 business days) will be calculated for each share that had its rating changed from the date of the change, as expressed in equation (1). The same will be done for all other shares that did not had their ratings changed but which make up the Ibovespa for the same period. Of these shares, some will be selected to compose the reference portfolio, which will be explained later, whose average return will be used to calculate the abnormal return. Thus, the buy-and-hold return of a company whose rating has changed minus the buy-and-hold return of the reference portfolio is the abnormal return, as expressed in (2).

$$R_{i,t} = (P_{i,t} / P_{i,t-T}) - 1 \qquad [1]$$

$$BHAR_{i,t} = R_{i,t} - R_{portfolio,t} \qquad [2]$$

Where:
- $BHAR_{i,t}$ is the combination of abnormal returns of company i on date t;
- $AR_{i,t}$ is the abnormal buy-and-hold return one year after the rating change of company i on date t;
- $R_{i,t}$ is the one-year buy-and-hold return of company i on date t;
- Portfolio is the one-year buy-and-hold return of the reference portfolio (i.e. the average return of the constituent companies) on date t, chosen from 27 book-sized tertiles - market and risk class, and;
- T is the window (term) considered, of twelve months and six months.

For comparative purposes, the CAR methodology conventionally used in the literature would calculate a company's one-year abnormal

return as the sum of the difference between the monthly (or daily) return on the stock and the Ibovespa (or another desired index) for 12 months (or 252 days). That is, the vast majority of the studies in the literature use the main stock exchange index of the respective country where the study was conducted as the reference to calculate the abnormal return, regardless of the company under analysis.

In this study, different reference portfolios are composed based on explanatory variables of stock returns, to mitigate the presence of bias as indicated in other studies. The advantage of using the reference portfolio is that the companies that make up the portfolio operate as a "control" group, i.e. those that suffered a rating change. Barber and Lyon (1996) pointed to companies' market value and book-to-market as variables that influence the return on their shares. Subsequently, Vassalou and Xing (2003, 2004) confirmed and further pointed out credit risk and credit risk variation as new variables. Finally, Jorion and Zhang (2006) pointed to the initial and final rating. Therefore, seeking to adjust the model to these proposals, reference portfolios are composed based on these three variables: market value, book-to-market, and rating tertiles. The companies' own ratings were used as a proxy for credit risk, thus making it impossible to incorporate the risk variation as well. Since rating scores are qualitative variables, a cardinal scale is assigned between them, each tertile being represented by the initial letter of the rating: tertile "A" encompasses ratings from AAA (Aaa) to A- (A3); tertile "B" ranges from BBB + (Baa1) to B- (B3); and tertile "C" ranges from CCC + (Caa1) to D.

The following control variables are used to compose the reference portfolios:

1. Size (or market value): represented by the company's market capitalization in reais (the Brazilian currency).

2. Book-to-market: represented by the total value of the assets listed on the company's balance sheet, discounted by intangible assets and liabilities and then divided by market capitalization.

3. Rating: represented by the rating assigned to the company by S&P or Moody's, on a cardinal scale of 3 categories.

Thus, we formed a total of 27 different reference portfolios. For each company that had its rating changed, we compare its buy-and-hold return with the return on its respective benchmark portfolio, the combination of which results in BHAR (as described in equation 2).

As an example, consider Suzano, which had its rating downgraded from BBB- to BB + on 3/16/2018. On this date, Suzano is in the third size tertile and second book-to-market tertile for the whole BOVESPA index at the time. Eight other Brazilian companies that did not change their rating are in the same size and book-to-market tertiles. Among these eight companies, five are also in the "B" rating tertile, similar to Suzano, thus constituting a reference portfolio, whose 12-month Rportfolio return of -21.11% was obtained by combining the individual returns of each company in the year (buy-and-hold style). Thus, if our sample of rating changes were only from Suzano, which had an individual 12-month return of -40.34%, BHAR would be Rx, 1 - Portfolio, t = -40.34% - (-21, 11%) = -19.23%.

Finally, the null and alternative hypotheses were defined to determine if the calculated BHAR is significant and to describe its implications, as follows:

- H_0: μ BHAR = 0. There is no abnormal return for shares of Brazilian companies one year after the announcement of a rating change. That is, rating changes have no impact on long-term stock returns in the Brazilian market.

- H_1: μ BHAR$\neq$ 0. Abnormal returns on shares of Brazilian companies are verified one year after the announcement of a rating change. That is, rating changes have an impact on long-term stock returns in the Brazilian market.

The test used to verify the significance of BHAR is the Student t-test, calculated by equation (4). The Jarque-Bera (JB) test is also performed to

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verify that the BHAR variable is normal, since the t-test works with this assumption. If normality is rejected, it represents a limitation of the model.

$$t = \frac{\overline{BHAR}}{s/\sqrt{n}} \quad\quad\quad [4]$$

Where:

- BHAR is the arithmetic mean of the sample of abnormal returns;
- s is the standard deviation of the sample of abnormal returns; and
- n is the sample size of abnormal returns.

The same methodology was used for the abnormal return after one year and 6 months. This methodology is more appropriate because it incorporates potential return influencers in the reference portfolio, not creating a bias in the significance result for abnormal return. Most previous studies do not apply this correction and,

in the end, perform a regression of abnormal return to evaluate which variables best explain it. Although the regression points out which variables impacted the abnormal stock return besides the rating change, these effects have not been previously isolated as they are not incorporated into the reference portfolio and thus the impact of the rating changes is uncertain.

In addition to the averaging test, multiple linear regression models were used to verify the impact of rating class upgrades and downgrades on the BHARs of credit rating companies and to verify the existence of a non-linear U-shaped relationship in the Brazilian market, as detected in Vassalou and Xing (2003, 2004). A residual analysis was performed by using the White and Jarque-Bera test to verify homoscedasticity and error normality, respectively.

Thus, equation (5) represents the complete regression model:

$$BHAR_i = \beta_0 + \beta_1 Raises_i + \beta_2 Lowers_i + \beta_3 Rating_i + \beta_4 Rating_i^2 + \varepsilon_i$$

Where BHAR is the abnormal buy-and-hold return of company i, *Raises* is a rating class upgrade dummy variable, *Lowers* is a rating class downgrade dummy variable, *Rating* is an ordinal categorical variable with values from 1 (class AAA) to 9 (classes C and D), and *Rating²* was included in the model to represent the nonlinear relationship between BHAR and credit rating.

It is important to remember that we worked with rating class changes in this article, as in Dichev and Piotroski (2001). However, the same tests were performed by using the rating changes and not the rating class changes and the results were not statistically relevant, which probably indicates that investors do not react to rating changes within the same rating class, but there is a reaction to a change in rating class. For example, if an asset has a rating change from BBB to BBB-, the investor does not seem to see this as a material change, as both ratings are in the

same class ("lower medium grade"). A downgrade from BBB- to BB + is more relevant, as it implies a change from the "lower medium grade" class to the "non-investment grade speculative" class.

4 Results

The final sample used in this paper contains 161 effective issuer rating changes by Moody's and S&P of the Brazilian companies that make up the Ibovespa index, excluding concomitant changes within one year.

Mostly, in previous studies, there has been a negative impact on stock returns for rating downgrades, but not for upgrades. Dichev and Piotroski (2001) was the first prominent paper that differed from what was becoming a trend in the literature by incorporating book-to-market and size adjustments in the model, as well as using the BHAR methodology to measure abnormal returns. However, the conclusion that

the impact of rating changes was significant only in the event of downgrades was later accused of being biased by the effect of corporate risk. Vassalou and Xing (2003, 2004) and Jorion and Zhang (2006) recognized the influence of risk on business return and relied on Dichev and Piotroski (2001) to develop models that also incorporate this factor, each in their own way. The model used here applies the same adjustments incorporated by these authors. However, the conclusion of this paper resembles the results of Dichev and Piotroski (2001), even with the inclusion of the moderating effect of rating.

Table 2 presents the descriptive measures of the BHAR variable for companies that were downgraded, upgraded, and that had no changes in their credit rating class. Following the vast majority of the results previously obtained in the literature, there was an average negative abnormal return of 25% in the case of downgrades and a 2.6% positive one in the case of upgrades in the rating class. In the case of companies with no change in their rating class, this average was 3.2%. Regarding the results of the t-test to verify the existence of an abnormal return equal to zero, only for class downgrades can we consider that there is an abnormal return and it is negative. It is important to note that these results are in line with Vassalou and Xing (2003, 2004), which used data from 1971 to 1999, covering 5,034 rating changes in the US market, and obtained positive results after adjusting for size, the book-to-market indicator, and the probability of default (DLI), measured by the Black and Scholes (1973) model.

Table 2

BHAR Descriptive Measures for Downgrades, Upgrades, and No Change in Sample Rating Class

	Class downgrade	No class change	Class upgrade
Mean	-25,0%	3,2%	2,6%
Median	-21,7%	0,14%	8,0%
Minimum	-52,6%	-98,8%	-68,2%
Maximum	5,58%	99,8%	93,6%
Standard deviation	19,2%	33,7%	32,4%
Sample size	42	105	14
T-test statistics	-3,91***	1,01	0,49

Note: t-test for abnormal return 0. *** p <0.01; ** p <0.05; and * p <0.1.

To assess the effect of Brazilian companies' credit rating downgrades and credit rating upgrades, and to investigate the existence of a curvilinear relationship between the rating and the abnormal U-shaped return as suggested by the nonlinear relationship obtained by Vassalou and Xing (2003, 2004), multiple linear regression models were proposed. The response variable considered was the BHAR, while the explanatory variables are two indicator variables: one for rating downgrades and one for rating upgrades, and one for the company's credit rating, assuming values from 1 to 9, i.e. the rating of 1 represents companies with an AAA rating and the rating of 9 represents companies in category C and D.

As the BHAR already incorporates market value, book-to-market, and rating controls in its reference portfolios, we decided to present the results of the regression model without these control variables, for the sake of obtaining greater accuracy of ordinary least squares estimators, since the sample size is limited. The estimated model with these control variables showed no change in results or control relevance and can be obtained upon request from the authors.

Tables 3 and 4 present the results of one-year and six-month BHAR regression models,

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respectively. Three models were estimated: Model 1 considers only the variables that indicate credit rating class upgrades and downgrades; Model 2 includes only the rating and its quadratic form to evaluate the curvilinear relationship; while Model 3 includes all the variables involved in the analysis to consider their joint effects. In all models a residual analysis was performed, verifying: (1) normality of the errors, which was rejected, but

the results are considered robust to the lack of normality because this sample is considered large enough, being composed of more than 15 to 20 observations for each explanatory variable included in the model (Hair et al., 1998); (2) homoscedasticity of the errors, which was also rejected, so White's robust standard error was used.

Table 3

Results of 12-month BHAR regression models

Variable	Model 1			Model 2			Model 3		
	Coefficient		SE	Coefficient		SE	Coefficient		SE
Raises	-0,02173		0,0620				0,0131		0,0631
Lowers	-0,25519	***	0,0688				-0,2495	***	0,0813
Rating				0,7543	***	0,2455	0,6416	**	0,2737
Rating^2				-0,0832	***	0,0245	-0,0733	***	0,0268
Intercept	0,004865		0,0320	-1,6755	***	0,6188	-1,3566	**	0,7033
n	159			159			159		
R^2	0,0321			0,0625			0,0921		
adjusted R^2	0,0187			0,0505			0,0686		
F Test	2,50	*		5,20	***		5,92	***	

Note: *** $p < 0.01$; ** $p < 0.05$; and * $p < 0.1$. SE = standard error.

In Model 1 (Table 3), it can be seen that a downgrade of the credit rating of Brazilian companies leads to a statistically significant drop in the BHAR, while a class upgrade has no significant impact on BHAR compared to non-BHAR companies which experienced a change of rating class. These results can be verified descriptively in Table 2. Model 2 indicates that there is a curvilinear effect of credit rating on the BHAR, i.e., higher rated (category A) and lower rated (category C) Brazilian companies have a lower BHAR, while those with an intermediate rating (BBB and BB categories) get a slightly higher BHAR. In the case of the Brazilian market, the companies presented credit ratings from A to B in the period evaluated, so the curve is ultimately only estimated for these ratings so that there is no extrapolation error, since there are

no companies in the sample from other rating categories.

Based on the results of Model 3, which includes all variables analyzed, it is noted that the effects remain. Evaluating the results from an economic point of view, it can be concluded that the companies with a credit rating downgrade had, on average, a 25.52% higher BHAR when compared with the companies that did not change their rating class, thus keeping their rating fixed. Similarly, companies that had a credit rating upgrade had a 2.17% lower average BHAR compared to those that did not change their rating class in the period. In addition, a downgrade of the rating class causes a decrease in the BHAR which is statistically significant, while a class upgrade does not cause a statistically significant change in the BHAR.

As for the result of the curvilinear relationship between BHAR and rating (Models 2 and 3 in Table 3), it is proved that the relationship is statistically relevant and has an inverted U-shape, since the squared rating coefficient has a negative sign. To illustrate the effect, Figure 2, which represents the curvilinear effect of the

BHAR rating classification, separates companies with a downgrade, an upgrade, and no change in their rating class. As the Brazilian companies are only rated A, BBB, BB, and B, we leave the extrapolation of the results to the other rating categories in a different format in Figure 2 to draw the reader's attention.
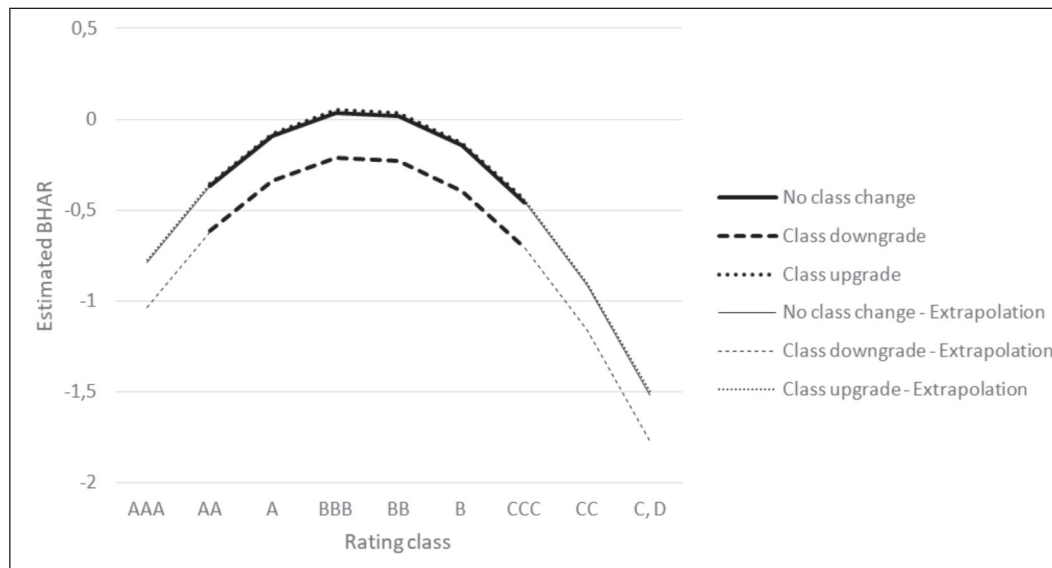

Figure 2. Graphical representation of the curvilinear effect of the credit rating classification for the BHAR in 12 months, separating the companies that presented a downgrade, an upgrade, and no change of rating.

Table 4 presents the results of the models using the BHAR at six months as the response variable, a shorter period than one year, as used in Table 3. This evaluation allows us to verify if there are differences in the market evaluation in different observed periods. It would be expected that if the rating changes somehow incorporated some type of private information obtained from the interviews conducted by the agencies, the impact of this information on the results would be greater in the short term and dissipated in the long term.

Based on the results of Model 1 (Table 4), it is noted that the signs of the coefficients are negative, indicating a decrease in BHAR for companies with rating class upgrades and

downgrades; however, these results are not statistically relevant. This indicates that the market has a particularly negative perception of class downgrades as early as six months after the announcement, but this drop only becomes statistically significant after one year. For the Brazilian market, for rating downgrades, there is a 10.15% drop in BHAR in six months and a 25.52% drop in one year.

In the case of the curvilinear relationship, this is already detected in six months and the results are similar to what happens with the BHAR in one year. This confirms the existence of this inverted U format in the Brazilian market in both six months and one year.

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Table 4

Results of 6-Month BHAR Regression Models

Variable	Model 1		Model 2			Model 3		
	Coefficient	SE	Coefficient		SE	Coefficient		SE
Raises	-0,0075	0,0570				-0,0280		0,0529
Lowers	-0,1015	0,0818				-0,0435		0,0929
Rating			0,6432	***	0,4869	0,6253	**	0,2453
Rating^2			-0,0594	***	0,0333	-0,0574	**	0,0242
Intercept	-0,0281	0,0254	-1,7256	***	1,4883	-1,6779	***	0,6150
n	161		161			161		
R^2	0,0076		0,0555			0,0582		
adjusted R^2	0,0049		0,0436			0,0341		
F Test	0,61		4,64	***		4,48	***	

Note: *** $p < 0.01$; ** $p < 0.05$; and * $p < 0.1$. SE = standard error.

The explanation proposed by Vassalou and Xing (2003, 2004) regarding the result, which seems counterintuitive to most authors, is that higher returns are associated with higher credit risks. That is, although the majority opinion in the literature is that downgrades are naturally followed by negative returns, the opposite should occur because companies whose ratings are downgraded are higher risk and therefore should have higher expected returns, incorporating "bad news" immediately, and showing higher returns due to the price drop. Another way of thinking about this same factor is that investors require higher returns the higher the systematic degree of risk of an investment is, so investors who buy stocks from newly downgraded companies expect and require higher returns to offset the higher risk.

Furthermore, the results obtained here represent the disciplining effect that a rating change imposes on a company, as also cited by Vassalou and Xing (2003, 2004). Rating downgrades can be considered as acting to discipline companies, which reshape their practices and strategies as much as possible when their ratings are downgraded. Some companies (particularly larger ones) are able to effectively reduce their default likelihood index (DLI) consistently with lower rates of return. Other companies that do not achieve this result will see their profitability rates increase with increased risk. Similarly, a rating upgrade may lead a company to settle down and not seek significant improvements or changes in its practices, thus explaining virtually unchanged performance afterward.

5 Conclusion

This study analyzes the long-term return of Brazilian stocks following rating changes. We conclude that there is a sharp 25% reduction in long-term profitability generated by rating downgrades but not by rating upgrades. This result is statistically and economically significant, and consistent with Dichev and Piotroski (2001) and Vassalou and Xing (2013). Although the literature predicts that higher credit risk firms should have higher expected returns, our results show the opposite. The explanation is given by Vassalou and Xing, who put forth the proposition that fluctuations in the default likelihood index (DLI) around rating changes occurs in an inverted V format, especially regarding downgrades. Therefore, some firms use the disciplining effect of a downgrade to reduce their credit risk and thus have lower returns consistent with risk reduction and theoretical predictions. Other companies, especially small ones (which are not in our sample because it is limited to listed companies

and participants in the Bovespa index of the B3 exchange) could have higher expected returns because they are unable to reverse their probability of default, as according to Vassalou and Xing. These effects in the Brazilian case were enhanced by the economic crisis that began in 2015.

Our results are obtained by a non-traditional event study (BHAR) to measure how the stock market reacts to rating downgrades and upgrades by Moody's and S&P over six-month and one-year intervals.

Most previous literature shows significant negative returns for rating downgrades, but non-significant results for rating upgrades - the BHAR methodology was used to compute the abnormal return and multiple reference portfolios were created to control the biasing effects of the confounder variables (size, book-to-market, and credit risk). The methodology used here applies the adjustments suggested by Vassalou and Xing (2003, 2004) and Jorion and Zhang (2006), so the conclusion of this study was expected to resemble theirs, as in fact occurred.

First, the abnormal return was negative and significant for rating downgrades and not significant for upgrades. This finding is consistent with the idea of economic agents requiring a higher return as the risk of the investment rises, and it is also consistent with the disciplining effect that a downgrade imposes on the company. Second, the significance of the abnormal return for rating downgrades and upgrades was not symmetrical, which is consistent with the idea that the effect of the announcement of a rating downgrade has a different behavioral effect to that of an upgrade.

Finally, we also detected that the previous rating has a significant impact on the magnitude of the non-linear BHAR. Thus, downgrade announcements for B-rated companies have a smaller impact than those for A- or C-rated companies. A possible explanation could be that of the ability to react more quickly to announcements made by companies that do not want to lose their reputation as low-risk (A)

companies, as well as by companies that would be entering a situation of imminent default (C).

Two limitations of the model that may hamper our conclusions are the non-normal distribution of the series of abnormal returns and the small sample size used in this study, as the Brazilian market has a modest number of listed firms. The rating change database containing 161 elements is far smaller than those obtained from more developed countries in the previous studies mentioned here. This issue explains the lower significance and power of the statistical testing in our work. In spite of these pitfalls, this study was conducted meticulously in order to reconcile the suggestions of other authors and apply the necessary adjustments to mitigate any bias. We confirm the relevant informational content of rating announcements and the contributions of rating agencies, which benefit investors with a free corporate monitoring service that mitigates potential information asymmetries.

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APPENDIX

Table A-1

Overview of Related Works

Year	Authors	Data	Main results
1978	Pinches & Singleton	1959-72; Moody's; 207 companies; monthly abnormal return between [-30,12]	Anticipation of the rating changes, there is no abnormal reaction after the announcement.
1982	Griffin & Sanvicente	1960-75; Moody's and S&P; 180 rating changes; monthly abnormal return between [-11,1]	There is no anticipation, but there is a negative reaction after downgrades.
1986	Holthausen & Leftwich	1977-82; Moody's and S&P; 1014 rating changes; 256 S&P Credit Watch additions; daily abnormal return between [-300,60]	Significant negative reaction after downgrades, not significant for upgrades.
1987	Glascock, Davidson, & Henderson	1977-81; Moody's; 162 rating changes; daily abnormal return between [-90,90]	Significant negative abnormal return before and around downgrades, reversed after announcement.
1992	Hand, Holthausen, & Leftwich	1977-82 / 1981-83; Moody's and S&P; 1100 rating changes and 250 S&P Credit Watch additions	Significant negative abnormal return for S&P Credit Watch downgrades and unexpected additions, no significant abnormal return for upgrades.
1993	Goh & Ederington	1984-86; Moody's; daily abnormal return between [-30,30]	Significant negative abnormal return for downgrades due to profit deterioration, positive abnormal return for downgrades due to higher leverage.
1997	Followill & Martell	1985-88; Moody's; 64 reviews and effective rating changes; daily abnormal return between [-5,5]	Significant negative feedback from downgrade revisions, negligible abnormal performance around effective downgrades.
2001	Dichev & Piotroski	1970-97; Moody's; 4727 rating changes; abnormal daily return; long term	Significant negative abnormal return during the first month after a downgrade, there is no significant abnormal return for upgrades.
2003	Vassalou & Xing	1971-99; Moody's; 5034 rating changes; abnormal monthly return on portfolios between [-36,36]	Stock returns on rating-related event studies should be adjusted for size, book-to-market, credit risk, and credit risk variance over the period; higher returns are associated with higher credit risks.
2004	Norden & Weber	2000-02; Moody's, S&P, and Fitch; 166 reviews and 231 effective rating changes; daily abnormal return between multiple time intervals	Anticipation of downgrades; significant negative abnormal return after revisions for downgrades; past rating and rating following a change are significant in explaining the abnormal return.
2004	Linciano	1991-2003; Moody's, S&P, and Fitch; 141 Credit Watch additions and 158 effective rating changes; daily abnormal return between [-20,20]	Significant abnormal returns following downgrades and Credit Watch additions to downgrades, apparently conditioned by the rating change.
2006	Jorion & Zhang	1996-2002; Moody's and S&P; 2356 rating changes; daily abnormal return between [-3,3]	The effect of rating changes on the share price depends on the rating before and after the change, the effect being greater the lower the previous rating.
2008	Benjamin EE	1991-2007; Moody's and S&P; 4039 rating changes and 3287 Credit Watch additions; daily abnormal return between [-1,1]	Significant long-term negative abnormal return for downgrades, but lower for emerging countries.
2013	Freitas & Minardi	2000-09; Moody's and S&P; 221 rating changes and 49 Credit Watch additions; daily abnormal return between [-14,30]	Anticipation and significant negative abnormal return for downgrades, insignificant for upgrades.
2013	Avramov et al. (2013	1985-2008; 4953 observations; ranking of portfolio results composed of long-short strategy in price anomalies	Positive results in lower-rated short-selling strategies and these momentum gains are higher for lower-rated companies in monthly-adjusted strategies.
2014	Friewald et al.	2001-10; 491 firms using CDS spread change in default risk proxy	By forming portfolios buying companies with high credit risk and selling companies with low credit risk, we get a positive alpha after controlling for standard risk factors.

Source: Adapted from Norden, Lars, Weber, Martin (2004), translated and modified by the authors.

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2. Development of hypotheses or research questions (empirical studies)	√	√	√
3. Development of theoretical propositions (theoretical Work)	√	√	√
4. Theoretical foundation/ Literature review	√	√	√
5. Definition of methodological procedures	√	√	√
6. Data collection	√		√
7. Statistical analysis	√	√	
8. Analysis and interpretation of data	√	√	√
9. Critical revision of the manuscript		√	√
10. Manuscript Writing	√	√	√
11. Other (please specify which)			

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