Accounting and Management Review
Revista de Contabilidade e Gestão

No. 27, 2023
pp. 67-86
Published by OCC
DOI https://doi.org/10.55486/amrrgg.v27i1.3

Relationship of the rating of the companies with the forecast error of market analysts

Rafael Confetti Gatsios[a], Gabriella Minati Ribeiro[b], Fabiano Guasti Lima[c], Vinicius Magnani[d]

ABSTRACT

This study sought to assess the existence of a relationship between the *rating* and the earnings forecast error of market analysts. The sample relates to 44 companies for the period from 2010 to 2018, which was selected from the data collected on the *Thomson Reuters®* platform, in the I/B/E/S database. The methodology chosen was panel data analysis. The results showed that the *rating* impacts the level of analysts' forecast error, so companies with better credit risk rating have lower error in their earnings forecasts. The study contributes to the literature on capital market, specifically that of analysts' forecasts, focusing on the *rating* variable as an important factor to be considered by market analysts and contributes to the literature on the predictive quality of accounting information.

Keywords: Rating; Forecast error; Analysts' forecast; Predictive quality of accounting information.

[a] *FEARP -Universidade de São Paulo - Departamento de Contabilidade* **E-mail address:** *rafaelgatsios@fearp.usp.br*
[b] *FEARP -Universidade de São Paulo - Departamento de Contabilidade* **E-mail address:** *gabriella.minati@usp.br*
[c] *FEARP -Universidade de São Paulo - Departamento de Contabilidade* **E-mail address:** *fgl@usp.br*
[d] *FEARP -Universidade de São Paulo - Departamento de Contabilidade* **E-mail address:** *vinicius_magnani@hotmail.com*

[This page is intentionally left blank]

1. Introduction

Analysts' forecasts are fundamental for market participants to allocate their resources at different levels of risk (Antônio et al*.,* 2017). Such forecasts may present errors that form a fundamental concept in the market analyst literature, that of precision. This term is an estimator that has an inverse relationship with the standard deviation, so the lower the standard deviation, the higher the forecast accuracy (Martinez & Dumer, 2013).

The literature shows that analysts do a good job of predicting profits but underestimate losses. This fact is linked to analysts' reluctance to report negative earnings forecasts (Martinez, 2004). In Brazil, studies presented address the analysts' forecast error with the aim of understanding what can influence it, for example the size of the brokerage firm where the analyst works, the complexity of the portfolio analysed, the analyst's professional experience (Martinez, 2007), the level of corporate governance (Dalmácio, 2009) and the implementation of the International Financial Reporting Standards (IFRS) (Gatsios, 2013). Such factors previously established in the literature show that there is a probability that the projection will diverge from the disclosed result.

From the perspective of shareholders and creditors, the granting of funds to companies is linked to an expectation of risk and return, risk being a variable that links to the probability of not obtaining the expected return on the investment made (Soares et al., 2012). A variable commonly used by the capital and credit markets is that of *rating*. This measure refers to the credit notes issued by rating agencies on the credit quality of public and private organisations. Credit *ratings* "represent a forward-looking opinion of a debtor's overall credit quality, reflecting the ability and willingness of the debtor to honour its financial commitments as they come due" (Standard & Poor's Financial Services LLC, 2019) .

In Brazil, there are several studies that address the variables that determine the *rating* classifications of companies. Among the main ones are: a study that analyses whether structural models predict *rating* changes by credit agencies (Kanandani & Minardi, 2013), which are the main accounting indicators, such as the level of indebtedness, fixed assets, profitability and liquidity, and market indicators such as the company's risk, the number of analysts who cover it and the level of specialisation of analysts (Damasceno et al., 2008; Soares, et al., 2012).

As for international research, recent articles are looking for the relationship between *rating* classifications and the effects of corporate decisions from ESG (Saadaoui, et al., 2022; Zanin, 2021). Other papers also explore the relationship between accounting indicators and *ratings and* incorporate the effects of company risk into the models, measuring them mainly by the volatility of their earnings (Jiang, 2022; Magnani, 2017; Magnani et al., 2022).

Thus, the credit *rating* and the analysts' forecast are linked to the company's risk, given that companies with higher risk present greater volatility in their profits and can impair the analysts' predictability ((DeMarzo & Duffie, 1995; Magnani, 2017; Magnani et al., 2022). Thus, the following research question arises: What is the relationship between credit *ratings* and the error of analysts' forecasts?

In view of the established context and according to the impact that the risk of companies can cause on the *rating* disclosed by credit agencies and on the predictability of market analysts, the following research hypothesis is made:

The higher the company's *rating*, i.e. the greater the risk of lending funds to the company, the more difficult it will be for analysts to forecast its earnings.

This paper aims to analyse the relationship between the *rating* and the predictability of market analysts, specifically the errors in their forecasts. As such, the aim is to show market agents that forecasts for companies classified with higher *ratings* may have higher forecast errors. As a result, we hope this study will facilitate decision making and improve the predictive quality of information.

2. Theoretical framework

2.1. Analysts' forecasting error

Market analysts are professionals responsible for assisting companies in decision making, performing market analyses, developing growth strategies and making predictions about the future of companies.

A relevant line of research is the aptitude of market analysts, since they are the main users of financial information. Such research provides important information to investors on how far they should rely on the projections, in addition to knowing the main limitations of forecasting models (Martinez, 2007). Other studies have found that there is optimism in loss projections and a reluctance on the part of analysts to report on negative results (Martinez, 2004).

Another line of research seeks to analyse the determinants of analysts' forecast error. The first variable is the brokerage firms that the professional is linked to, i.e. analysts linked to large brokerage houses have more accurate forecasts. Another variable is the analysts' projection track record, because when analysts have performed well on past forecasts, they tend to continue developing good projections (Martinez, 2007). A third variable is the number of analysts covering the companies, so the more analysts working on the coverage of the companies, the lower the error in projections. The fourth variable is the size of the entity, given that in large institutions there are several accounting standards and this increases the complexity for analysts to predict value indicators (Martinez & Dumer, 2013). The Fifth variable relates to the corporate governance mechanisms, which are negatively linked to the error of analysts' consensus projections as well as the error of individual analysts' projections (Dalmácio, 2009).

The adoption of standards can also influence the forecast error, Gatsios (2013) and Gatsios et al. (2018) showed interesting results on the relevant drop in the accuracy of analysts' projections after the implementation of the IFRS standard in Brazil. Also, De Marzo and Duffie (1995) and later Saito et al. (2008) specifically analysed the quality of analysts' projections, showing that the variability of profit and indebtedness have a positive relationship with the forecast error, that is, the projection error is higher when indebtedness and variability are higher.

Martinez (2004) compared the performance of company analysts in Brazil and abroad. It was evidenced that in Brazil, the longer the analyst has been in the position, there is negative interference in the error of projections, however, experience in a specific company improves the forecast performance. Meanwhile, in the United States and in European countries, experience in years of performance influences an improvement in projection performance. In addition, the complexity of the portfolio was studied, which in the Brazilian case did not influence the forecast error, while in the case of North American and European cases, the complexity of the portfolio interferes with the error.

Still on analysts' forecasts, Magnani et al. (2022) evaluated the effects of *hedging* on analysts' forecasts. The authors concluded that in emerging markets, with high volatility of macroeconomic variables and political instability, the corporate *hedging* policy, the *rating* assigned to the credit ratings of public companies and liquidity indices are key variables that influence analysts' forecasts.

2.2. Credit rating

Rating is the classification of the credit risk of a company, a security, a bank, another financial entity or even a country . Its purpose is to constitute an opinion on the possibility of non-fulfilment of financial obligations, including delays and/or actual non-payment. It presents a global language to express the level of debt risk. They are used by investors to demonstrate the likelihood of receiving the amount invested (Fitch Rating, 2019).

The *rating* has three classifications: International Rating in Local Currency, International Rating in Foreign Currency and National Rating. The first, does not consider the risk of not being able to convert the currency, since in this case it is allowed, the remuneration in local currency at the exchange rate, at the time of delivery to the investor, the second considers the risk of not being able to convert the local currency into foreign currency, since in this case it is necessary that the remuneration is made in foreign currency, at the time of delivery to the investor. (Fitch Rating, 2019). Both consider "the risks of sovereign equities, since the measures adopted by the government of that country may jeopardise the ability to pay financial commitments." (Kanandani & Minardi, 2013).

And finally, the National Rating which is designated "to bonds of local issuers issued in the local currency of the country where the issuer is located" (Fitch Ratings, 2019), this type excludes the effects of transfer risk and sovereign risk, however it takes into account the company's financial risk, competitive position and industry risk (Soares et al., 2012).

Since comparisons between an international and a national scale are not feasible, only Foreign Currency and Local Currency *Ratings are* comparable (Fitch Rating, 2019).

"This *rating* does not apply to any specific financial obligation, nor does it consider the nature and provisions of the obligation, or its position in the event of bankruptcy or liquidation, statutory preferences, or the legality and enforceability of the obligation." Standard & Poor's Financial Services LLC. The main rating agencies are Fitch Ratings, Moody's and Standard & Poor's (S&P), known as the Big Three.

Typically, rating forms are expressed through letters ranging from 'AAA' to 'D' to express the agency's opinion of the risk level (Standard & Poor's Financial Services LLC, 2019). 'AAA' being the highest credit quality, reflecting the lowest expectation of default risk, assigned only in cases of exceptionality of payment of financial obligations. And so, reducing to 'AA' (very high credit quality), 'A' (high credit quality), 'BBB' (good credit quality), 'BB' (speculative), 'B' (highly speculative), 'CCC' (substantial credit risk), 'CC' (very high credit risk), 'C' (credit risk close to default, 'RD' (restricted default) and 'D' (default) being the last level and indicating that the "issuer has filed for judicial reorganisation, administrative intervention, liquidation or other formal closure process or has ceased its activities" (Fitch Rating, 2019). Fitch´s classification rating is only one example, given that in the case of other companies, such as S&P and Moody's, this classification may undergo some changes in the way the scale is presented, nevertheless the purpose and interpretation will follow the same pattern.

Ratings are relevant, given the difficulty for a company to be able to issue debt securities without the opinion of some rating agency on the quality of its credit.

In addition, it is also reported that, after several crises between 1994 and 2002, investors began to develop a more critical eye on rating agencies, which generated greater transparency in the criteria used for credit analyses (Damasceno et al., 2008).

Amongst the literature focusing on identifying variables capable of explaining the *rating of* companies is the work of Soares et al. (2012) who identified as main drivers, the size of the companies, the interest coverage ratio and the corporate governance mechanisms implemented by corporate management. Subsequently, Lima et al. (2016) identified market risk, calculated through the set of variables, systematic risk, general indebtedness ratio and weighted average cost of capital, operational risk, formed by return on investment and degree of operational leverage, liquidity risk, represented through the size of the company and credit risk, represented by the degree of financial leverage and ability to pay debts, as variables that drive the *rating* level of companies. These relationships were not previously identified in the study by Damasceno et al. (2008).

Brito and Assaf Neto (2008) estimated a credit risk model combining default events and accounting ratios and found evidence, for public companies on the Brazilian stock exchange over 10 years, that confirms an improvement in the quality of financial information disclosed by accounting. Subsequently, Kanandani and Minardi (2013) aimed to anticipate credit *rating* changes. Structural equation modelling was used and the sample included companies listed on the stock exchanges for Brazil, Argentina, Chile and Mexico over a 12-year period. There was no empirical evidence to support the proposed models.

Gomes Neto (2017) analysed the segregation of credit *ratings of* financial institutions in emerging and non-emerging countries. In emerging countries, the risk attributed to the country issuing the debt securities is a crucial factor in determining the risk rating of financial institutions, as well as the level of leverage. In non-emerging countries, the credit quality and size of the institutions are the crucial factors in determining the *rating*.

In an emerging discussion, , Zanin (2022) sought to estimate the effects of ESG indices on the *ratings of* companies in North America, Europe and Asia. Mixed results were found for the effects of ESG pillars on ratings, according to different sectors.

Subsequently, Saadaoui et al. (2022) examined the effects of the information content of *ratings* in emerging countries on debt market liquidity. The sample covered the period from 2009 to 2017 and the results indicated that market liquidity is positively related to better debt ratings. In the same year, Jiang (2022) examined the relationship between financial *ratios*, company risk and ratings for

Moody's, Standard & Poor's and Fitch's agencies. The author found that company risk increased in significantly over agency ratings, while financial ratios declined notably.

Finally, two tables were established to summarise the literature on analyst forecast error and the determinants of credit *ratings*.

Table 1. Distribution of studies, by authorship, year and objectives, on forecast error

Author	Objectives
Martinez (2004)	Analyse analysts' consensus and individual earnings forecasts, identify factors that may explain forecast errors, and document analysts' ability to identify overvalued or undervalued stocks.
Martinez (2007)	Measure the effect of experience on analyst forecast error, the effect of portfolio complexity on forecast error, and the effect of broker characteristics.
Saito et al. (2008)	Determine possible factors for the size of analysts' forecast error and the bias of these forecasts.
Dalmácio (2009)	Demonstrate that the adoption of different corporate governance practices is positively related to analysts' individual and consensus forecast error.
Martinez and Dumer (2013)	Determine whether the adoption of IFRS in 2013 led to material changes in the statistical properties of analysts' projections.
Gatsios (2013); Gatsios et al. (2018)	To study the relationship between the error of market analysts' estimates after the adoption of IFRS in Brazil and the relationship between the dispersion of analysts' estimates after the adoption of IFRS in Brazil.
Magnani et al. (2022)	To analyse the effects of corporate hedging, credit ratings and accounting indicators on companies' agency costs as measured by analysts' forecast errors.

Source: Prepared by the authors.

Table 2. Distribution of studies, by authorship, year and objectives, on credit ratings

Authors	Objectives
Damasceno et al. (2008)	Look for evidence that a company with the same accounting indicators over time currently receives a worse credit rating than that assigned in previous years.
Brito and Assaf Neto (2008)	To develop a credit risk rating model for large companies operating in Brazil.
Soares et al. (2012)	To analyse the effect of possible determinants of credit *rating*, which are: Indebtedness indicators, profitability indicators, coverage variables and immobilisation variables.
Kanandani and Minardi (2013)	To assess whether structural models predict in advance *rating* changes by credit agencies in Latin America. The research used companies listed on the stock exchanges of Brazil, Mexico, Chile and Argentina.
Lima et al. (2016)	They analysed possible determinants of rating classification in Brazilian non-financial publicly traded companies.
Gomes Neto 2017	Present whether there is a distinction between the determinants of credit ratings of financial institutions located in emerging and non-emerging countries.
Zanin (2022)	It sought to estimate the effects of ESG indices on the ratings of companies in North America, Europe and Asia
Saadaoui et al. (2022)	Examined the effects of the information content of emerging country ratings on debt market liquidity.
Jiang (2022)	Examined the relationship between financial ratios, company risk and ratings across Moody's, Standard & Poor's and Fitch's.

Source: Prepared by the authors.

3. Methodology

3.1. Database

The work followed the methodology used by Gatsios (2013) for analysts' forecast errors and Lima et al. (2016) for *ratings*.

The data collected for the research was obtained through the Thomson Reuters® platform, in the I/B/E/S databases. Information was collected from 44 companies listed on B3 that had a credit rating from Moody's and S&P rating agencies from 2010 to 2018. Therefore, the companies' *rating* database depends on the coverage of the rating agencies, which limited the sample size. Also, it should be noted that insurance and financial companies were excluded from the sample because they have different financial indicators and business characteristics compared to other companies.

The variables total assets, debt and ROE were collected from the Economática® database.

3.2. Sample analysis l

The total sample included 44 publicly traded non-financial companies, of which at least one forecast value for EPS was reported in the years of collection and had at least one credit rating in the period analysed. It should be noted that this is due to the coverage of credit *rating* agencies. Thus, 369 observations of forecast error and 2,259 observations of *rating* classification were totalled, as shown in Tables 3 and 4 below.

Table 3. Number of observations of the forecast error variable by year

Years	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
Remarks	37	42	39	42	42	42	41	42	42	369
% of Total	10%	11,4%	10,6%	11,4%	11,4%	11,4%	11,1%	11,4%	11,4%	100%

Source: Prepared by the authors.

Table 4. Number of observations of the rating variable by agency year

Agencies	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
Fitch	112	120	126	135	136	136	143	152	152	1.370
S&P	76	86	107	112	115	122	128	134	136	1.016
Moody's									31	31
Total	188	206	233	247	251	258	271	286	319	2.259
% do Total	8,3%	9,1%	10,3%	10,9%	11,1%	11,4%	12%	12,7%	14,1%	100%

Source: Prepared by the authors.

Regarding table 3, the number of observations was constant over time, which indicates low adherence to analyst coverage in relation to companies listed on B3. As for table 4, the number of companies with credit ratings increased over time. This movement can be interpreted by the need for greater transparency of companies with information users and by the increase of companies with capital trading in the Brazilian stock market.

3.3. Model

In order to test the hypothesis proposed by the study, the model shown in equation (7) was proposed:(7)

$$ACURÁCIAj,\ t = \beta 0 + \beta 1RATINGj,t + \beta 2LNATIVOj,t + \beta 3ENDIVIDAMENTOj,\ t + \beta 4DUMMY\ SETORj,t + \beta 5ROEj,\ t + ej,t \quad (7)$$

Where, the coefficient of interest is $\beta 1$ and the expected sign is positive, as it reflects the relationship between market analysts' error and credit risk rating. In addition, in order to control for other factors that influence the forecast error and have already been analysed by other studies, we will use control variables such as: size, indebtedness, *ROE* and *dummy* variables for sectors.

The panel data methodology was used to analyse the data. According to Gujarati (2011), this method makes it possible to work with a large number of data, taking into account companies over time, and this methodology offers greater efficiency for the estimators.

3.4. Variables

3.4.1. Dependent variable

The analysts' forecast error was calculated by dividing the Absolute Forecast Error, calculated by the modulus of the difference between the entities' actual earnings per share (*actualEPS*) and the median of the analysts' estimate for the companies' earnings per share in the last month of the year (*EPSprev*), with the value of the actual result for the period (*actualEPS*), as shown in equation (5):

$$EPAj,t = \left| \frac{LPAreal - LPAprev}{LPAreal} \right| \quad (5)$$

Where:

Actual EPS = Actual/effective earnings per share for the period

EPSprev = Earnings per share forecast by analysts

In this research, to obtain the Forecast Error, the actual EPS was used as the denominator in the calculation of the APS, as well as other studies that used the same approach by Martinez (2004, 2007). The data used to compose the profit was that of the month of December, because the forecasts made previously, up to 11 months before the disclosure, do not capture all the information available to make the forecasts. In addition, it is possible to capture forecasts from a larger number of analysts with revisions on their projections (Martinez, 2004). Finally, the use of the median as a construct statistic for analysts' forecasts aims to mitigate the effect of discrepant projections between peers (Gatsios, 2013).

3.4.2. Independent variables

The rating variable is disclosed by the rating agencies (S&P, Fitch and Moody's), through a scale represented by letters. According to previous studies by Damasceno et al. (2008), Lima et al. (2016), and Soares et al. (2012) and it is necessary to adopt a numerical scale that corresponds to the rating letters.

Credit rating scores were listed from 0 to 7, as shown in Table 1, with level 0 corresponding to the best ratings and level 7 to the worst.

If there are differences between the *rating* data collected from the three agencies, the value will be calculated using the weighted average of the three ratings obtained, rounding to the nearest whole value on the scale shown in Table 5.

Table 5. Numerical scale of S&P, Moody's and Fitch Ratings

Credit risk level adopted	S&P and Fitch	Moody's	Meaning
0	AAA	Aaa	High credit quality and low risk.
1	AA+ AA AA-	Aa1 Aa2 Aa3	
2	A+ A A-	A1 A2 A3	
3	BBB+ BBB BBB-	Baa1 Baa2 Baa3	Average credit quality.
4	BB+ BB BB-	Ba1 Ba2 Ba3	
5	B+ B B-	B1 B2 B3	Low credit quality.
6	CCC+ CCC CCC-	Caa1 Caa2 Caa3	
7	CC C D	Ca C	High risk.

Source: Adapted from Lima et al. (2016).

In addition to what is shown in the table above, it is possible to find ratings such as 'NR' which "indicates that a rating has not been assigned or is no longer assigned" (Standard & Poor's Financial Services LLC, 2019) and 'RET', or in English 'WD', which indicate "Ratings that have been withdrawn" (Fitch Rating, 2019).

For the other variables, the study based itself on the works of Saito et al. (2008), Gatsios (2013) and Lima et al. (2016), and Saito et al. (2008). The debt variable was added to assess its relationship with the error due to the complexity it can bring to the analyst, since there is debt in foreign currency, debts with variable rates and which are often not disclosed with full disclosure. Based on the work of Saito et al. (2008), the ROE variable was changed, not using its standard deviation, but its actual value. Finally, the size variable was represented by the ln of the companies' total assets.

4. Presentation of results

4.1. Descriptive statistics

This section shows the descriptive statistics of the variables proposed and used in the model. Firstly, we chose to analyse the statistics for each year of the selected sample. It can be observed that the highest level of indebtedness of the companies was reached in 2015. In 2018, companies reached the highest average volume of total assets. The lowest level of indebtedness occurred in 2010, along with the highest average *ROE* (Return on Equity). The average *rating* was constant at 1 over the years covered by the sample.

Table 6. Descriptive statistics of variables separated by year

2010

	Error	*Rating*	Total Assets	Indebtedness	ROE
Average	0.43	1	R$ 82,481,216,43	32.67%	22.82%
Median	0.18	1	R$ 12,808,909,50	34.39%	18.75%
Maximum	5.06	3	R$ 811,172,208,00	64.70%	178.22%
Minimum	0.00	0	R$ 1,328,168,00	2.62%	-1.46%

2011

	Error	*Rating*	Total Assets	Indebtedness	ROE
Average	0.88	1	R$ 94,602,529,19	32.51%	16.10%
Median	0.15	1	R$ 13,750,271,50	33.90%	12.23%
Maximum	5.73	3	R$ 981,229,907,00	59.50%	138.76%
Minimum	0.00	0	R$ 2,831,721,00	2.61%	-29.27%

2012					
	Error	*Rating*	Total Assets	Indebtedness	ROE
Average	0.84	1	R$ 109,968,774,38	33.98%	11.85%
Median	0.34	0	R$ 16,008,721,50	32.41%	11.75%
Maximum	11.51	3	R$ 1,150,486,189,00	61.17%	125.08%
Minimum	0.00	0	R$ 2,738,159,00	3.58%	-102.96%

2013					
	Error	*Rating*	Total Assets	Indebtedness	ROE
Average	3.08	1	R$ 119,866,880,71	34.71%	9.97%
Median	0.22	0	R$ 17,394,765,50	33.03%	8.38%
Maximum	85.13	3	R$ 1,303,915,123,00	68.89%	95.43%
Minimum	0.00	0	R$ 3,211,167,00	3.06%	-74.27%

2014					
	Error	*Rating*	Total Assets	Indebtedness	ROE
Average	0.57	1	R$ 131,924,634,12	35.98%	9.37%
Median	0.11	0	R$ 18,698,228,00	35.07%	10.70%
Maximum	3.72	3	R$ 1,437,485,512,00	73.72%	84.35%
Minimum	0.00	0	R$ 3,209,768,00	3.64%	-90.51%

2015					
	Error	*Rating*	Total Assets	Indebtedness	ROE
Average	2.41	1	R$ 140,028,185,26	38.08%	9.51%
Median	0.21	1	R$ 20,684,045,00	37.55%	10.09%
Maximum	87.74	3	R$ 1,401,128,757,00	89.74%	80.16%
Minimum	0.00	0	R$ 3,203,997,00	3.99%	-54.14%

2016					
	Error	*Rating*	Total Assets	Indebtedness	ROE
Average	0.64	1	R$ 135,878,086,41	35.74%	6.74%
Median	0.21	1	R$ 22,419,938,50	35.72%	11.51%
Maximum	7.36	6	R$ 1,425,638,779,00	76.21%	40.69%
Minimum	0.00	0	R$ 3,005,820,00	6.42%	-65.08%

2017					
	Error	*Rating*	Total Assets	Indebtedness	ROE
Average	1.85	1	R$ 141,149,550,32	33.58%	10.65%
Median	0.15	0	R$ 26,882,950,50	34.00%	13.62%
Maximum	28.20	4	R$ 1,503,503,484,00	80.70%	111.54%
Minimum	0.00	0	R$ 3,527,332,00	2.94%	-94.64%

2018					
	Error	***Rating***	**Total Assets**	**Indebtedness**	**ROE**
Average	1.61	1	R$ 150,445,517,66	33.45%	14.92%
Median	0.23	0	R$ 27,719,384,50	32.25%	14.16%
Maximum	46.35	4	R$ 1,649,613,394,00	81.62%	64.82%
Minimum	0.00	0	R$ 3,549,313,00	1.97%	-46.42%

Source: Prepared by the authors.

Subsequently, the same sample was divided according to the *rating* score. The data is presented in table 6 below. The risk ratings were changed to numbers as previously set out in the methodology. It should be noted that grades 5 and 7 did not appear in the sample and grade 6 was assigned to only one company.

The lowest average forecast errors are seen when the risk ratings are 0 and 3, while the ratings with the highest forecast errors are 1 and 2. Rating 0 shows the lowest debt ratio and the highest *ROE*. The lowest *ROE* is observed in rating 2, and the lowest average in 3. The highest average volumes of total assets were found in better *ratings* such as 0 and 1, the lowest volume observed was in rating 4 and in this same credit note, the highest average *ROE is* observed.

Finally, the highest debt ratio is seen in *rating* classification 6. However, only one company presented this classification, which justifies the same value for averages, medians, maximums and minimums. In addition, there was no data on ROE in 2016 for this company on the Economática® platform.

Table 7. Descriptive statistics of variables by rating

***Rating* 0**				
	Error	**Total Assets**	**Indebtedness**	**ROE**
Average	0.77	R$ 195,926,313,38	29.61%	17.45%
Median	0.11	R$ 28,656,371,00	30.92%	15.24%
Maximum	26.86	R$ 1,649,613,394,00	66.26%	178.22%
Minimum	0.00	R$ 1,328,168,00	0.00%	-47.68%

***Rating* 1**				
	Error	**Total Assets**	**Indebtedness**	**ROE**
Average	1.29	R$ 59,353,399,79	33.72%	13.25%
Median	0.22	R$ 17,904,891,00	33.45%	14.20%
Maximum	87.73	R$ 1,417,143,716,00	81.62%	64.82%
Minimum	0.00	R$ 2,294,331,00	2.61%	-65.08%

Rating 2

	Error	Total Assets	Indebtedness	ROE
Average	4.87	R$ 26,637,002,29	47.52%	-11.14%
Median	0.67	R$ 14,142,108,00	42.40%	-0.93%
Maximum	85.14	R$ 126,591,612,00	84.31%	62.47%
Minimum	0.00	R$ 3,212,014,00	24.68%	-102.96%

Rating 3

	Error	Total Assets	Indebtedness	ROE
Average	0.77	R$ 15,797,109,67	60.00%	-19.46%
Median	0.52	R$ 10,638,448,00	58.25%	-20.10%
Maximum	4.60	R$ 44,153,623,00	89.74%	7.24%
Minimum	0.11	R$ 2,628,350,00	42.83%	-74.27%

Rating 4

	Error	Total Assets	Indebtedness	ROE
Average	7.81	R$ 32,149,314,00	52.80%	25.81%
Median	1.00	R$ 45,209,970,00	60.91%	19.19%
Maximum	22.14	R$ 47,327,524,00	65.28%	56.83%
Minimum	0.29	R$ 3,910,448,00	32.20%	1.42%

Rating 6

	Error	Total Assets	Indebtedness
Average	0.13	R$ 8,404,355,00	75.90%
Median	0.13	R$ 8,404,355,00	75.90%
Maximum	0.13	R$ 8,404,355,00	75.90%
Minimum	0.13	R$ 8,404,355,00	75.90%

Source: Prepared by the authors.

4.3. Model results

Table 8 shows the results of the estimation of the proposed model by the panel data methodology, specifically the *pols* method.

A positive and statistically significant relationship can be observed, at a level of 5%, between the *rating of* the companies and the analysts' forecast error. This relationship confirms the non-rejection of the research hypothesis proposed by the study that the higher the company's *rating* (the greater the risk in lending funds to it), the greater the difficulty of market analysts in predicting its earnings.

In relation to the other variables, a positive and statistically significant relationship was presented at 5% between company size and analysts' forecast error. This relationship corroborates the study by Martinez and Dumer (2013) that reports the increased complexity of accounting standards in larger companies, which generates an increase in the difficulty of analysts' forecasts.

The relationships of the variables *ENDIV* and *ROE* with the analysts' forecast error were statistically non-significant, so no statistical inference can be made regarding the relationships. These relationships are in line with the work of Gatsios (2013) and Martinez (2004). The R^2 of the model was 4.6%.

Table 8. Panel data results

Forecasting Error	Coefficient	Standard Deviation	P > z
Rating	**1,309012**	**0,600207**	**0,029**
ln Assets	**1,132818**	**0,568829**	**0,046**
Total Indebtedness	-3,96048	3,368014	0,24
ROE	-1,3632	2,092373	0,515
Constant	**-19,9193**	**10,64629**	**0,061**

Source: Prepared by the authors.

Analysts' forecasts have substantial value for market agents, so in addition to understanding how professionals act, it is necessary to know and understand what can influence their actions. In this sense, the results showed that the rating is significant and positively impacts the analysts' forecast error, so companies with a better rating have fewer errors in their earnings projections and companies with a worse rating show more errors in their forecasts.

In short, this ratio increases the market's range of options for carefully analysing analysts' projections, and helps market analysts themselves to better weigh their projections against the *ratings* provided by bond rating agencies.

5. Final considerations

This study aimed to analyse the relationship between analysts' forecast error and the rating provided by credit rating agencies to publicly traded non-financial companies in Brazil. To this end, data from 44 companies was collected between 2010 and 2018 in the Thomson Reuters® and Economática® platform database, and the hypothesis was tested that the higher the company›s rating, the greater the difficulty in forecasting its earnings by market analysts.

With the results obtained by the present study, the hypothesis that the forecast error of the results is positively related to the risk rating on credit quality was confirmed. As it is a primitive study, no previous work was found on the relationship between forecast error and rating, however the research advances and connects the works of Gatsios (2013), Gatsios et al. (2018), Jiang (2022), Lima et al. (2016), Magnani et al. (2022), and Saadaoui et al. (2022).

In this sense, analysts' forecasts have substantial value for market agents, so in addition to understanding how professionals act, it is necessary to know and understand what can influence their actions. In this sense, the results showed that the *rating* is significant and positively impacts the analysts' forecast error, so companies with a better *rating* have fewer errors in their earnings projections and companies with a worse *rating* show more errors in their forecasts.

In short, this ratio increases the market's range of options for carefully analysing analysts' projections, and helps market analysts themselves to better weigh their projections against the *ratings* provided by bond rating agencies.

It should be noted that we only used data from companies that presented a forecast of earnings and credit risk rating for at least one year of the period analysed. Therefore, the number of companies was limited in the period analysed. For future studies, it is suggested that the sample be expanded, to include, in particular public companies in emerging economies. In doing so, it will be possible to increase the empirical evidence of the relationship established by this study.

References

Antônio, R. M., Ambrozini, L. C. S., Gatsios, R. C., & Magnani, V. M. (2017). Analysts' consensus and target price accuracy: A study in Latin America. *Brazilian Administration Review,* 14(4). https://doi.org/10.1590/1807-7692 bar2017170036

Brito, G. A. S., & Assaf Neto, A. (2008). Modelo de classificação de risco de crédito de empresas. *Revista Contabilidade & Finanças,* 19(46), 18–29.

Dalmácio, F. Z. (2009). *Mecanismos de governança e acurácia das previsões dos analistas do mercado brasileiro: Uma análise sob a perspectiva da teoria de sinalização.* [Unpublished doctoral dissertation]. University of São Paulo.

Damasceno, D. L., Artes, R., & Minardi, A. M. A. F. (2008). Determinação de rating de crédito de empresas brasileiras com a utilização de índices contábeis. *Revista de Administração,* 43(4), 344–355.

DeMarzo, P. M., & Duffie, D. (1995). Corporate incentives for hedging and hedge accounting. *The Review of Financial Studies*, 8(3), 743–771.

Fitch Ratings. (2019). Definições de rating. https://www.fitchratings.com/site/dam/jcr:ec7dec6c-3b1a-47dc-974e4dddd3da5c24/Rating%20Definitions%20 Maio%202019_final. pdf

Gatsios, R. C. (2013). *Acurácia e dispersão das estimativas dos analistas no mercado de capitais brasileiro: Impacto da adoção do padrão IFRS sobre a qualidade preditiva da informação contábil*. [Unpublished dissertation]. University of São Paulo.

Gatsios, R. C., Lima, F. G., & Magnani, V. M. (2018). The impact of IFRS adoption on the accuracy and dispersion of analysts' forecasts in the Brazilian stock market. *Economics Bulletin*, 38(4), 2389–2398.

Gomes Neto, J. T. (2017). *Determinantes do rating de instituições financeiras: Uma análise em países emergentes e não emergentes*. [Unpublished dissertation]. University of Brasilia.

Gujarati, D. N. (2011). *Econometria básica.* (5th edition). Elsevier.

Jiang, Y. (2022). Credit ratings, financial ratios, and equity risk: A decomposition analysis based on Moody's, Standard & Poor's and Fitch's ratings. Finance Research Letters, 46(PB), 102512.

Kanandani, F. H., & Minardi, A. M. A. F. (2013). *Modelos estruturais antecipam alteração de rating de crédito de agências?* Insper Working Paper.

Lima, F. G., Fonseca, C. V. C., & da Silveira, R. L. F. (2016). The determinants of credit rating levels: Evidence from Brazilian non-financial companies. [Conference presentation]. International Conference on Emerging Market Economies, Porto, Portugal. https://www.researchgate.net/publication/305919274_The_determinants_of_credit_rating_levels_evidence_from_Brazilian_non-financial_companies

Magnani, V. M. (2017). *Análise do impacto da política de hedge na redução do conflito de agentes no Brasil.* [Unpublished Master's thesis]. University of São Paulo.

Magnani, V. M., Ambrozini, M. A., Antonio, R. M., & Gatsios, R. C. (2022). Hedging policies to reduce agency costs in Brazil. *Journal of Risk and Financial Management,* 15(8), 365.

Martinez, A. L. (2004). *Analisando os analistas: Estudo empírico das projeções de lucros e das recomendações dos analistas de mercado de capitais para as empresas brasileiras de capital aberto.* [Unpublished doctoral dissertation]. São Paulo School of Business Administration of São Paulo of the Getúlio Vargas Foundation.

Martinez, A. L. (2007). Determinantes da acurácia das previsões dos analistas. *Revista UnB Contábil,* 10(2), 69–96.

Martinez, A. L., & Dumer, M. C. R. (2013). Adoção das IFRS e as propriedades das previsões de lucros dos analistas: Caso brasileiro. *Revista Mineira de Contabilidade*, 14(52), 53–62.

Saadaoui, A., Elammari, A., & Kriaa, M. (2022). Credit rating announcement and bond liquidity: The case of emerging bond markets. *Journal of Economics, Finance and Administrative Science*, 27(53).

Saito, R., Villalobos, S. J. S., & Benetti, C. (2008). Qualidade das projeções dos analistas sell-side: Evidência empírica do mercado brasileiro. *Revista de Administração*, 43(4), 356–369.

Soares, G. O. G., Coutinho, E. S., & Camargos, M. A. (2012). Determinantes do rating de crédito de companhias brasileiras. *Revista Contabilidade Vista & Revista*, 23(3), 109–143.

Standard & Poor's Financial Services LLC (2019). *Definição de rating*. https://www.standardandpoors.com/pt_LA/web/guest/regulatory/ratings-definitions

Zanin, L. (2022). Estimating the effects of ESG scores on corporate credit ratings using multivariate ordinal logit regression. *Empirical Economics,* 62(6), 3087–3118.