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Accuracy in Earnings Forecast and Organizational Life Cycle Stages: Evidences in the Brazilian Capital Market

Abstract

Objective: This study aimed to investigate the effect of the organizational lifecycle on the accuracy of analysts' forecasts in the Brazilian capital market, presupposing that the challenges for the financial analysts' projections can vary in the course of the companies' evolution.
Method: The sample consisted of 713 companies per year in the period from 2008 till 2014. This information was used to measure the accuracy of the earnings forecasts, and Dickinson's model (2011) was used to measure the companies' life cycle stages. As for the analysis methods, linear and quantile regression and sensitivity test models were used.
Results: The results revealed that the analysts' earnings projections are affected more problematically for companies in the birth and decline stages, despite controlling for several common factors in the literature on analysts' forecast errors. An additional control was included for financial difficulties, but the results remained qualitatively similar. As for the optimism and pessimism in the forecasts, the results appointed that, depending on the life cycle stage, the optimistic or pessimistic bias can particularly increase or decrease; the decline stage lead to projections with a lesser bias in comparison with the other non-mature stages, despite the previously mentioned controls.
Contributions: The study can contribute to the literature by evidencing that environmental factors tend to play a determinant role in the accuracy of the earnings forecast.
Key words: Analysts, Accuracy, Organizational Life Cycle Stages.

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1. Introduction

The determinants of the accuracy of analysts' forecasts are mainly due to characteristics related to analysts' experience and coverage, brokerage size, firm size and corporate governance (Martinez, 2004; Hirst, Koonce & Venkataraman, 2008; Dalmácio 2009). Nevertheless, in a current scenario of ongoing crises and constant changes in firms, there is a need to identify the influence of internal and external environmental factors, such as life cycle stages (LCSs) in the accuracy of analysts' earnings predictions.

The Business Life Cycle theory, which guides this study, can evidence aspects of businesses' evolution, demonstrating an alternative economic scenario, motivated by internal environmental factors, such as the adopted strategy, financial slack, management capacity, among others, and external environmental factors such as corporate competition and macroeconomics (Costa, 2015). Thus, growth tactics and the ability to raise capital can vary in different stages of a company's life cycle, which can be divided into five phases: birth, growth, maturity, turbulence and decline (Mueller, 1972; Dickinson, 2011). Thus, for each stage of the life cycle, the analysts are expected to behave differently.

In the birth stage, the firm's value depends entirely on its future growth potential. Thus, estimates are prone to error due to the context of uncertainties (Miller & Friesen, 1984; Costa, 2015). According to Dickinson (2011) and Hribar and Yehuda (2015), mispricing occurs throughout the life cycle, but is especially perceived during the early stages when the signs of different performance measures are more distinct. In addition, there is little publicly available information about these new companies. Thus, there is more private information, which tends to increase uncertainty, hindering the analysts' accuracy (Girão, 2016).

In the growth stage, the valuation is still limited and unreliable, which may compromise the accuracy of analysts' forecasts (Costa, 2015; Koh, Dai & Chang, 2015). In this phase, the forecasting difficulty is increased and, consequently, the costs and efforts for analysts to follow the companies in the growth phase are increased (Hamers, 2017). In addition, the reduced visibility of firms in the growth phase may limit the benefits of analysts that could derive from these firms' coverage (Bushee & Miller, 2012).

At maturity, in turns, analysts tend to make more accurate forecasts, as firms are less prone to the predictability risk (Costa, 2015). Mature companies have a stable operating environment, reflected in persistent profits, thereby facilitating analysts' ability to predict future performance more easily (Easley & O'Hara, 2004, Donelson & Resutek, 2015). Mature companies do not have many investments to make, nor are they likely to default (life cycle classification based on cash flow signs evidences this), making profit more predictable when compared to the early stages.

In the turbulent stage, accounting information loses relevance and may undermine the analysts' performance (Dickinson, 2011; Costa, 2015). Companies in turbulence can migrate to earlier stages, deploy new ideas or improve their efficiency, or they can move into the decline stage. Little is known about these companies though, leading to uncertainty about the implications for the financial analysts' difficulties (Girão, 2016).

Finally, in the decline stage, analysts' earnings forecast tend to be easier because they are based on existing assets and past practices (Damodaran, 2012). Thus, due to the visibility of these companies and the analysts' greater knowledge, this stage tends to present more accuracy. Investors need to know how long these companies will be able to continue the activity or whether they will be able to pay dividends (Girão, 2016). Therefore, the analysts' monitoring should be more prioritized, also facilitating the accuracy of the earnings.

There also exists a hypothesis that, in different conditions of the economy and, consequently, of firms, the analyst's degrees of uncertainty and confidence affect their beliefs about the future of firms. Evidence (Jiang, Habib & Gong, 2015) indicates that economic recession is positively associated with error accuracy, but negatively associated with forecast accuracy. Nonetheless, not only these economic aspects influence the firms, and the recession will not necessarily affect all firms.

Hamers (2017), in turn, investigated how the enterprise life cycle affects the analyst and the properties of the analyst's forecast, presenting the first international evidence. Using a sample of listed companies in the United States between 1994 and 2012, it was verified, as far as the accuracy of analysts' forecasts is concerned, that analysts' individual forecasts are less accurate for companies in the introduction, turbulence and decline phases in relation to forecasts issued for mature companies. The predictions of individual analysts are more accurate for companies in the growth phase though, countering theoretical assumptions.

Thus, although evidence on the subject is scarce and limited in developed markets, there are indications that life cycle stages can determine analysts' earnings forecasts. Thus, the main objective of this article is to investigate the effect of the organizational life cycle on the accuracy of analysts' forecasts in the Brazilian capital market.

The justification of the study is due to the importance of the factors that determine the accuracy of earnings forecasts as, internationally, evidence is found that considers the effects of companies' internal and external environmental factors. A wider debate is necessary in the literature though and the findings of other works need to be expanded, considering the influence of life cycles on the quality of earnings forecasts (e.g. Jiang *et al.*, 2015 and Hamers, 2017), with a different form of capturing the effect of each stage of the enterprise life cycle by analyzing the optimistic or pessimistic bias of the forecasts, as well as by investigating an emerging capital market, such as Brazil, due to its various informational peculiarities (obscurities), (Girão, 2016).

In addition to the factors that determine the accuracy of earnings forecasts, it is important to emphasize the relevance of analysts' projections, which deserves attention and debate, as they reduce informational asymmetry and influence the decision-making process of investors and other users (Sun, Carrete & Tavares, 2017).

In order to meet the proposed objective, we used Dickinson's (2011) classification model of LCSs, which classifies companies into 5 stages: (1) birth; (2) growth; (3) maturity; (4) turbulence and (5) decline, based on the signs of the cash flow statement. Then, dummy variables were created for each stage, except for maturity, to serve as a reference in the analysis of the results and to avoid the trap of the dummy variable.

To analyze the accuracy of the analysts' forecasts, a model based on the studies of Jiao, Koning, Mertens and Roosenboom (2011), Gatsios (2013) and Martinez and Dummer (2014) was used, using a measure called Absolute Forecast Error (AFE), being used as a proxy for accuracy. In order to analyze the pessimistic and optimistic biases, the forecast error was used without the application of the module to obtain the absolute error, so that the negative errors (observed earnings - expected earnings) represent the analysts' optimism and positive errors represent pessimism.

The main results of the survey pointed out that the analysts' earnings projections for companies in the birth and decline stage are the most problematic, despite controlling for several common factors in the literature on analysts' forecast errors and financial difficulties. With regard to optimism and pessimism in the analysts' projections, in short, the declining stage has led to less biased projections comparing with the other non-mature stages, even when controlling for the various factors that may affect analysts' forecasts.

2. Development of Hypothesis

Life cycle literature suggests three key aspects: (1) life cycle stages may explain the differences in the underlying economy of value attributes, such as the production function and companies' investment opportunity; (2) companies in different stages of the life cycle need customized management of their business in order to be successful and; (3) the knowledge of the company's specific life cycle stage may favor the understanding of where the firm is and where it intends to go (Park & Chen 2006).

This research focuses on the first aspect, because analysts tend to check the evolutionary stages of firms in the valuation process, as business fundamentals (which create value) tend to vary throughout the stages of the life cycle and the asymmetric information level also differs between the stages, which may affect the valuation process and the analysts' accuracy.

According to Dalmácio, Lopes, Rezende and Sarlo Neto (2013), analysts, when projecting future earnings, evaluate firms' observable and individual characteristics, in which they can determine whether to acquire the investment, considering the accuracy of their projections. Investigations aimed at understanding the activities of analysts are important, as not every earning forecast produced is useful, often due to bias, as well as lack of accuracy and precision (Myring & Wrege, 2009). Nevertheless, there is little evidence that considers the individual economic characteristics of firms, such as the life-cycle stages in the analysts' earnings predictions (Jian *et al*., 2015).

Almeida and Dalmácio (2015) investigated how the interaction of competitive environments and corporate governance has improved the accuracy of analysts' forecasts and deviations from forecasts. Their results revealed that, despite the fact that competition increases the flow of information, it negatively influences the accuracy of analysts' forecasts and increases the deviation of the forecasts. Corporate governance mitigates informational problems though. Thus, it is expected that the influence of competition on the evolution of the company's life phases may compromise analysts' accuracy in forecasting future earnings.

Lima, Carvalho, Paulo and Girão (2015) carried out a study to analyze the effect of the life cycle stages of the companies listed on BM & FBOVESPA (currently Brazil Stock Exchange - B3) regarding the quality of their accounting information, in the period from 1995 to 2011. The model by Anthony and Ramesh (1992) was used to measure the stage of the life cycle. The evidence from the survey suggests that there are significant differences in the quality of accounting information, except for the management of accounting results between the life cycle stages of Brazilian publicly traded companies. Thus, it has been suggested that this behavior may influence the valuation process.

Costa (2015) investigated the effects of life cycle stages on the quality of accounting information, from 2008 to 2013, considering as attributes: relevance, timeliness and conservatism, as well as Dickson's model (2011) to measure the stages of the life cycle. Their results indicated that in the growth and maturity phases, accounting information is more relevant and timely, whereas conservatism was not statistically significant in the life cycle stages.

Some authors have investigated the factors affecting analysts' accuracy in predicting Initial Public Offering (IPO) gains, using the company's life cycle, company size, forecast period, leverage, industry classification, volatility of the stock price and audit quality (Lonkani & Frith, 2005, Bahramian, 2006, Sareban & Ashtab, 2008) as proxies.

The results of the research by Lonkani and Frith (2005) revealed that there exists an exclusive positive relationship between errors in earning predictions and size and forecast horizon. The evidence presented by Bahramian (2006) indicated that the earnings forecast error is positively associated with the forecast period and stock price volatility. There was no significant relationship between the error of earning forecasting and size, life cycle, leverage and audit quality though.

In turn, Sareban and Ashtab (2008) examined the determinants of earning forecasting errors in 107 companies recently listed in the TSE during the period 1999-2006. The results indicated that the prediction, leverage and life cycle period has a significant negative effect on the accuracy of the predicted results. The significant relationship was also observed among the auditors' opinions.

Uncertain economic environments, with expansions or recessions, can substantially affect the life cycle stages of a business, and affect analysts' accuracy, precision and bias. In Brazil, Martinez (2004) studied the relationship between the oscillations of the Gross Domestic Product (GDP) in a given year and the performance of analysts' forecasts. The results showed that, in periods of economic growth, analysts are more optimistic; on the other hand, their forecasts are more accurate. For this purpose, this study presented trends, although it did not accurately capture the effects of crisis periods.

Jian *et al*. (2015) evaluated whether economic recession influences the characteristics of analysts' earnings forecasts, such as frequency, pessimism, and forecast accuracy. The results indicated that the frequency of forecasting is higher during the recession, but pessimism and precision are lower during the recession, while analysts' error has shown an opposite sign to the forecast.

In turn, Hamers' research (2017) investigated the role of the life cycle in the capital market. Specifically, it verified how the company life cycle affects the analyst and the predictor properties of the analyst. Using a sample of listed companies in the United States over the period 1994 to 2012, it was verified, as far as the accuracy of analysts' forecasts is concerned, that analysts' individual forecasts are less accurate for start-ups, turbulence and decline in relation to forecasts issued to mature companies.

It should be noted that the evidence presented, while demonstrating that life cycle stages may affect the accuracy of earning forecasts, does not precisely detail the effect of each specific phase (birth, growth, maturity, turbulence and decline) on analysts' decisions, whether optimistic or pessimistic, and in emerging markets, which can have particular effects on business life cycles. Thus, according to Figure 1, a theoretical survey was carried out to justify analysts' performance in predicting earnings for each life cycle stage.

Birth Stage	
Characteristics	**Accuracy Problems**
The companies in this stage are typically small, dominated by their owners (entrepreneurs), with a simple and informal structure and with functional systems without a focus on the interaction among sectors. The company does not make profit, its operational flow will probably be equal to zero, despite expected future receivables (Costa, 2015).	The products offered have not been tested yet and have no established Market, so that the company value depends totally on its future growth potential. Therefore, the estimates are prone to errors due to the context of uncertainties (Damodaran, 2012). According to Dickinson (2011) and Hribar and Yehuda (2015), mispricing happens throughout the lifecycle, but is particularly noticed during the initial phases, when the signs of different performance measures are more distinct. In addition, there is little publicly available information on these new companies, so that there is more private information, factors that tend to increase the cost of capital, due to the uncertainty, making the analysts' precision more difficult (Girão, 2016).
Growth Stage	
Characteristics	**Accuracy Problems**
The basic aspect of this phase is the change from the birth to the growth stage, mainly related to market expansion, thus increasing the companies' needs when compared to the previous phase (Costa, 2015). Companies in the growth stage are generally medium-sized with multiple shareholders, and achieve rapid growth, because they attract more clients and establish their presence in the market (Koh *et al*., 2015).	Normally, their revenues increase rapidly, although this can still turn into losses. Hence, the valuation is still limited and hardly reliable, factors that can compromise the accuracy of analysts' forecasts (Damodaran, 2012). In this phase, forecasts become more difficult and, consequently, the analysts' costs and efforts to follow the companies in the growth stage increase (Hamers, 2017). In addition, the companies' limited visibility in the growth stage can limit the analysts' benefits that could derive from covering these companies (Bhushan 1989; Bushee & Miller, 2012). Nevertheless, the evidence by Costa (2015) appoints that, in the growth stage, the accounting information is more relevant when compared to other phases. Hence, the analysts' accuracy, although the companies are still in an uncertain stage, can be less biased.
Maturity Stage	
Characteristics	**Accuracy Problems**
In the maturity stage, the companies are less prone to assuming innovative or risky strategies than in their birth and growth stages. Their revenues will grow at a stable rate and the cash flows increase continuously. In this phase, the operational performance stabilizes and the focus changes to the organizational efficiency (Miller & Friesen, 1984).	Mature companies have a stable operational environment, reflected in persistent earnings, thus facilitating the analysts' capacity to predict the future performance (Easley & O'Hara, 2004, Donelson & Resutek, 2015). The study by Costa (2015) appoints that, in this stage, together with the growth stage, the accounting information is relevant and hence possesses explanatory and predictive power. Hence, the analysts tend to provide accurate and precise earnings forecasts, as the companies are less risk-prone. Mature companies do not have many investments to make, nor is a default probably (the classification of the life cycle based on the signs of the cash flows evidences this), so that the earnings are more predictable when compared to the initial stages.

Turbulence Stage	
Characteristics	**Accuracy Problems**
Dickinson (2011) appoints that the literature lacks information on the cash flow for these companies. Thus, when the companies do not rank in the other cycles, they fit into the turbulence stage. For the same author, in this stage, the number of producers starts to decline. Nevertheless, this stage is marked by the company's oscillations.	According to Costa (2015), in case of turbulence, the companies are in a phase of change and may migrate to another stage. Hence, the accounting information loses information contents and can negatively affect the analysts' performance in the earnings forecast process. In the same sense, according to Girão (2016), companies in the turbulence stage can migrate to previous stages, implementing new ideas or improving their efficiency, or can move to the decline stage. Nevertheless, little is known on these companies, leading to uncertainty about the implications in the financial analysts' activities.

Decline Stage	
Characteristics	**Accuracy Problems**
In the Companies' decline stage, the revenues and earnings start to decrease; existing investments will probably continue to produce cash flows, although with a downward rhythm; and the firm has little need for new investments (Damodaran, 2012). In this phase, the companies are stuck in a vicious circle of bad performance due to their stagnated business models and face difficulties to attract and retain clients (Miller & Friesen, 1984).	The company value completely depends on existing assets due to past practices. Hence, the analysts' earnings forecast tends to be easier, that is, more accurate and less biased. Nevertheless, in this phase, the investors gradually leave the companies, as they have no incentives to invest in the companies, leading to a lesser quality of the accounting information and, consequently, the analysts may face some difficulty to predict future earnings (Costa, 2015).

Figure 1. Analysts' accuracy in company life cycle stages

Source: elaborated by the authors, 2016

Thus, according to all the arguments presented above, we postulate that the life cycle stages have different economic characteristics, in which they serve as support for financial analysts to make predictions. Given this, we have the following main hypothesis, and its consequences:

- **H1:** the accuracy of earnings forecasts is influenced by the life cycle stages of firms in the Brazilian capital market.
- **H1a:** Firms in the birth stage have their earnings predicted less accurately when compared to companies in the maturity stage
- **H1b:** Growth-stage companies have their earnings predicted less accurately when compared to companies in the maturity stage
- **H1c:** Companies in the turbulence stage have their earnings predicted less accurately when compared to companies in the maturity stage
- **H1d:** Firms in the decline stage have their earnings predicted more accurately when compared to companies in the maturity stage.

3. Method

3.1 Sample Selection and Composition

The universe of this study will consist of all the non-financial companies listed on BM&FBOVESPA. For the composition of the (non-probabilistic) sample, those companies were selected whose information was available in the database of Economatica® and Thomson Reuters Eikon®. Financial companies were excluded from the population because they have specific accounting regulations and equity structures.

The period used for the assessment and, consequently, for the constitution of the sample was from 2008 to 2014, in order to capture some effects in the market in relation to the convergence process with the international accounting standards and the economic crisis from 2008 to 2010. After complying with the criteria listed above, the sample was composed of 713 companies a year.

3.2 Description of Models

3.2.1 Classification of Life Cycle Stages (LCS)

Dickinson's (2011) ranking of the LCSs was used, as shown in Table 3, which classifies the companies into five stages: (1) birth, (2) growth, (3) maturity, (4) turbulence and (5) decline. This model is based on the combination of signs of each of the three cash flow components, i.e. operational, investment and financing.

In order to illustrate this ranking, the companies in the birth stage are taken as an example. These companies need operating cash and negative investment cash as well as positive financing cash, as the company is not yet able to generate cash through its operating activities (negative sign) and needs to have cash outflow to invest (negative sign) in its projects, therefore resorting to financing (positive sign). Otherwise, it should be classified in the other life cycle stages, whose respective criteria are displayed in Figure 2.

Cash Flow	Birth	Growth	Maturity	Turbulence	Decline
Operational	-	+	+	+ - +	- -
Investment	-	-	-	+ - +	+ +
Financing	+	+	-	+ - -	+ -

Figure 2. Classification of Life Cycle Stages

Source: Dickinson (2011, p. 9)

Dickinson (2011) appoints that the measuring method of the LCSs using cash flow patterns can absorb the effects of measures such as sales growth and dividend distribution, used in methods like Anthony and Ramesh (1992). In addition, it does not need the researcher's own arbitrary classifications. Hence, Dickinson (2011) measures the life cycle stages using the signs of the components in the cash flow statement.

3.3.1 Accuracy measuring model of analysts' earnings forecasts

To analyze the accuracy of the analysts' forecasts, a model based on the studies by Jiao *et al.* (2011), Gatsios (2013) and Martinez and Dummer (2014) was used, by means of a measure called Absolute Forecast Error (AFE). The AFE results from the absolute difference, using the module, between the annual earnings per share (EPS) of company" j" in the period of the income presentation ($A_{j,r}$) and the analysts' mean forecast for EPS on April 1st ($F_{j,t}$), dividing this difference by the companies' stock price ($P_{j,t}$), as described next:

$$EPA_{j,t} = \left| \frac{A_{j,r} - F_{j,t}}{P_{j,t}} \right|$$

According to Martinez and Dummer (2014), in this model, all errors can be considered, as it does not depend on whether the errors are negative or positive, while other methods, such as those that measure the analysts' bias, considered that the positive errors cancel the negative errors of the same magnitude.

3.2.2 Proposed Regression Model

To investigate the effects of the life cycle stages as environmental determinants in the accuracy of earnings forecasts in the Brazilian capital market, a model was used based on the studies by Gatsios (2013) and Jiang *et al.* (2015), described next. Nevertheless, as dummy variables are used to capture the life cycle stages, the maturity stage had to be removed for the sake of comparison in the results analysis. Therefore, two linear equations were created: the first containing only the variables of interest; and in the second, the control variables were inserted as described next:

$$AFE_{it} = \alpha + \beta_1 * DBIRT_{it} + \beta_2 * DGROW_{it} + \beta_3 * DTURBU_{it} + \beta_4 * DDECLI_{it} + \varepsilon_{it} \quad (1)$$

$$\begin{aligned} AFE_{it} = \alpha + \beta_1 * DBIRT_{it} + \beta_2 * DGROW_{it} + \beta_3 * DTURBU_{it} + \beta_4 * DDECLI_{it} + \beta_5 \\ * DLOSS_{it} + \beta_6 * QANALYST_{it} + \beta_7 * DOPTIM_{it} + \beta_8 * PTB_{it} + \beta_{10} \\ * LnSIZ_{it} + \beta_{11-29} * \sum DSECT + \beta_{29-35} * \sum DYEAR \ \varepsilon it \end{aligned} \quad (2)$$

Where:
AFE = Absolute Forecast Error (Accuracy measure)
DNASC = Dummy variable that indicates the Birth Stage of the Life Cycle, with score 1 for companies in the Birth Stage and 0 for the others.
DCRES = Dummy variable that indicates the Growth Stage of the Life Cycle, with score 1 for companies in the Growth Stage and 0 for the others.
DTURBU = Dummy variable that indicates the Turbulence Stage of the Life Cycle, with score 1 for companies in the Turbulence Stage and 0 for the others.
DDECLI = Dummy variable that indicates the Decline Stage of the Life Cycle, with score 1 for companies in the Decline Stage and 0 for the others.
DLOSS = Dummy variable that indicates 1 for loss in the year and 0 for the others.
QANALYST= Control variable that indicates the analysts' total coverage.
DOPTIM = Dummy control variable that indicates 1 for optimistic forecast and 0 for pessimistic forecast.
PTB = The Price-to-book is a control variable that measures the relation between the market value and equity value of company i in time t.
LnSIZ = Control variable that indicates the company size through the Natural Logarithm of Total Assets.
∑DSECT = Control variable that indicates the sector the company acts in. Eighteen (19-1) dummies were included for the sectors.
∑DYEAR = Control variable that indicates each year analyzed. Six (7-1) dummies were included for the years.
ε = Error term of the regression of company *i* in period *t*.

The control variable DLOSS was used, which indicates negative results of the period, as the studies by Dalmácio *et al.* (2013), Gatsios (2013) and Jian *et al.* (2015) revealed that analysts tend to decrease their accuracy with companies' negative results.

The control variable QANALYST was used in the studies by Martinez (2004) and Dalmácio *et al.* (2013) and indicates that, the more analysts monitor the company, the more information will be disseminate and the lesser the earnings forecasting errors will be. This information for QANALYST was collected by means of the total recommendations each company in the sample received.

The variable DOPTIM was also used, which according to Martinez (2004) and Almeida and Dalmácio (2015) represents the analysts' bias, whether pessimistic or optimistic.

The PTB variable, in turn, used in the studies by Martinez (2004) and Almeida and Dalmácio (2015), reveals that, the higher the PTB, the greater the analysts' accuracy will be. This same behavior is also expected for LnSIZ, as greater accuracy is expected for larger companies, being better known. Finally, the sector is used as a control variable as, according to Pessotti (2012), Gatsios (2013) and Jian *et al.* (2015), the analysts' forecasts can be associated with the companies' activity branches.

4. Results and Discussion

4.1 Descriptive statistics

The data presented in Table 1 provide information on the descriptive statistics for the non-dummy (control) variables in the measuring model of the life cycle stages' effects on the accuracy of the analysts' earnings forecasts.

Table 1
Descriptive statistics of continuous variables – total and per LCS

Variables	Mean	Median	Maximum	Minimum	Standard Dev.
AFE	0.387	0.040	120.484	1.84e-6	4.735
QANALYST	11.533	11	26	1	5.670
PTB	5.015	1.690	309.580	-12.812	21.446
SIZ	21,100,000	5,370,000	793,000,000	333,000	67,300,000
LnSIZ	15.616	15.497	20.491	12.717	1.416
			Birth Stage (n = 25)		
AFE	1.224	0.357	13.626	0.004	2.764
QANALYST	9.800	9	21	1	6.021
PTB	1.997	1.862	11.503	-10.437	3.617
SIZ	9,890,000	3,280,000	58,200,000	493,000	14,900,000
LnSIZ	15.158	15.002	17.880	13.109	1.451
			Growth Stage (n = 306)		
AFE	0.518	0.040	120.484	0.000	6.889
QANALYST	11.556	11	25	1	5.709
PTB	5.540	1.579	309.580	-4.855	26.163
SIZ	21,800,000	5,090,000	678,000,000	466,000	64,400,000
LnSIZ	15.623	15.443	20.334	13.051	1.445
			Maturity Stage (n = 330)		
AFE	0.097	0.030	1.920	0.000	0.198
QANALYST	11.906	12	26	1	5.683
PTB	5.195	1.927	287.160	-12.812	18.850
SIZ	20,200,000	5,230,000	793,000,000	333,000	65,000,000
LnSIZ	15.610	15.469	20.492	12.717	1.391
			Turbulence Stage (n = 48)		
AFE	0.945	0.098	34.572	0.003	4.975
QANALYST	9.729	9.5	21	2	5.193
PTB	2.111	1.385	23.690	-0.080	3.565
SIZ	28,900,000	6,930,000	753,000,000	477,000	109,000,000
LnSIZ	15.768	15.751	20.440	13.076	1.379
			Decline Stage (n = 4)		
AFE	2.346	0.537	8.309	0.002	3.992
QANALYST	11.500	12.5	19	2	7.047
PTB	3.663	0.475	13.894	-0.190	6.829
SIZ	24,400,000	21,300,000	47,400,000	7,370,000	20,100,000
LnSIZ	16.676	16.608	17.674	15.813	0.987

Obs.: AFE = Absolute Forecast Error, QANALYST = Control variable indicating how many analysts monitor the company, PTB = The Price-to-book is a control variable that measures the relation between the company's market value and equity value, SIZ = Company's total assets and LnSIZ = Is the natural logarithm of SIZ.

Source: research data

Based on the results presented in Table 1 for the AFE variable, which indicates the analysts' absolute forecasting errors, the mean values corresponded to 0.387 in the period analyzed (2008 till 2014), with a median value of 0.040. The minimum was approximately 0.000 and the maximum 120.484.

The results corroborate the common and known heterogeneity in accounting and financial data (Ohlson & Kim, 2015; Duarte, Girão & Paulo, 2016), and the variance is also different for AFEs among the different stages of the life cycle, based on the Levene test (p-value = 0.000, not tabulated), which will justify the analyses presented in sections 4.2.2 and 4.4, where this heterogeneity will be better explored.

In addition, the AFEs vary according to the life cycle stages, based on a Kruskal-Wallis test (p-value = 0.000, not tabulated). This indicates that this study will seek to confirm, through the analyses in the following sections, that the "unripe" (birth, growth, turbulence, and decline) stages of the company life cycle increase analysts' propensity towards mistaken earnings predictions.

It should be noted, based on the theoretical-empirical framework adopted, that in the growth phase for example, companies are adopting a posture of putting new products on the markets, hiring more qualified employees to meet their needs, and often with high profits, but still with many investments to be made, a post-birth stage, which is less complex and less profitable (Dickinson, 2011), which may disrupt the accuracy of analysts' predictions.

In the maturity phase, in turn, firms tend to have more stable/persistent results because the growth costs are lower and the operating environment is more stable than for turbulent and declining firms (Easley & O'Hara, 2005; Donelson & Resutek, 2015) which consequently facilitates analysts' forecasting work when we compare the non-mature stages with maturity.

Thus, we can already notice a U-shaped pattern for the average AFE, based on the life cycle stages, respectively: birth = 1.224, growth = 0.518, maturity = 0.097, turbulence = 0.945 and decline = 2.346. The following sections may corroborate these previously found results in a descriptive way. This pattern is similar to that found for the average cost of capital in the life cycle stages in Brazil (Girão, 2016), but with an inverted "U", as expected.

The average value of QANALYST was 11,533, with a median of 11. The maximum number of analysts who monitored a company was 26 and the minimum 1 (to be included in the sample, being monitored by analysts was a requirement), a factor that influenced the high standard deviation for this variable, indicating that firms may have disparities in accuracy as some receive more attention from analysts, leading to greater dissemination of information and less informational asymmetry (Girão, 2016).

The second control variable was PTB, which presented an average value of 5.015 and a median of 1.690. The maximum value was 309.580 and the minimum -12.812. The standard deviation was 21.446, corroborating the previous results that indicated the heterogeneity of the sample, consequently entailing possible prediction errors for the groups of companies with lower PTB coefficients. Negative PTB indicates that there are companies with short-term liabilities due to financial difficulties, which should also affect the analysts' accuracy (Moses, 1990; Behn, Choi & Kang 2008), but are not directly captured by PTB.

Finally, the last control variable was company size, represented by total assets (SIZ). The average value was R$ 21 billion, with a median of R$ 53 billion. Theoretically, the larger the company size, the better the analysts' performance, especially when linked to the life cycle, which helps to reduce informational asymmetry. No evidence was found that enterprise size varies according to the life cycle stages though (p-value> 10%), even when the natural logarithm of the total asset is used, indicating that the company life cycle is really indifferent to size because cash flow patterns are used to classify firms (Dickinson, 2011).

In addition to the AFE variable, which presented different means among the life cycle stages as indicated by the abovementioned Kruskal-Wallis test, at a significance level of 1%, PTB also presented different means among the stages, at the level of 1%, whereas QANALYST presented different means among the stages at 10% (p-value = 0.064). Only SIZ did not present evidences of difference among the means of the life cycle stages (p-value = 0.223).

4.2 Linear models

4.2.1 General model

Table 2 indicates the empirical results of the two equations proposed to capture the effects of the life cycle stages in the accuracy of the analysts' forecasts. The first of them relates to the analysis in which only the variables of interest are considered, while the control variables were included in the second.Due to the identified autocorrelation and heteroscedasticity problems, Newey-West's robust standard erros were estimated.

Table 2

Equations measuring the effects of the life cycle stages on the accuracy of the analysts' earnings predictions between 2008 and 2014

Variables	(1)	(2)
DBIRT	1.354**	0.933
	(0.614)	(0.794)
DGROW	0.551	0.450
	(0.450)	(0.486)
DTURBU	1.354*	1.270
	(0.842)	(0.802)
DDECLI	2.620*	2.358*
	(1.553)	(1.421)
DLOSS	-	0.382
	-	(0.353)
QANALYST	-	-0.033*
	-	(0.019)
DOPTIM	-	0.538
	-	(0.452)
PTB	-	-0.005
	-	(0.005)
LnSIZ	-	0.092
	-	(0.095)
Const	-0.463	-2.221
	(0.356)	(2.157)
F statistics	0.700	0.890
R^2 adjusted	0.028	0.026
White statistics	358.450***	481.960***
Wooldridge statistics	31,781.318***	37,175.755***
Obs.	713	713
Sector dummy	YES	YES
Year dummy	YES	YES

Obs.: *, ** indicate 10% and 5% significance. Newey-West standard error between brackets.
VIF: the dummy variable for the year 2012 presented the highest VIF, equal to 1.66, for model (1), indicating no multicollinearity problem.

$$AFE_{it} = \alpha + \beta_1 {*} DBIRT_{it} + \beta_2 {*} DGROW_{it} + \beta_3 {*} DTURBU_{it} + \beta_4 {*} DDECLI_{it} + \beta_5 {*} DLOSS_{it} + \beta_6 {*} QANALYST_{it} + \beta_7 {*} DOPTIM_{it} + \beta_8 {*} PTB_{it} + \beta_{10} {*} LnSIZ_{it} + \beta_{11\text{-}29} {*} \sum DSECT + \beta_{29\text{-}35} {*} \sum DYEAR + \varepsilon_{it}$$

AFE = Absolute Forecast Error, DBIRT = Dummy indicting the Life Cycle Stage of Birth, DGROW = Dummy indicting the Life Cycle Stage of Growth, DTURBU = Dummy indicting the Life Cycle Stage of Turbulence, DDECLI = Dummy indicting the Life Cycle Stage of Decline, DLOSS = Dummy indicating 1 for loss in the year and 0 for the others, QANALYST = Control variable indicating how many analysts monitor the company, DOPTIM = Control dummy for optimistic forecasts, PTB = The Price-to-book is a control variable that measures the relation between the company's market value and equity value, SIZ = Company's total assets and LnSIZ = Natural logarithm of SIZ.

Source: research data

With regard to equation (1), it was observed that the stages of birth, turbulence and decline seem to affect the accuracy of analysts' predictions at the level of 5%, 10% and 10%, respectively. As indicated in the analysis of descriptive statistics, these were the life cycle stages with the highest AFE, justifying their significance, which tend to make analysts err more, corroborating the positive signs of these variables in the regression.

A possible theoretical justification for this effect would be the challenge that the stages of birth, turbulence and decline generate for analysts, making it difficult to forecast revenues and costs as, often, this type of company does not generate revenue and often incurs debts to finance its activities (Lima, Carvalho, Paulo & Girão, 2015), while mature firms remain institutionalized and formalized, favoring an increase in analysts' accuracy (Hamers, 2017).

Non-tabulated data confirm that, although not statistically significant (p-value = 0.136), mature companies show a negative sign (-0.714), which would reduce the analysts' forecast error. This means that it cannot be argued that business maturity has any impact on accuracy, as mature firms are less problematic, less risky, and therefore easier to analyze (e.g. Easley & O'Hara, 2005; Dickinson, 2011; Donelson & Resutek, 2015; Girão, 2016).

When analyzing equation (2), with the inclusion of control variables, only the decline stage remained significant at 10% and with a positive coefficient, indicating that, even though controlling for several factors, the companies' decline offers some important information, which is not captured by the controls, for the analysts to calibrate their forecast models.

With respect to the controls inserted in equation (2), only the analysts' coverage was statistically significant at 10% and with a negative sign, as expected, as analysts' coverage is able to reduce informational asymmetry (Girão, 2016).

The results remain similar when the dummies of birth, growth, turbulence and decline are exchanged for their maturity counterpart, but the signal of the maturity, as expected, is negative, but without statistical significance.

It should be emphasized that, overall, the models presented above were not statistically significant. Some sensitivity tests for outliers were used though (Winsorization in section 4.2.2 and a different estimator in section 4.4), demonstrating that the results were statistically more acceptable, but with qualitatively similar results of the variables' signs.

4.2.2 Control for outliers by winsorization

The analysts' forecast error has a very high dispersion for the sample used in this research, ranging from 1.84e-6 to 120.484 (mean 0.377 and standard deviation 4.735), which may pollute the analysis of the results.

In this way, we tried to control the dispersion of this variable with the Winsorization procedure at 5% in each tail of the variable distribution.

Table 3

Equations that measure the effects of the life cycle stages on the accuracy of the analysts' earnings forecasts in the period from 2008 till 2014, with 5% winsorization in each tail

Variables	(3)	(4)
DBIRT	0.236***	0.050
	(0.048)	(0.050)
DGROW	0.130	0.006
	(0.010)	(0.008)
DTURBU	0.056**	0.027
	(0.028)	(0.024)
DDECLI	0.191*	0.113
	(0.113)	(0.078)
DLOSS	-	0.209***
	-	(0.018)
QANALYST	-	-0.003***
	-	(0.001)
DOPTIM	-	0.004
	-	(0.013)
PTB	-	-0.000
	-	(0.003)
LnSIZ	-	0.001
	-	(0.003)
Const	0.072***	0.050
	(0.017)	(0.049)
F statistics	7.320***	12.930***
R^2 adjusted	0.232	0.489
White statistics	215.77*	448.970***
Wooldridge statistics	5.595**	1.627
Obs.	713	713
Sector dummy	YES	YES
Year dummy	YES	YES

Obs.: *, **, *** indicate 10%, 5% and 1% significance. Standard errors between brackets - Newey-West for equation (3) and White for equation (4).
VIF: the dummy variable for the year 2011 presented the highest VIF, equal to 1.67, for model (7), indicating no multicollinearity problem.
$AFE_{it} = \alpha + \beta_1 * DBIRT_{it} + \beta_2 * DGROW_{it} + \beta_3 * DTURBU_{it} + \beta_4 * DDECLI_{it} + \beta_5 * DLOSS_{it} + \beta_6 * QANALYST_{it} + \beta_7 * DOPTIM_{it} + \beta_8 * PTB_{it} + \beta_{10} * LnSIZ_{it} + \beta_{11-29} * \sum DSECT + \beta_{29-35} * \sum DYEAR + \varepsilon_{it}$
AFE = Absolute Forecast Error, DBIRT = Dummy indicting the Life Cycle Stage of Birth, DGROW = Dummy indicting the Life Cycle Stage of Growth, DTURBU = Dummy indicting the Life Cycle Stage of Turbulence, DDECLI = Dummy indicting the Life Cycle Stage of Decline, DLOSS = Dummy indicating 1 for loss in the year and 0 for the others, QANALYST = Control variable indicating how many analysts monitor the company, DOPTIM = Control dummy for optimistic forecasts, PTB = The Price-to-book is a control variable that measures the relation between the company's market value and equity value, SIZ = Company's total assets and LnSIZ = Natural logarithm of SIZ.
Source: research data

As can be observed, when comparing tables 2 and 3, in Table 3, the models presented statistical significance and a better fit (through the adjusted R^2), due to the control for outliers by the winsorization process.

The results remained qualitatively similar for the uncontrolled model [equation (3)], with the same variables remaining statistically significant. In the winsorized model, however, the significance increased for the turbulence stage.

When adding the controls, the results are somewhat different as, when comparing equation (2) with equation (4), we can verify that no stage in the life cycle of the companies seemed to affect the analysts' forecast error, not even at a 10% significance level.

The variable DLOSS (dummy for loss in the current year), however, was statistically significant at 1% level and with a positive sign, indicating that, when there is a loss, analysts tend to err more in their earnings projections. These results support the studies by Dalmácio *et al.* (2013), Gatsios (2013) and Jian *et al.* (2015), who realized that losses tend to worsen the analysts' performance.

In turn, the QANALYST variable, which represents analysts' coverage, was significant at 1% with a negative coefficient. As previously mentioned, the increase in analysts' coverage is expected to favor the analysts' performance (Martinez & Duma, 2014).

4.3 Analysis of the Bias of Optimism and Pessimism

In order to analyze the effects of the life cycle stages in detail, serving as economic determinants or not, of the accuracy of earnings forecasts in the Brazilian capital market, quantile regression was used because, due to the heterogeneity of the sample, this is a more robust method than OLS, previously used (Ohlson & Kim, 2015, Duarte, Girão & Paulo, 2016).

In addition, there may be particularities in the distribution of the analysts' accuracy, that is, extreme forecast errors that may be optimistic or pessimistic ex-post (Martinez, 2004). Testing this characteristic is not possible with the use of the OLS models, without incurring a greater sample selection bias. When using the quantile regression, this test is possible, because we can test the tails of the distribution of the analysts' forecast error without major problems.

Thus, the two tails of the distribution were tested by means of the first quartile (p25%) and the last quartile (p75%), according to Table 4. It is noteworthy that, for this test, the analyst's absolute forecast error was not used (in module), because the focus now is not the size of the error per se, but its sign.

Table 4

Equations that measure the effects of the life cycle stages on the accuracy in the tails of the analysts' earnings predictions between 2008 and 2014

Variables	(5) p.25	(6) p.75
DBIRT	-0.476***	0.013
	(0.019)	(0.010)
DGROW	-0.008	-0.004
	(0.007)	(0.004)
DTURBU	-0.060***	-0.004
	(0.014)	(0.007)
DDECLI	-0.436***	-0.157***
	(0.041)	(0.023)
DLOSS	-0.371***	-0.109***
	(0.010)	(0.005)
QANALYST	0.003***	0.000
	(0.001)	(0.000)
DOPTIM	-0.051***	-0.092***
	(0.009)	(0.005)
PTB	0.000	-0.000**
	(0.000)	(0.000)
LnSIZ	0.000	0.001
	(0.002)	(0.001)
Const	-0.013	0.067***
	(0.041)	(0.020)
Wald test	145.480***	58.740***
Pseudo R^2	0.107	0.060
Obs.	713	713
Sector dummy	YES	YES
Year dummy	YES	YES

Obs.: *, **, *** indicate 10%, 5% and 1% significance. Standard error between brackets.
VIF: the dummy variable for the year 2011 presented the highest VIF, equal to 1.67, for model (7), indicating no multicollinearity problem.
$AFE_{it} = \alpha + \beta_1 * DBIRT_{it} + \beta_2 * DGROW_{it} + \beta_3 * DTURBU_{it} + \beta_4 * DDECLI_{it} + \beta_5 * DLOSS_{it} + \beta_6 * QANALYST_{it} + \beta_7 * DOPTIM_{it} + \beta_8 * PTB_{it} + \beta_{10} * LnSIZ_{it} + \beta_{11\text{-}29} * \sum DSECT + \beta_{29\text{-}35} * \sum DYEAR + \varepsilon_{it}$
AFE = Absolute Forecast Error, DBIRT = Dummy indicting the Life Cycle Stage of Birth, DGROW = Dummy indicting the Life Cycle Stage of Growth, DTURBU = Dummy indicting the Life Cycle Stage of Turbulence, DDECLI = Dummy indicting the Life Cycle Stage of Decline, DLOSS = Dummy indicating 1 for loss in the year and 0 for the others, QANALYST = Control variable indicating how many analysts monitor the company, DOPTIM = Control dummy for optimistic forecasts, PTB = The Price-to-book is a control variable that measures the relation between the company's market value and equity value, SIZ = Company's total assets and LnSIZ = Natural logarithm of SIZ.

Source: research data

Equation (5), which aims to measure the effect of the life cycle stages on the accuracy of profit forecasts for p.25%, a group of companies with more optimistic forecasts by analysts (forecasted earnings higher than observed earnings) showed that the stages of birth, turbulence and decline were significant, as well as the control variables analysts' coverage, DLOSS and DOPTIM, all at a significance level of 1% and with negative signs, except for analysts' coverage.

The results reveal that the stages of birth, turbulence, and decline lead to less optimistic projections of earnings by analysts, possibly because birth-stage estimates are prone to error due to the context of uncertainty about the company's development (Damodaran, 2012). In turbulence, the results are inconstant (Dickinson, 2011) and, in decline, companies decrease the quality of accounting information, which tends to lead to a decrease in analysts' accuracy if they do not control these factors (Costa, 2015; Lima *et al.*, 2015).

Analyzing the right end (tail) of the distribution, which deals with the most positive (pessimistic) forecast errors in equation (6), when the projected profit is lower than the observed profit, only the decline stage remained significant at 1 % and with a negative sign, indicating that, in companies in the decline stage, the tendency is for the forecast errors to be close to zero, in view of a lesser bias in both the pessimistic and the optimistic environment, possibly because enough is known about the company and that it is going through a process that will tend towards discontinuity.

Regarding the control variables, a similar behavior was observed with p.25%, as only the variables DLOSS and DOPTIM were significant at 1% and with a negative sign.

4.4 Estimation Sensitivity Testing

4.4.1 Quantile Regression

Additionally, in order to capture the effect of possible outliers of the sample with an estimator different from the OLS, a sensitivity test was performed by means of quantile regression in the median (p50%), according to Table 5.

Table 5

Equation that measures the effect of the life cycle stages on the accuracy in the median of the analysts' earnings forecasts between 2008 and 2014

Variables	(7) p.50
DBIRT	0.113***
	(0.010)
DGROW	0.003
	(0.004)
DTURBU	0.008
	(0.007)
DDECLI	0.594***
	(0.012)
DLOSS	0.223***
	(0.005)
QANALYST	-0.001***
	(0.000)
DOPTIM	-0.006
	(0.005)
PTB	-0.000*
	(0.000)
LnSIZ	-0.000
	(0.001)
Const	0.036*
	(0.020)
Wald test	167.500***
Pseudo R^2	0.062
Obs.	713
Sector dummy	YES
Year dummy	YES

Obs.: *, **, *** indicate 10%, 5% and 1% significance. Standard error between brackets.
H0 of the Wald Test: all estimated betas are equal to zero.
$AFE_{it} = \alpha + \beta_1 * DBIRT_{it} + \beta_2 * DGROW_{it} + \beta_3 * DTURBU_{it} + \beta_4 * DDECLI_{it} + \beta_5 * DLOSS_{it} + \beta_6 * QANALYST_{it} + \beta_7 * DOPTIM_{it} + \beta_8 * PTB_{it} + \beta_{10} * LnSIZ_{it} + \beta_{11\text{-}29} * \sum DSECT + \beta_{29\text{-}35} * \sum DYEAR + \varepsilon_{it}$
AFE = Absolute Forecast Error, DBIRT = Dummy indicting the Life Cycle Stage of Birth, DGROW = Dummy indicting the Life Cycle Stage of Growth, DTURBU = Dummy indicting the Life Cycle Stage of Turbulence, DDECLI = Dummy indicting the Life Cycle Stage of Decline, DLOSS = Dummy indicating 1 for loss in the year and 0 for the others, QANALYST = Control variable indicating how many analysts monitor the company, DOPTIM = Control dummy for optimistic forecasts, PTB = The Price-to-book is a control variable that measures the relation between the company's market value and equity value, SIZ = Company's total assets and LnSIZ = Natural logarithm of SIZ.

Source: research data

The results of equation (7) showed that the stages of birth and decline were significant at 1% and with a positive sign, as expected. In comparison with the previous estimates of equations (2) and (4) in Tables 2 and 3, we can see that, although all the signs of the variables of interest were the same, only the decline showed statistical significance at 10% in equation (2).

As the quantile regression, when compared to the OLS, may be more suitable for the analysis of accounting and financial models, being less sensitive to the outliers, there is no need to lose information with the use of winsorization, and it is robust to the heterogeneity so common in this type of data (Ohlson & Kim, 2015; Duarte, Girão & Paulo, 2016). The estimates presented in Table 5 are considered safer, although they are qualitatively in line with the estimates in Tables 2 and 3.

This supports the previous results that companies in the birth and decline stages lead to an increase in analysts' absolute forecast error in general.

Figures 3 and 4 below show these variables' behavior along the quantiles, although the differences between the 1st and 3rd quartiles were statistically significant for the stages of birth (p-value = 0.066) and decline (p-value = 0.067) only at 10%. One can see that the effect of the birth stage increases with the AFE. The same happens, but more sharply, with the stage of decline.

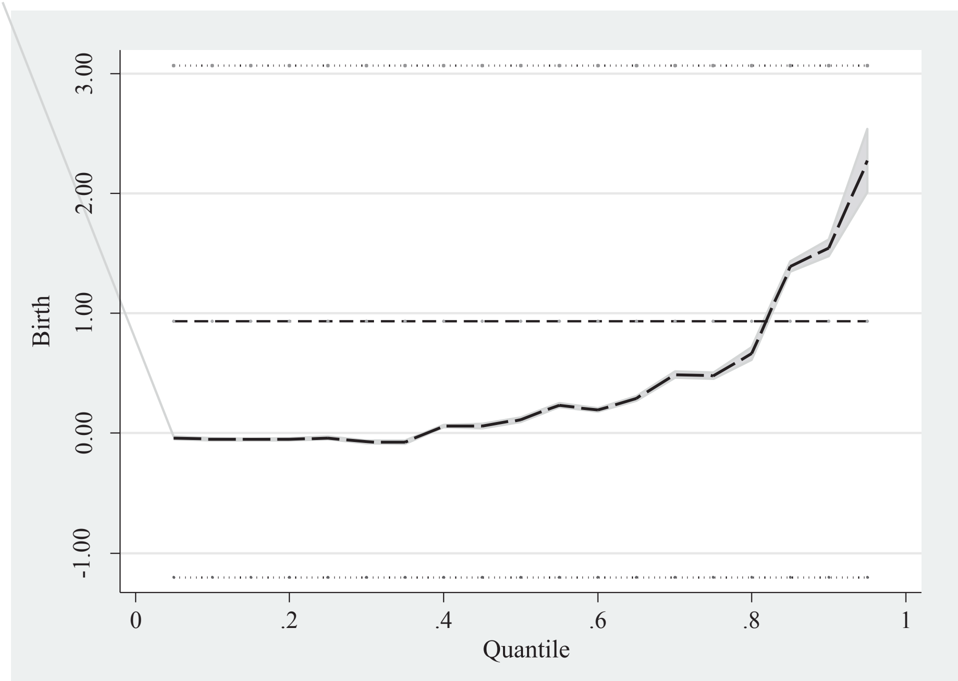

Figure 3. Effect of dummy variable representing the companies in the decline stage throughout the quantiles of the AFE variable between 2008 and 2014

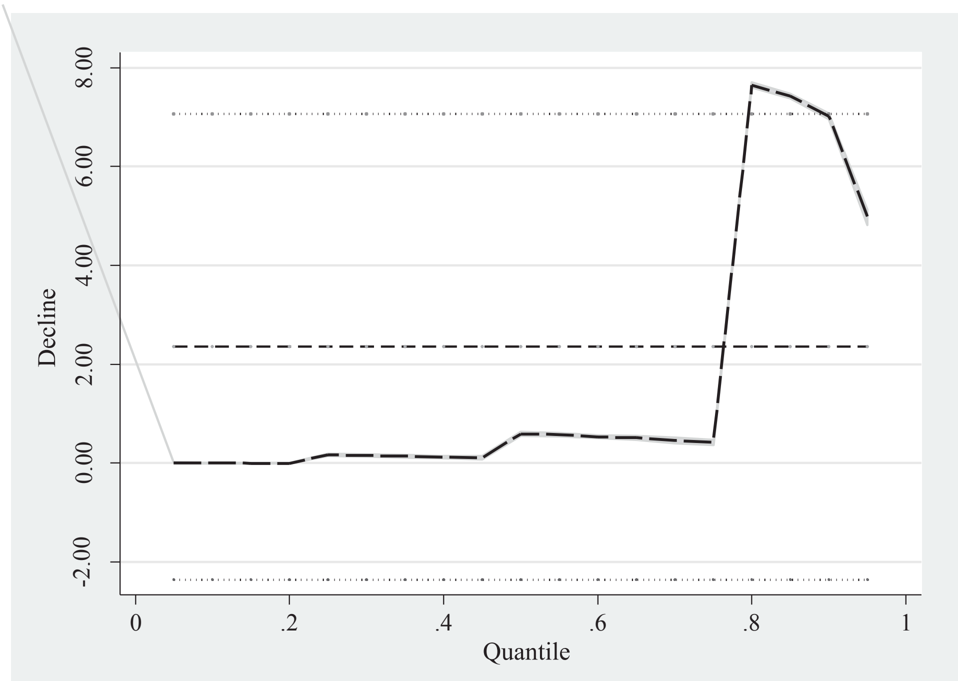

Figure 4. Effect of dummy variable representing the companies in the decline stage throughout the quantiles of the AFE variable between 2008 and 2014

4.4.2 Analysis of unsecured liability effect (financial difficulty)

As mentioned earlier, negative PTB indicates that there are companies with unsecured liabilities due to financial difficulties, which should also affect the analysts' accuracy (Moses, 1990; Behn, Choi & Kang, 2008; Jiang, Habib & Gong, 2015), but which are not directly captured by PTB.

In the sample, only the company Gol Linhas Aéreas Inteligentes SA (Gol) had uncovered liabilities and, consequently, PTB <0, in the year 2014 (final year of the sample). Thus, a dummy variable (PLDESC) was inserted into the quantile regression model in the median, presented in equation (7), now represented by equation (8), to control this specific effect of a company classified as mature, by the cash flow patterns (Dickinson, 2011), but at a high level of financial difficulty that lasts until today (2017).

To gain a more empirical idea of the effect this specific case may have on the results, Gol's AFE was 0.272 (the error was negative, indicating analysts' optimism), while the mean (median) AFE of mature companies corresponded to 0.097 (0.030) and there were 10 analysts following its activities - below the average and median of the mature companies and the average and median of the general sample.

The results remained qualitatively similar with respect to the signs, in that all signs of the variables of interest (including the dummy for Gol in 2014) and of DLOSS were positive and the other control variables presented negative signs, as expected.

Concerning statistical significance, the results of equation (8) corroborate those presented in equation (7), where only birth and decline were statistically significant at 1% and the PLDESC variable was also significant at 1%, but with the highest magnitude among all other variables of interest, with its coefficient equal to 2.766, indicating that Gol's financial difficulty has a significant impact on the AFE, corroborating the previous results that companies in financial difficulties get less accurate forecasts from analysts, or a higher AFE (Behn, Choi & Khang, 2008).

Table 6

Equation that measures the effect of the life cycle stages on the accuracy in the median of the analysts' earnings forecasts between 2008 and 2014

Variables	(8) p.50
PBIRT	2.766***
	(0.017)
DNASCI	0.136***
	(0.09)
DGROW	0.004
	(0.003)
DTURBU	0.008
	(0.007)
DDECLI	0.088***
	(0.018)
DLOSS	0.200***
	(0.005)
QANALYST	-0.001***
	(0.000)
DOPTIM	-0.006
	(0.005)
PTB	-0.001**
	(0.000)
LnTAM	-0.000
	(0.001)
Const	0.037**
	(0.018)
Wald test	1,158.920***
Pseudo R²	0.073
Obs.	713
Sector dummy	YES
Year dummy	YES

Obs.: *, **, *** indicate 10%, 5% and 1% significance. Standard error between brackets.
H0 of the Wald Test: all estimated betas are equal to zero.
$AFE_{it} = \alpha + \beta_1{*}DBIRT_{it} + \beta_2{*}DGROW_{it} + \beta_3{*}DTURBU_{it} + \beta_4{*}DDECLI_{it} + \beta_5{*}DLOSS_{it} + \beta_6{*}QANALYST_{it} + \beta_7{*}DOPTIM_{it} + \beta_8{*}PTB_{it} + \beta_{10}{*}LnSIZ_{it} + \beta_{11\text{-}29}{*}\sum DSECT + \beta_{29\text{-}35}{*}\sum DYEAR + \varepsilon_{it}$
AFE = Absolute Forecast Error, DBIRT = Dummy indicting the Life Cycle Stage of Birth, DGROW = Dummy indicting the Life Cycle Stage of Growth, DTURBU = Dummy indicting the Life Cycle Stage of Turbulence, DDECLI = Dummy indicting the Life Cycle Stage of Decline, DLOSS = Dummy indicating 1 for loss in the year and 0 for the others, QANALYST = Control variable indicating how many analysts monitor the company, DOPTIM = Control dummy for optimistic forecasts, PTB = The Price-to-book is a control variable that measures the relation between the company's market value and equity value, SIZ = Company's total assets and LnSIZ = Natural logarithm of SIZ.

Source: research data

5. Final Considerations

Analysts play a relevant role in the capital market, as they provide additional information to the decision-making process (Sun, Carrete & Tavares, 2017). The internal and external environmental factors that determine the analysts' predictions, however, such as the life cycle stages (birth, growth, maturity, turbulence and decline), are still a gap in the literature though.

The main results of the research pointed out that the analysts' earnings forecasts for companies in the birth and decline stage are the most problematic (statistical significance at 1%), despite controlling for several common factors in the literature on analyst forecast error, and the addition of a dummy variable to control the shortfall as a proxy for financial difficulties.

The control for short-term liabilities, specifically, was significant at the 1% level and had the greatest magnitude among the variables of interest used in this study, indicating their relevance and opening the scope for further research in Brazil on analysts' forecast error for companies in financial difficulties, mainly because the sample of this work did not cover the years referring to the recent Brazilian crisis, which may have affected the financial health of companies and, as one of the consequences, the analysts' forecasts.

Analyzing the signs of prediction errors (optimism and pessimism), the stages of birth, turbulence and decline lead to less optimistic earnings forecasts whereas, for pessimistic predictions, only the decline stage was significant, reducing the pessimistic bias. In short, the decline stage led to less biased projections compared to the other, non-mature stages.

These results remain qualitatively similar despite the inclusion of control for the financial difficulty, with the difference that, for forecasting errors with optimistic bias, firms at birth are significant at 1% and reduce this bias. For forecasting errors with a negative bias, on the other hand, firms at birth increase bias at the 10% level (non-tabulated data).

Therefore, one cannot reject the hypothesis that the companies' life cycle stages affect the analysts' accuracy but, against expectations, the decline stage seems to reduce rather than increase the accuracy, as presented in the research assumptions. When the forecasting bias is analyzed, however, only the decline stage reduced the more pessimistic and optimistic bias in situations of more extreme forecasting errors (p.25 and p.75).

In this scenario, this study may contribute to the still scarce literature at the international level, especially at the Brazilian level, that environmental factors, whether internal or external to companies, such as life cycle stages, in which they already improve the quality of accounting information (Sun, Carrete & Tavares, 2006), are likely to play a determinant role in the accuracy of error forecasts - an important topic in financial market research, as analysts' forecasts and reports are able to influence investors (Sun, Carrete & Tavares, 2017).

It should be emphasized that these results cannot be generalized to the entire reality of Brazilian companies, as analysts did not evaluate all companies listed on the stock market.

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