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Effects of the life cycle stage on errors in earnings forecasts and their value relevance

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Abstract

Objective: This study analyzed the effects of the firm's life cycle stages on analysts' earnings forecast error and on their value relevance.
Method: A sample of companies listed on the Brazilian capital market was analyzed from 2011 to 2022, with data collected from Refinitiv Eikon® and analyzed using regression models estimated using the System Generalized Method of Moments (System GMM).
Results: The results suggest a lower error in earnings per share forecasts in the maturity phase and that investors respond negatively to earnings forecast errors with an optimistic bias, with different intensities depending on the firm's life cycle stage. Therefore, the characteristics of the operating environment and more persistent results of mature companies are associated with lower forecast errors. In addition, the relevance of analysts' forecasts of earnings is significantly associated with share prices.
Contributions: The findings provide useful evidence for different market agents, including investors, financial analysts, and corporate managers. Studies that investigate the value relevance assigned by investors to different types of information - such as analysts' forecast errors - are essential for a better understanding of how the market reacts to signals about the quality of information provided by financial intermediaries, such as financial analysts.
Keywords: Financial Analysts, Analysts' forecasts, Forecast Error, Value Relevance, Firm Life Cycle.

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1 Introduction

Analysts' forecasts, whether related to earnings or future stock prices, play a significant role in the capital market (Covrig & Low, 2005; Healy & Palepu, 2001; Karamanou, 2012; Novaes et al., 2018; Wei & Zhu, 2023). Analyst forecast quality is considered by the literature to be associated with the quality of firms' informational environments (Karamanou, 2012). Specifically, firms with more transparent disclosure practices, stronger corporate governance, and earnings quality provide analysts with better information, enabling more accurate and reliable earnings forecasts (Almeida & Dalmácio, 2015; Dalmácio et al., 2013; Novaes et al., 2018; Oliveira & Coelho, 2018; Pain & Bianchi, 2025; Wei & Zhu, 2023). Consequently, a greater relevance of the analysts' forecasts suggests that these earnings forecasts have high quality (Karamanou, 2012).

Given the important role analysts play in the financial market, the informational relevance of their forecasts (Covrig & Low, 2005; Karamanou, 2012; Tan & Lim, 2007), as well as the impact of analysts' forecast quality on the value relevance of accounting information, have been examined in previous literature (Johnston et al., 2021; Ou & Sepe, 2002; Schaberl, 2016). However, this literature still presents gaps regarding the effects of low-quality forecasts (i.e., a higher level of earnings forecast errors) on stock prices following the announcement of firms' actual earnings. This gap is particularly relevant because optimistic forecast errors may lead investors to form overly positive expectations about firm performance (Abarbanell & Lehavy, 2003; Schaberl, 2016). When actual earnings are disclosed and fall short of these expectations, an adverse market reaction is likely to occur (Jha et al., 2003).

The relationship between analysts' forecast quality and characteristics of the informational environment, financial reporting, accounting standards, and corporate governance has been widely discussed in the literature (Akintoye et al., 2016; Almeida & Dalmácio, 2015; Chen et al., 2017; Dalmácio et al., 2013; Novaes et al., 2018; Oliveira & Coelho, 2018; Pain & Bianchi, 2025; Wei & Zhu, 2023). Understanding the issues that influence analysts' forecast quality is important for assessing the accuracy and usefulness of these forecasts in investment decision-making. Previous studies suggest that greater accuracy tends to increase investor reliance, improve valuation outcomes, corporate investment efficiency, and reduce uncertainty in capital allocation (Choi et al., 2020; Chen et al., 2017; Hashim & Strong, 2018; Simon & Curtis, 2011).

Another key area of accounting research investigates the notion that organizations develop through distinct life cycle stages (LCS) (Al Hadi & Alazzani, 2025; Dickinson, 2011; Habib & Hasan, 2019; Lester et al., 2003; Mikosz et al., 2019; Oliveira & Monte-Mor, 2022; Penrose, 1952). The characteristics of each LCS can influence the analysts' forecast quality and affect how the market responds to lower forecast accuracy, due to differences in high levels of uncertainty and visibility, information asymmetry, financial statement comparability, conservatism, accruals quality, financial distress, and market and financial performance stability (Al Hadi & Alazzani, 2025; Almeida & Kale, 2024; Biswas et al., 2022; Dickinson, 2011; Oliveira & Girão, 2018). Compared to the growth and decline stages, mature firms generally present higher earnings quality (Almeida & Kale, 2024; Biswas et al., 2022; Habib & Hasan, 2019; Lima et al., 2015; Ribeiro et al., 2024), offering better conditions for analysts' forecast predictability.

Prior literature examines LCS from various perspectives. Some studies indicate that the relevance of performance measures varies across LCS (Chen et al., 2010). Other research has explored the relationship between LCS and the value relevance of earnings components (Jenkins et al., 2004), the earnings quality in general (Lima et al., 2015), and exploring specific dimensions such as accruals quality (Almeida & Kale, 2024), conservatism (Meucci et al., 2025), matching quality (Bandeira & Almeida, 2024; Krishnan et al., 2021), earnings management (Bansal, 2024; Jaggi et al., 2022; Ribeiro et al., 2024; Xiu et al., 2022) and financial statement comparability (Biswas et al., 2022). Other aspects associated with LCS have also been studied, including capital structure (Victor et al., 2018), strategy preference (Zheng & Du, 2025), the likelihood of covenant violations (Oliveira & Monte-Mor, 2022), ESG performance (Moreira et al., 2023; Hu et al., 2025), analyst recommendation (Al Hadi & Alazzani, 2025), earnings forecasts accuracy (Oliveira & Girão, 2018), and the difference on value relevance of accounting numbers and analysts' earnings forecasts (Dickinson et al., 2018).

However, the informational role of LCS and its relationship with the relevance of other factors considered in value relevance models remain a fruitful area of future research (Dickinson et al., 2018; Fodor et al., 2024). Moreover, there is a scarcity of studies examining the relationship between LCS and analysts' earnings forecasts (Oliveira & Girão, 2018), as well as the effects of earnings forecast error on stock prices. This study aims to fill these gaps; thus, we analyze the effects of firms' life cycle stages on analysts' earnings forecast errors and their value relevance.

Our analysis was conducted using regression models with the GMM-System estimator, based on a sample of 176 Brazilian listed companies from 2010 to 2022. This sample is particularly relevant, as firm characteristics across different LCS may influence the value relevance of both accounting information and analysts' earnings forecasts, especially in an environment characterized by lower information accuracy, an emerging stock market and higher information asymmetry, such as Brazil (Mikosz et al., 2019; Ferreira et al., 2025). Our main results suggest that firms in the maturity stage present lower earnings per share (EPS) forecast errors, contributing to a reduction in analysts' forecast biases, particularly optimistic biases. Furthermore, the extent of this reduction in forecast errors during the maturity stage is less pronounced for forecasts with an optimistic bias. Additionally, investors react negatively to optimistic forecast errors, with the intensity of their response varying across firms' LCS.

Our study extends previous studies regarding analysts' forecast quality across life cycle stages and the value relevance of analysts' forecasts. While Oliveira and Girão (2018) and Pain and Bianchi (2025) analyze analysts' forecast accuracy across life cycle stages, they do not examine whether these forecast errors are value relevant. Moreover, Dickinson et al. (2018) analyze the value relevance of accounting figures and analysts' forecasts across life cycle stages. However, Dickinson et al. (2018) did not investigate the role of forecast errors or investor reactions to biased forecasts. Our study builds upon and goes beyond their approach by focusing on the market consequences of forecast errors, especially those with an optimistic bias, and by exploring how these effects differ depending on firms' life cycle stage. This perspective allows us to advance the understanding of the informational content of analysts' forecasts and their implications for investor behavior.

Our findings provide useful evidence for different market agents, including investors, financial analysts, and corporate managers. Additionally, studies that investigate the value relevance assigned by investors to different types of information - such as analysts' forecast errors - are essential for a better understanding of how the market reacts to signals about the quality of information provided by financial intermediaries, such as financial analysts (Healy & Palepu, 2001). Beyond reinforcing the informational role of analysts' forecasts, especially in more mature firms, our results contribute to the academic literature by integrating analysts' forecast errors and life cycle theory into value relevance models, advancing the gaps in previous literature (Dickinson et al., 2018; Oliveira & Girão, 2018; Pain & Bianchi, 2025). From a market perspective, the evidence supports the need for greater scrutiny of optimistic forecasts, particularly in mature firms where investors show stronger reactions. Additionally, our findings highlight the relevance of firm-level informational dynamics, suggesting that advances in disclosure quality environment and better analysts' forecast quality could enhance market efficiency, especially in emerging economies such as Brazil.

2 Background and Hypothesis Development

Research on firms LCS examines the organizational changes over time (Frezatti et al., 2017; Lester et al., 2003; Zheng & Gu, 2025). These studies are particularly relevant given that LCS influence decisions regarding financing sources and investment demands and affect firms' operational performance. Additionally, LCS shape the relevance and quality of accounting information, influence investor attraction and decision-making, and impact firm valuation (Almand et al., 2023; Bandeira & Almeida, 2024; Dickinson et al., 2018; Habib & Hasan, 2019; Hasan et al., 2015; Lima et al., 2015; Ribeiro et al., 2024).

Dickinson (2011) suggests a classification methodology for LCS based on cash flow patterns, identifying five stages: Introduction, Growth, Maturity, Shake-Out, and Decline. In contrast, the model designed by Park and Chen (2006) uses the accounting variables from Anthony and Ramesh (1992) and firm age. Park and Chen (2006) propose an aggregate classification index that positions firms relative to their peers across four proxies (capital expenditures, sales growth, dividend payout and firm age). Under this framework, firms can be classified into Growth, Maturity, or Decline stages. We employed this framework in our analysis.

Some characteristics of firms at different LCS may affect the analysts' forecast quality (Oliveira & Girão, 2018). Analysts' forecast quality can be assessed by the proximity between forecasted and actual values, measured through the magnitude of the difference between them, both in absolute terms of reported earnings per share and about stock prices at the end of the fiscal year (Dalmácio et al., 2013; Oliveira & Coelho, 2018).

Firms in the introduction stage aim to establish themselves in the market (Lima et al., 2015), a process that requires significant investments (Dickinson, 2011; Victor et al., 2018), creating more intangible-intensive (Kayo et al., 2006). However, the literature suggests that there is limited publicly available information for analysts and investors and high information uncertainty regarding firms in this stage (Fodor et al., 2024; Oliveira & Girão, 2018), leading to a high level of information asymmetry and, consequently, a higher cost of capital (Hasan et al., 2015; Jaggi et al., 2022; Xie et al., 2022).

The growth stage is characterized by notable increases in production and sales volumes, and firms begin to operate profitably. Firms at this stage usually invest a lot in technology to improve product differentiation. Research suggests that firms in the growth stage still experience high levels of information asymmetry, which creates challenges for analysts who must exert greater effort to enhance the accuracy of their forecasts (Oliveira & Girão, 2018). Corporate policies, including investment decisions, are influenced by LCS (Faff et al., 2016). During the growth phase, firms often have more intangible-intensive assets to establish competitive advantages, while in maturity, the focus is on optimizing existing assets for value creation (Kayo et al., 2006). This context can reflect on analysts' forecast quality, since prior studies highlight that investors' and analysts' only partial recognition of the long-term benefits of these investment decisions leads to the market's difficulty in accurately valuing intangible-intensive firms (Banker et al., 2019).

In the Brazilian context, evidence indicates that investors acknowledge the materiality of assets in firms with intangible intensity as relevant information (Sousa et al., 2024). However, the relationship between intangibility and performance remains uncertain (Carvalho et al., 2023), and some studies suggest a negative association between the level of intangibility and performance persistence (Medeiros & Mol, 2017). Thus, these findings suggest that the mismatching induced by accounting rules on intangible recognition can deepen valuation challenges (King et al., 2024; Sinclair & Keller, 2014) and affect the analysts' forecast quality.

During maturity, firms maximize profit margins, reduce costs, and improve profitability (Lima et al., 2015). At this stage, they operate a more diversified and optimized market value by reducing the cost of capital and risks (Hasan et al., 2015; Lima et al., 2015; Ribeiro et al., 2021). This risk reduction is associated with decreased information asymmetry, increasing analyst coverage and accuracy. Furthermore, firms in this stage operate in a more stable environment and produce more financial statement comparability and persistent earnings (Biswas et al., 2022; Dickinson, 2011; Hasan et al., 2015; Oliveira & Girão, 2018; Xie et al., 2022), which, in turn, enhances the quality of inputs in valuation models (Pimentel & De Aguiar, 2016).

Structural transformations mark the shake-out stage to reposition the firm for restarted growth (Lester et al., 2003). Finally, the decline stage is critical for firm survival, often encouraging firms to adopt a more conservative strategy than earlier stages (Almeida & Kale, 2024; Nizar et al., 2025). Regarding forecast quality, the impact of the shake-out stage remains uncertain. In contrast, analysts may have a greater understanding of firms in decline due to their extended market presence; lower analyst coverage in this stage may result in lower forecast quality (Hasan et al., 2015; Oliveira & Girão, 2018).

Given the above, we expect that the factors described influence LCS and can significantly impact firms' decision-making processes and the ability to estimate their financial results (Al Hadi & Alazzani, 2025; Biswas et al., 2022; Dickinson, 2011). Consequently, information regarding LCS can affect analysts' forecast quality, and the market assigns to these earnings forecasts. This leads to the following hypothesis:

H1: Compared to other life cycle stages, firms in the maturity stage are associated with lower earnings per share forecast errors.

Value relevance refers to the extent to which accounting information is associated with stock prices or returns, indicating its usefulness to investors in valuing firms (Barth et al., 2023). This has been a topic of discussion in accounting literature for several decades (Ball & Brown, 2019; Nicolò et al., 2024), with seminal studies acting as key references in the field (Ohlson, 1995). Value relevance research evaluates how investors perceive accounting information as relevant (Barth et al., 2023; Ball & Brown, 2019). Regarding the information that may be relevant in value relevance models, empirical evidence suggests that LCS provide meaningful insights into firm valuation, influencing the type of information that better explains firms' market value (Dickinson et al., 2018).

Financial analysts play an essential role as spreaders of firms' disclosed information and as evaluators of their present and future performance through earnings forecasts and investment recommendations (Al Hadi & Alazzani, 2025; Dalmácio et al., 2013; Healy & Palepu, 2001; Novaes et al., 2018). Their primary function is forecasting earnings and future stock prices, supplying investors with investment recommendations (Novaes et al., 2018). Given their access to a broad range of information, further book value and earnings, analysts' forecasts on future earnings and growth are expected to provide incremental insights and be considered relevant for firm valuation (Tan & Lim, 2007).

Furthermore, due to their ability to interpret market signals, financial analysts play a relevant role in supporting owners' capital and investors to gain deeper insights into firms' prospects (Chen et al., 2017; Dalmácio et al., 2013; Singla et al., 2023). Analysts' earnings forecasts can offer additional and high-quality information regarding the aspects that contribute to the cross-sectional variation in the relative relevance of earnings and book value in explaining firms' market value (Ou & Sepe, 2002; Schaberl, 2016; Johnston et al., 2021). However, the analysts' forecast quality should be considered, specifically, the earnings forecast error on consensus earnings forecasts and the market reaction when the firm's actual results are announced.

Analysts' forecasts are often positively biased. This bias may diminish the usefulness of their information in investment decision-making, as investors might discount recommendations (Jha et al., 2003). Previous studies indicate that optimism biases in forecasts can lead to negative market reactions, lower credibility in analysts' forecasts, and lead the investors to have more positive expectations about firm performance (Abarbanell & Lehavy, 2003; Schaberl, 2016). Accordingly, the following hypothesis is proposed:

H2: Higher earnings forecast errors with optimistic biases negatively affect firms' stock prices.

The literature documents significant differences in earnings quality across different LCS (Almeida & Kale, 2024; Bandeira & Almeida, 2024; Lima et al., 2015; Jaggi et al., 2022; Ribeiro et al., 2024; Xie et al., 2022). These differences may affect analysts' forecast errors once earnings quality is associated with more accurate forecasts (Akintoye et al., 2016). In contrast, lower-quality information or higher uncertainty levels lead to more significant forecast errors. The accuracy of analysts' earnings forecasts may be influenced by a firm's LCS (Al Hadi & Alazzani, 2025; Oliveira & Girão, 2018; Pain & Bianchi, 2025), influencing investors' responses to such information at different stages. In both the early and final stages, the impact of LCS on analysts' forecast errors tends to be more critical (Al Hadi & Alazzani, 2025; Oliveira & Girão, 2018).

LCS may also affect how the market reacts to different performance measures, which are key indicators of firm value (Habib & Hasan, 2019; Jenkins et al., 2004; Park & Chen, 2006). Moreover, the relevance of earnings components in explaining firm value may vary depending on the LCS (Jenkins et al., 2004). Studies suggest that accounting information and analysts' earnings forecasts are value relevant, but in different ways depending on the LCS (Dickinson et al., 2018). Analysts' forecasts play a relevant role in firm valuation in contexts with restricted financial disclosure (Covrig & Low, 2005).

However, prior literature leaves gaps regarding the value relevance of forecast errors and the effects of LCS on their significance. Since uncertainty levels fluctuate across LCS, analysts' earnings forecast accuracy is expected to vary significantly depending on a firm's LCS. Due to lower uncertainty and lower risks related to earnings forecast quality, firms in the maturity stage are expected to show a less adverse market reaction to forecast errors after announcing actual earnings. This is because smaller errors are expected at this stage. In other words, the reduced quality issues in analysts' forecasts for mature firms, compared to other LCS, may mitigate the association between forecast consensus errors and the market's response to reported earnings. By contrast, in early and final LCS, such as growth and decline, firms face higher uncertainty and less stable performance, making forecast errors more expected and less informative. Therefore, it is possible that the market to react less strongly to lower analysts' forecast quality in these stages. Thus, the following hypothesis is proposed:

H3: The negative effect of optimistic earnings forecast errors on stock prices is mitigated for firms in the maturity stage.

3 Research design

We used a sample of firms listed on B3 S/A Brasil, Bolsa, Balcão (B3) from 2010 to 2022. We obtained the financial, market and earnings per share (EPS) forecast data from the Refinitiv Eikon® database, currently known as LSEG Workspace®. Our analysis period began in 2010, as it was the first year of full IFRS adoption in Brazil. Our initial sample of 1,915 firm-year observations covered by analysts and EPS forecasts available in the Refinitiv Eikon® database. This sample was reduced by excluding firms from the financial industry (16%) due to their specific accounting regulations and capital structure (Hasan et al., 2015; Lima et al., 2015). We also excluded firms with negative shareholders' equity (3%), negative dividend payout (10%), and other missing data, including price close one day after date reporting of the balance sheet (8%), capex (3%), and incorporation date (2%), as well as insufficient observations to estimate industry quintiles (8%) according to the model by Park and Chen (2006). Thus, we obtain a final sample that consists of an unbalanced panel of 956 firm-year observations from 176 companies.

We classified the LCS based on the model by Park and Chen (2006), which categorizes firms into three stages: Growth, Maturity, or Decline. This model follows a method that employs the accounting variables capital expenditures (CEV), sales growth (SG), dividend payout (DP), and firm age (AGE) (Anthony & Ramesh, 1992) to make a classification index that ranks firms compared to their industry peers. According to the model, this index is the basis for assigning firms to LCS categories. Table 1 exhibits proxies used for calculating the model variables.

Table 1

Variables of the Park and Chen (2006) Model for Life Cycle Identification

Variables	Code	Proxies
Capital Expenditures	CEV	$Capex_{it}$ /Total $Equity_{it}$ * 100
Sales Growth	SG	(Net $Sales_{it}$ – Net $Sales_{it-1}$) / Net $Sales_{it-1}$ * 100
Dividend Payout	DP	Dividends $Paid_{it}$ / Net $Income_{it}$ * 100
Firm Age	AGE	Current Year – Year of Incorporation

Source: Adapted by Park and Chen (2006).

Capital expenditures (CEV) and sales growth (SG) reflect a firm's investment and expansion activities, typical of the growth stage in the firm's life cycle (Anthony & Ramesh, 1992; Park & Chen, 2006). Dividend payout (DP) indicates dividend policy, with higher payouts usually seen in mature firms distributing stable earnings, while lower payouts occur in both growth firms reinvesting earnings and declining firms facing financial constraints (Anthony & Ramesh, 1992; Park & Chen, 2006). Additionally, firm age (AGE) serves as a proxy for corporate maturity, as older firms are more likely to be in maturity or decline stages (Faff et al., 2016; Park & Chen, 2006). These variables serve as a basis for categorizing firms based on their life cycle stage. Based on the variables presented in Table 1, the method proposed by Park and Chen (2006) requires firms to be segmented by industry to identify industry quintiles for the four proxies, thereby generating a classification index. The combined score of this index ranges from 4 to 20 points (Park & Chen, 2006). Table 2 shows the categorization method.

Table 2

Classification index score according to the Park and Chen Model (2006)

Quintis		Variáveis			
		DP	SG	CEV	AGE
1st quintile	0% – 20%	5(1)[1]	1	1	5
2nd quintile	20% – 40%	4(2)[1]	2	2	4
3rd quintile	40% – 60%	3	3	3	3
4th quintile	60% – 80%	3	4	4	2
5th quintile	80% –100%	3	5	5	1

Note:[1] Regarding classification, it is important to highlight that a low dividend payout may indicate either high growth opportunities or liquidity problems. However, while a low dividend payout in a firm at the decline stage may be associated with liquidity problems, this is unlikely for a firm that falls within the highest quintile of sales growth or capital expenditures (Park & Chen, 2006). Therefore, if the total score for AGE, SG, and CEV is low (i.e., below 7) and the score for DP is 5 (or 4), an adjustment is made by assigning a score of 1 (or 2) for DP in observations classified as being in the Decline stage (Park & Chen, 2006).

Source: Adapted by Park and Chen (2006).

For each year in analysis, the firms are classified into one of the three ECV stages. Firms with a combined score between 16 and 20 are classified in the Growth stage. Firms with a combined score between 9 and 15 are classified in the Maturity stage. Firms with a combined score between 4 and 8 are classified in the Decline stage (Park & Chen, 2006).

We measured the Forecast Error of Financial Analysts as the difference between the actual earnings per share (EPS actual) and the median consensus of earnings per share forecasts (EPS forecast), scaled by the stock price at the end of the fiscal year. Following previous literature (Chen et al., 2017; Dalmácio et al., 2013; Karamanou, 2012; Oliveira & Girão, 2018), we used the absolute value of forecast errors. To identify forecast bias, we used the actual EPS of firm *i* in year *t* as a benchmark. If the actual ESP is lower than the median EPS forecast, this suggests an optimistic bias in the forecast error. The definitions of all our variables are presented in Table 3.

Table 3
Variable measurements

Variables	Measurement	Authors
	Panel A – Variables to Model 1	
	Dependent	
$\|ERRO\|_{it}$	$\|(EPS^{actual} - EPS^{forecast})\| / P_{it-1}$	Chen et al., (2017), Chourou et al. (2021), Dalmácio et al., (2013), Karamanou (2012), and Oliveira and Girão (2018)
	Independent	
$Maturity_{it}$	Dummy that assumes a value equal to 1 for firms in Maturity stage and 0 otherwise	Lima et al. (2015), Park and Chen (2006), and Ribeiro et al. (2024)
$Optm_{it}$	Dummy that assumes a value equal to 1 when the forecast is optimistic and 0 otherwise	Almeida and Dalmácio (2015) and Dalmácio et al., (2013)
$Disp_{it}$	Analyst forecast dispersion, measured as the standard deviation of the forecast earnings per share (EPS)	Dalmácio et al., (2013) and Karamanou (2012)
$Size_{it}$	Natural logarithms of total assets	Brown, (1997), Dalmácio et al., (2013) and Shan et al. (2023)
$Coverage_{it}$	The natural logarithm of the number of analysts following the firm during the year.	Almeida and Dalmácio (2015), Brown, (1997), Chourou et al. (2021), and Shan et al. (2023)
$Market\text{-}to\text{-}Book_{it}$	Ratio of market value and book value of firm i at time t	Almeida and Dalmácio (2015) and Dalmácio et al., (2013)
$Loss_{it}$	Dummy that assumes a value equal to 1 when actual result for the company is a loss and 0 otherwise	Almeida and Dalmácio (2015), Chourou et al. (2021), and Dalmácio et al., (2013)
	Panel B – Variables to Model 2	
	Dependent	
P_{it+1}	Price per share after the reporting of the balance sheet	Ohlson (1995)
	Independent	
$BVPS_{it}$	Book value of equity per share, subtracted from net income for period t	Ohlson (1995)
EPS_{it}	net income per share	Ohlson (1995)
$\|ERRO\|_{it}$	$\|(EPS^{actual} - EPS^{forecast})\| / P_{it-1}$	Chen et al., (2017), Chourou et al. (2021), Dalmácio et al., (2013), Karamanou (2012), and Oliveira and Girão (2018)

Source: Own elaboration.

We test our hypotheses using the econometric models presented in Equations 1 and 2. The first model aims to identify the effects of the firm's life cycle on analysts' forecast errors while controlling for other determinants highlighted in the literature (Almeida & Dalmácio, 2015; Dalmácio et al., 2013; Karamanou, 2012; Novaes et al., 2018; Oliveira & Girão, 2018; Oliveira & Coelho, 2018). This model includes fixed effects for industry, as the literature suggests that $|ERRO|_{it}$ tends to vary across industry (Brown, 1997). Additionally, interactions between the maturity stage and the type of forecast bias with some of these determinants were incorporated into the model. The variable Maturity is a dummy that equals 1 for firm-year observations classified in the maturity stage and 0 otherwise. Therefore, the coefficient $\beta1$ captures the main effect of being in the maturity stage on earnings forecast errors. A negative and statistically significant $\beta1$ would support H1, indicating that mature firms tend to have lower forecast error magnitudes.

To test H2 and H3, we use the model presented in Equation (2), which is an adaptation of Ohlson's (1995) model, designed to evaluate the influence of analysts' forecast errors on stock prices. This model is also estimated separately by LCS to evaluate the differential effects across LCS. The model also includes the interaction term $Optim_{it} * |ERRO|_{it}$, which captures whether the market reacts differently to forecast errors when forecasts are optimistically biased. H2 is tested by examining the coefficient of this interaction term. A negative and significant coefficient would indicate that stock prices respond more negatively to forecast errors when they are optimistic bias, supporting the hypothesis that optimism bias amplifies the adverse valuation effect of lower analysts' forecast quality. H3 is evaluated by estimating the model separately for firms in the maturity stage and those in other life cycle stages. If the negative impact of optimistic forecast errors on stock prices is less pronounced or insignificant in the maturity sub-sample compared to other stages, this would support the hypothesis that maturity mitigates the market penalty associated with optimistic forecast bias.

$$\begin{gathered}|ERRO|_{it} = \beta_0 + \beta_1 Maturity_{it} + \beta_2 Optim_{it} + \beta_3 (Optim_{it} * Maturity_{it}) + \beta_4 Disp_{it} + \\ \beta_5 (Optim_{it} * Disp_{it}) + \beta_6 (Optim_{it} * Maturity_{it} * Disp_{it}) + \beta_7 Size_{it} + \beta_8 (Optim_{it} * Size_{it}) + \\ \beta_9 Coverage_{it} + \beta_{10} (Optim_{it} * Coverage_{it}) + \beta_{11} Market\text{-}to\text{-}Book_{it} + \\ \beta_{12} (Optim_{it} * Market\text{-}to\text{-}Book_{it}) + \beta_{13} Loss_{it} + \gamma Year_t + \delta Industry_i + \varepsilon_{it}\end{gathered} \tag{1}$$

$$P_{it+1} = \beta_0 + \beta_1 BVPS_{it} + \beta_2 EPS_{it} + \beta_3 |ERRO|_{it} + \beta_4 Optim_{it} + \gamma Year_t + \delta Industry_i + \varepsilon_{it} \tag{2}$$

To enhance the robustness of the results, we employed different estimation approaches in the estimation of Equation 1. First, we estimated the model using OLS with industry and year fixed effects, controlling for unobservable heterogeneity across industries and time. Second, we used quantile regressions (Q25, Q50, and Q75) to capture potential heterogeneity along the conditional distribution of forecast errors, allowing us to assess whether the effects of the life cycle stage differ across firms with lower, median, and higher forecast errors. Finally, we estimated our models using the two-step System GMM (Generalized Method of Moments) estimator(Arellano & Bover, 1995; Blundell & Bond, 1998), aiming to mitigate potential endogeneity issues. Under the System GMM estimator, lagged values of the variables are used as instruments, allowing for better handling of endogeneity issues and delivering more consistent parameter estimates. We assessed the validity of these estimates using the significance of first- and second-order autocorrelations and the Hansen test, whose null hypothesis states that the instruments used are valid and exogenous. In the model presented in Equation 2, we report only the results obtained using the System GMM approach.

4 Empirical results

4.1 Descriptive statistics

Table 4 presents descriptive statistics for the variables used in analyses of the determinants and value relevance of analysts' forecast quality. Panel A shows statistics for the full sample of 956 firm-year observations. In Panels B and C, we split our sample, showing results for observations with optimistic and pessimistic biases, respectively. In Panels D and E, in turn, split the sample according to life cycle stage, distinguishing between firms in the Maturity stage and those in other stages.

Table 4
Descriptive statistics

Variables	Mean	Standard deviation	Minimum	p25	Median	p75	Maximum
Panel A – Total Sample (956 Observations)							
$\|ERRO\|_{it}$	0,062	0,102	0,001	0,013	0,029	0,067	0,694
$Disp_{it}$	0,022	0,024	0,000	0,005	0,014	0,029	0,137
$Size_{it}$	22,123	2,039	8,180	21,237	22,200	23,305	26,753
$Coverage_{it}$	1,947	0,588	0,693	1,609	2,079	2,398	2,773
$Market\text{-}to\text{-}Book_{it}$	2,157	2,184	0,000	0,843	1,439	2,647	13,258
$Loss_{it}$	0,031	0,174	0	0	0	0	1
P_{it+1}	18,646	29,895	1,214	6,576	11,845	19,533	250,306
$BVPS_{it}$	24,333	96,973	0,232	3,742	7,131	12,529	764,017
EPS_{it}	2,287	7,497	-3,166	0,387	0,892	1,763	67,357
Panel B – Forecast Errors with Optimistic Bias (701 Observations)							
$\|ERRO\|_{it}$	0,057	0,094	0,001	0,013	0,028	0,060	0,694
$Disp_{it}$	0,021	0,025	0,000	0,005	0,014	0,028	0,137
$Size_{it}$	22,142	1,833	8,773	21,239	22,19	23,259	26,583
$Coverage_{it}$	1,984	0,563	0,693	1,609	2,079	2,398	2,773
$Market\text{-}to\text{-}Book_{it}$	2,369	2,369	0,000	0,872	1,542	3,049	13,258
Lossit	0,043	0,203	0	0	0	0	1
Panel C – Forecasting Errors with Pessimistic Bias (255 Observations)							
$\|ERRO\|_{it}$	0,075	0,119	0,001	0,011	0,036	0,084	0,694
$Disp_{it}$	0,023	0,024	0,000	0,005	0,015	0,032	0,129
$Size_{it}$	22,072	2,524	8,180	21,212	22,251	23,416	26,753
$Coverage_{it}$	1,843	0,643	0,693	1,386	2,079	2,398	2,773
$Market\text{-}to\text{-}Book_{it}$	1,575	1,413	0,000	0,775	1,192	1,857	10,207
$Loss_{it}$	0	0	0	0	0	0	0
Panel D – Maturing Firms (693 Observations)							
$\|ERRO\|_{it}$	0,055	0,094	0,001	0,012	0,027	0,059	0,694
$Disp_{it}$	0,020	0,023	0,000	0,005	0,013	0,027	0,137
$Size_{it}$	22,331	1,737	8,180	21,351	22,288	23,459	26,753
$Coverage_{it}$	1,953	0,594	0,693	1,609	2,079	2,398	2,773
$Market\text{-}to\text{-}Book_{it}$	2,276	2,279	0,000	0,876	1,508	2,815	13,258
$Loss_{it}$	0,022	0,146	0	0	0	0	1
Panel E – Firms in the other stages (263 Observations)							
$\|ERRO\|_{it}$	0,079	0,118	0,001	0,017	0,04	0,084	0,694
$Disp_{it}$	0,026	0,028	0,000	0,007	0,018	0,035	0,137
$Size_{it}$	21,575	2,603	8,773	20,811	21,846	22,786	26,583
$Coverage_{it}$	1,931	0,572	0,693	1,386	2,079	2,398	2,773
$Market\text{-}to\text{-}Book_{it}$	1,843	1,878	0,000	0,650	1,267	2,297	13,258
$Loss_{it}$	0,057	0,232	0	0	0	0	1

Note: We winsorized all variables in the 1% and 99% percentiles.

Source: Own elaboration.

In Table 4, the variable $|ERRO|_{it}$ denotes the median error of the consensus earnings forecasts. The mean (and median) for the full sample, shown on Panel A, is approximately 0.062. As indicated in Panels B and C, there is a tendency for analysts to have an optimistic bias, with more than 70% of the sample following this trend, in line with findings from previous studies (Dalmácio et al., 2013; Healy & Palepu, 2001; Novaes et al., 2018; Oliveira & Coelho, 2018; Oliveira & Girão, 2018; Ou & Sepe, 2002). However, on average, the forecast errors tend to be greater when the bias is pessimistic.

Panels D and E show the descriptive statistics for firms in the Maturity stage and those in other stages, respectively. A lower average magnitude of forecast errors and a lower dispersion in forecasts are observed for firms in the Maturity stage compared to other LCS (Oliveira & Coelho, 2018; Pain & Bianchi, 2025). Additionally, firms in Maturity present lower variability in size and a greater difference between market value and book value than firms in other LCS.

Table 5 presents the results of the Mann-Whitney U tests examining mean differences between firms in the Maturity stage and those in other stages, as well as between optimistic and pessimistic forecast biases, for the variables ERRO, Disp, Size, Coverage, and Market-to-Book. The results suggest statistically significant differences for these variables across LCS, except for Coverage. This finding aligns with Moreira et al. (2023), who did not find significant differences in analyst coverage across life cycle stages. This suggests that firms in the maturity stage exhibit lower forecast error magnitudes and less dispersion among analysts' forecasts, indicating higher earnings forecast quality in this stage. This finding supports the idea that, compared to other stages characterized by higher levels of risk and informational uncertainty, firms in the Maturity stage present more predictable results and lower levels of information asymmetry (Dickinson, 2011; Hasan et al., 2015; Oliveira & Girão, 2018; Pain & Bianchi, 2025; Xie et al., 2022). Furthermore, there is a statistically significant negative difference in the magnitude of optimistic forecast errors compared to pessimistic ones.

Table 5

Testing of mean difference between LCS and by type of bias of forecast error

Variables	**Maturity versus other stages**		**Optimistic versus pessimistic bias**	
	Diferença de Média	***p-value***	**Diferença de Média**	***p-value***
$\|ERRO\|_{it}$	-0,024***	0,000	-0,018***	0,006
$Disp_{it}$	-0,006***	0,000	-0,002	0,110
$Size_{it}$	0,756***	0,000	0,069	0,320
$Coverage_{it}$	-0,021	0,306	0,141***	0,000
$Market\text{-}to\text{-}Book_{it}$	0,433***	0,003	0,793***	0,000

Note: ***, ** and * represent a statistical significance of 1%, 5% and 10%, respectively.

Source: Own elaboration.

4.2 Main findings

Table 6 shows the main findings from the analysis of the effects of the maturity stage on analysts' earnings forecast errors. This analysis aims to assess the impact of the LCS on the analysts' earnings forecast quality.

Table 6

Life Cycle effect on Analysts' Forecast Error

Dependent variable: $ERRO_{it}$	FE	Q25	Q50	Q75	GMM
$Maturity_{it}$	-0.0367**	-0.0054	-0.0220**	-0.0161	-0.022***
	(0.017)	(0.007)	(0.010)	(0.021)	(0.004)
$Optim_{it}$	-0.1746***	0.0183	-0.1208***	-0.2548***	-0.123***
	(0.065)	(0.026)	(0.037)	(0.077)	(0.007)
$Maturity_{it}$ * $Optim_{it}$	0.0490**	0.0065	0.0253**	0.0191	0.034***
	(0.020)	(0.008)	(0.011)	(0.024)	(0.003)
$Disp_{it}$	0.8613*	0.8278***	0.8412***	0.6320	0.246***
	(0.491)	(0.197)	(0.287)	(0.591)	(0.075)
$Optim_{it}$ * $Disp_{it}$	1.9321***	0.8928***	1.5846***	2.7562***	2.611***
	(0.206)	(0.080)	(0.117)	(0.242)	(0.050)
$Maturity_{it}$ * $Disp_{it}$	1.1582**	-0.0861	0.6755**	1.8333***	1.808***
	(0.532)	(0.214)	(0.312)	(0.642)	(0.094)
$Optim_{it}$ * $Maturity_{it}$ * $Disp_{it}$	-0.2989	-0.1223	-0.4261***	-0.8288**	-0.967***
	(0.280)	(0.113)	(0.165)	(0.339)	(0.109)
$Size_{it}$	-0.0125***	-0.0011	-0.0062***	-0.0110***	-0.008***
	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)
$Optim_{it}$ * $Size_{it}$	-0.0077***	-0.0024***	-0.0024**	-0.0013	-0.004***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
$Coverage_{it}$	-0.0243**	-0.0060	-0.0087	-0.0093	-0.029***
	(0.010)	(0.004)	(0.006)	(0.012)	(0.002)
$Optim_{it}$ * $Coverage_{it}$	-0.0247***	-0.0016	-0.0067*	-0.0163**	-0.043***
	(0.006)	(0.002)	(0.004)	(0.007)	(0.003)
$Market\text{-}to\text{-}Book_{it}$	-0.0060	0.0007	-0.0031	-0.0040	-0.003***
	(0.004)	(0.002)	(0.002)	(0.005)	(0.001)
$Optim_{it}$ * $Market\text{-}to\text{-}Book_{it}$	0.0014	0.0004	0.0002	-0.0001	0.001
	(0.002)	(0.001)	(0.001)	(0.002)	(0.000)
$Loss_{it}$	0.1496***	0.0604***	0.0587***	0.2703***	0.180***
	(0.016)	(0.006)	(0.009)	(0.019)	(0.008)
Constant	0.3939***	0.0409**	0.1955***	0.3287***	0.259***
	(0.050)	(0.019)	(0.028)	(0.058)	(0.023)
Industry-fixed effect	Yes	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	956	956	956	956	956
Firms	176	176	176	176	176
Wald chi^2 *(p-value)*	-	-	-	-	0.000
F test *(p-value)*	0.000	-	-	-	
Test of Arellano-Bond – AR1 *(p-value)*	-	-	-	-	0.019
Test of Arellano-Bond – AR2 *(p-value)*	-	-	-	-	0.237
Hansen Test *(p-value)*	-	-	-	-	0.762

Note: FE denotes the results estimated using OLS regression, controlling for year and industry fixed effects. Q1, Q2, and Q3 denote the results estimated using quantile regression on the 25th, 50th, and 75th percentiles, respectively. ***, ** and * represent a statistical significance of 1%, 5% and 10%, respectively. Standard error in parentheses. All continuous variables were winsorized at the 1% and 99% percentiles.

Source: Own elaboration.

First, we explored the results estimated using fixed effects (FE) in Table 6. These findings indicate a statistically significant negative coefficient for the maturity dummy, confirming that firms in the maturity stage exhibit lower forecast errors. The optimism dummy also shows a negative and significant coefficient, suggesting that optimistic forecasts are associated with lower errors than pessimistic forecasts. However, the interaction between maturity and optimism presents a positive coefficient, which indicates that the magnitude of optimistic forecast errors increases for firms in the maturity stage.

Second, we explored the effect of the conditional distribution of the dependent variable using quantile regressions (Q25, Q50, and Q75), which reveals important heterogeneity across the distribution of forecast errors. At Q25, the maturity dummy is not statistically significant, suggesting that the effect of maturity is less evident among firms with lower forecast errors. At Q50, maturity becomes negative and significant, and the effect persists at Q75, although with a lower magnitude. These findings indicate that the maturity stage reduces forecast errors, particularly in the middle and upper parts of the distribution, suggesting that the benefits of reduced information asymmetry and greater earnings persistence of the mature stage (Dickinson, 2011; Hasan et al., 2015; Oliveira & Girão, 2018) are important in contexts where forecast errors are larger.

Finally, the main results in Table 6, using the GMM approach, present a statistically significant negative average effect of the maturity dummy. This negative relationship with the forecast error measure reinforces that firms in the Maturity stage exhibit lower forecast errors. The optimism dummy also presents a statistically significant negative coefficient, suggesting that forecast errors with an optimistic bias tend to be lower than those with a pessimistic bias. This finding aligns with prior studies, suggesting that optimistic forecasts are more accurate on average (Almeida & Dalmácio, 2015).

However, the interaction between the maturity and optimism dummies shows a positive coefficient, lower than the optimism dummy alone. This finding suggests that the magnitude of optimistic forecast errors increases for firms in the maturity stage. This effect can be explained by the expectations of higher profitability and result persistence during this stage (Dickinson, 2011; Lima et al., 2015), as well as the tendency for firms to publish more favorable information (Oliveira & Monte-Mor, 2022) and for financial analysts to exhibit an optimistic bias (Dalmácio et al., 2013; Healy & Palepu, 2001; Novaes et al., 2018; Oliveira & Coelho, 2018; Oliveira & Girão, 2018; Ou & Sepe, 2002).

Overall, the analysts' forecasts for firms in the maturity stage are of higher quality, as indicated by the lower magnitude of their forecast errors. This finding supports the expectation that reduced information asymmetry and increased result persistence in the maturity stage (Dickinson, 2011; Hasan et al., 2015; Oliveira & Girão, 2018; Pain & Bianchi, 2025) lead to lower forecast errors and a smaller magnitude of optimistic forecast errors. Therefore, the first hypothesis (H1) is not rejected, as the more stable operating environment and the greater result persistence of firms in the maturity stage are associated with lower forecast errors (Dickinson, 2011; Hasan et al., 2015; Oliveira & Girão, 2018; Pain & Bianchi, 2025).

Regarding the control variables, we observed a positive relationship between the loss dummy and $|ERRO|_{it}$, suggesting that firms with negative earnings often show larger forecast errors. Thus, our results corroborate previous findings, demonstrating a negative relationship between firm losses and forecast accuracy (Dalmácio et al., 2013; Oliveira & Girão, 2018).

A positive coefficient is observed concerning the analysts' forecast dispersion, indicating that higher dispersion is associated with larger forecast errors. This finding supports previous evidence about the negative effect of forecast dispersion on analysts' earnings forecast quality (Dalmácio et al., 2013). This effect is more pronounced for firms in the maturity stage and with optimistic forecast errors, as reflected in the interaction coefficients between the maturity dummy, the dispersion variable, and the optimism dummy. As expected from prior literature, analyst coverage shows a statistically significant negative coefficient (Dalmácio et al., 2013; Oliveira & Girão, 2018). Additionally, greater analyst coverage is associated with a more pronounced reduction in the magnitude of optimistic forecast errors.

Table 7 presents the main results regarding the value relevance model. We aimed to analyze the effects of earnings forecast errors on the market response through stock prices at the earnings announcement date. The results are reported for three value relevance models: in Column 1, the variable $|ERRO|_{it}$ and the optimism dummy are added to the model proposed by Ohlson (1995), while in Columns 2 and 3, this model is estimated separately for firms in the maturity stage and those in other stages, respectively. These results were obtained using the GMM-System estimator (Arellano & Bover, 1995; Blundell & Bond, 1998).

Table 7

Effect of maturity stage on the Value Relevance of Forecasting Error

Dependent Variable: P_{t+1}	Full sample	Maturity	OtherStages
$BVPS_{it}$	0,035***	-0,168	0,132***
	(0,006)	(0,171)	(0,011)
EPS_{it}	1,744***	0,818**	1,442***
	(0,102)	(0,390)	(0,153)
$\|ERRO\|_{it}$	-9,419	-9,032	-42,142**
	(7,350)	(14,995)	(17,075)
$Optim_{it}$	9,892***	7,823***	2,502**
	(2,089)	(2,099)	(0,980)
$Optim_{it}$ * $\|ERRO\|_{it}$	-69,589***	-100,244***	16,440
	(10,659)	(33,146)	(24,327)
Constant	13,234***	24,102***	15,803***
	(3,137)	(5,649)	(5,641)
Industry-fixed effect	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes
Observations	956	693	263
Firms	176	157	111
Wald chi^2 *(p-value)*	0,000	0,000	0,000
Test of Arellano-Bond – AR1 *(p-value)*	0,005	0,043	0,003
Test of Arellano-Bond – AR2 *(p-value)*	0,551	0,920	0,300
Hansen Test *(p-value)*	0,266	0,750	0,273

Note: ***, ** and * represent a statistical significance of 1%, 5% and 10%, respectively. Standard error in parentheses. All continuous variables were winsorized at the 1% and 99% percentiles.

Source: Own elaboration.

For the results of the general model, shown in Table 7 and used in the analysis of the second hypothesis (H2), the traditional variables of the value relevance model, following Ohlson's (1995) model, exhibit a positive and statistically significant relationship with stock prices, as expected (Ohlson, 1995; Tan & Lim, 2007). Regarding the additional variables included in the model (ESP forecast error and the optimism dummy), a positive and significant coefficient is observed for the optimism dummy, suggesting that, on average, firms for which analysts make optimistic forecast errors have higher prices than those with pessimistic biases.

When analyzed in isolation, the variable $|ERRO|_{it}$ does not exhibit a statistically significant coefficient. However, when interacting with the Optimism dummy, we observed a negative and significant coefficient, suggesting that, on average, the market reacts negatively only to optimistic bias in analysts' consensus forecast errors at the announcement date. These findings indicate the informational relevance of analysts' forecasts, as forecast errors, at least those with an optimistic bias, are significantly associated with stock prices (Covrig & Low, 2005; Healy & Palepu, 2001; Karamanou, 2012; Tan & Lim, 2007). However, the Brazilian capital market is characterized by less accurate information and higher information asymmetry (Mikosz et al., 2019), which may explain why pessimistic forecast errors are not priced. In principle, one might expect such errors to have a positive effect on stock prices following the announcement of the report of annual results.

Some interesting findings emerge when the sample is separated into mature firms and those in other stages. Considering the baseline variables ($BVPS_{it}$ and EPS_{it}) for the sample of mature firms, earnings exhibit statistically significant results, suggesting greater value relevance of earnings for firms in this stage. Additionally, a stronger adverse market reaction to optimistic forecast errors is observed. These results provide important evidence regarding H3, as we expected that the negative effect of optimistic bias of earnings forecast errors on stock prices would be mitigated for firms in the maturity stage. However, contrary to the expectation, the coefficient for the interaction term remains significantly negative in the maturity subsample (-100.24^{***}), and even more negative than in the full sample. In contrast, this interaction becomes statistically insignificant in the group of firms in other life cycle stages. These results suggest that, rather than mitigating the market penalty, the maturity stage amplifies the adverse effect of optimistic forecast errors on stock prices. Therefore, H3 is not supported.

Additionally, these findings align with evidence that firms' LCS affect how the market responds to different performance measures (Habib & Hasan, 2019; Jenkins et al., 2004; Park & Chen, 2006) and support the literature linking the life cycle to the value relevance of earnings components (Jenkins et al., 2004). However, given the lower uncertainty and higher quality of earnings forecasts at this stage, a weaker market reaction to analysts' consensus forecast errors would have been expected. A possible explanation for this stronger reaction is that, at this stage, investors place greater weight on analysts' information and earnings rather than on the book value of equity (Dickinson et al., 2018; Jenkins et al., 2004). Consequently, when reported earnings fall short of the analysts' consensus EPS estimate, the market reaction tends to be more pronounced.

For firms in other LCS, which are generally associated with higher levels of uncertainty and lower analysts' forecast quality (Almeida & Kale, 2024; Fodor et al., 2024; Hasan et al., 2015; Oliveira & Girão, 2018), the market reacts negatively to earnings forecast errors regardless of analysts' bias, though with lower intensity. This finding may also be explained by the reduced informational relevance of analysts' forecasts in the early and final stages of the life cycle (Dickinson et al., 2018), where the earnings quality tends to be lower and earnings outcomes are more uncertain (Almeida & Kale, 2024; Biswas et al., 2022; Habib & Hasan, 2019; Lima et al., 2015; Ribeiro et al., 2024). In these stages, forecast errors are more expected and less informative, given the greater volatility in performance and higher risk levels. Consequently, the market reacts less intensely to forecast errors, as opposed to the maturity stage, where higher earnings quality and greater predictability amplify the market's sensitivity to deviations in analysts' expectations (Al Hadi & Alazzani, 2025; Almeida & Kale, 2024; Biswas et al., 2022; Dickinson, 2011; Oliveira & Girão, 2018). Therefore, LCS provide relevant information that affects the analysts' forecast quality and how the market responds to lower analysts' forecast quality.

5 Conclusion

In this study, we analyzed the effects of LCS on analysts' earnings forecast errors and their value relevance. We aimed to understand the impact of the firm's life cycle - particularly the Maturity stage - on analyst forecast quality. Additionally, we examined the effects of analyst forecast quality on stock prices by the firm's LCS. Our results demonstrate that firms in the Maturity stage are associated with lower earnings per share (EPS) forecast errors. Our findings align with the previous literature, which suggests a reduction in information asymmetry and greater earnings persistence during the Maturity stage (Dickinson, 2011; Hasan et al., 2015; Oliveira & Girão, 2018). Additional analysis, including an interaction term with a dummy variable for forecast bias, shows important insights. Specifically, the attenuation of forecast errors during Maturity is fewer forecast errors with an optimistic bias. Thus, the characteristics of the Maturity stage positively affect analyst forecast quality, mainly by reducing pessimistic bias, supporting our first hypothesis (H1).

Regarding the value relevance model, higher earnings forecast errors are associated with an adverse market reaction to firms' earnings announcements, but only for earnings forecasts with an optimistic bias, as stated in H2. Moreover, this effect is predominant among firms in the Maturity stage. Therefore, the results suggest that investors react negatively to analysts' optimistic forecast errors and that this reaction varies depending on the firm's life cycle stage. Concerning H3, our results do not indicate that the maturity stage mitigates the adverse market reaction to optimistic forecast errors. In fact, the effect is stronger at this stage. These findings suggest that the higher credibility attributed to analysts' forecasts at the maturity stage increases the market reaction to deviations, reinforcing the important informational role of LCS.

These findings provide important implications. For academic researchers, we extend the literature by jointly examining analysts' earnings forecast errors and their value relevance across LCS, an area still underexplored in emerging markets. In addition, our findings highlight that the informational environment of the maturity stage enhances the analysts' forecast quality but also increases the market's reaction to biased forecasts. For investors, our results underscore the importance of exercising greater caution when interpreting optimistic forecasts in mature firms. For financial analysts and corporate managers, our findings reinforce the importance of transparency and accuracy in forecast communication. Finally, these findings offer regulatory implications by showing how forecast biases can affect market reactions, especially in economies characterized by lower information accuracy and higher asymmetry, such as Brazil.

Furthermore, the generalizability of these findings should be interpreted with caution, as certain sample restrictions were necessary due to data availability for constructing some variables and the lack of EPS forecast data. Not all companies listed on B3 have earnings forecast data available in the Refinitiv Eikon® database. Additionally, our results are subject to the limitations of the firm life cycle classification model in accurately capturing a firm's development stage. Previous literature highlights that identifying a firm's LCS is a complex task with inherent limitations (Dickinson, 2011; Dickinson et al., 2018; Frezatti et al., 2017; Habib & Hasan, 2019). Future research could explore these limitations further and analyze the impact of the firm's life cycle on the value relevance of other measures of information quality provided by financial analysts. Other research avenues include analyzing how specific aspects of the informational environment, such as the level of earnings quality, financial statement comparability, or earnings management, may influence the value relevance of analysts' forecast errors.

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